The Impacts of Asian Immigrants on School Performance and Local Housing Markets in the US*

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Abstract

As the fastest-growing racial or ethnic group in the US, Asian immigrants have significantly impacted local housing markets. This paper investigates the effects of Asian immigrants' influx on housing price appreciation, decomposing it into education and non-education channels, using county-level data from 2009 to 2018. To address endogeneity issues, we employ instrumental variables for Asian immigrants' location choices and school performance outcomes. Our findings reveal that housing price appreciation due to Asian immigrants is mainly concentrated in the counties with the top 5% highest Asian population share. An increased Asian students presence leads to higher performance (in terms of test scores) for students of other races. Approximately one-third of housing price appreciation driven by a higher Asian share is attributed to improvements in school performance in neighborhoods. This study highlights a significant channel through which Asian immigration affects the US local housing markets.

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1 Introduction

The 21st century has witnessed a significant increase in the Asian population in the United States. This diverse group, made up of individuals of Chinese, Indian, Filipino, Vietnamese, Korean, Japanese and other origins, has had a transformative impact on the socioeconomic landscape of American cities. As the fastest-growing racial or ethnic group among eligible US voters in 2020[1], Asians have attracted attention from urban policymakers and economists alike. However, despite the growing prominence of this population, the literature on the multifaceted effects of Asian immigration on American cities remains limited.

The current consensus related to Asian immigrants in the housing market is that capital inflow from Asian countries, particularly Chinese housing purchases, has pushed up housing prices in US and Canada (Pavlov and Somerville (2020), Li et al. (2020), Gorback and Keys (2020)). This is in contrast to the literature on immigration, which often views neighborhoods with growing immigrant populations as 'relatively less desirable to natives,' (Saiz and Wachter (2011)), which may result in native flight and slower housing price appreciation in the neighborhood. Despite this observation on the aggregate effect, the underlying channels through which the influx of Asian immigrants in the US since the 2000s have changed the local characteristics and led to higher housing prices still remain unclear.

This paper investigates the housing price appreciation effects of Asian immigrants and the underlying channels driving these effects, particularly focusing on the role of school performance. We bridge the literature gap by examining how the inflow of Asian immigrants impacts local amenity quality and housing market outcomes. Asian preferences for certain amenities may differ from other ethnic groups, leading to endogenous changes in those local amenities as Asian immigrant share increases. Education, a top priority for Asian parents, is a key local amenity affected by their arrival. An influx of children from education-focused families may alter local educational outcomes and have spillover effects on other racial and ethnic groups (Hoxby (2000); Boustan et al. (2023)), eventually influencing housing prices. We explore school performance outcomes as a crucial channel to understand the dynamics triggered by Asian immigration inflow.

Using county-level outcomes from 2009 to 2018, this study examines the association be-

[1]Source: Key facts about Asian Americans — Pew Research Center, April 29, 2021. Accessed on 7/10/2021. Source: `https://www.pewresearch.org/fact-tank/2021/04/29/key-facts-about-asian-americans/`

tween a higher Asian population and housing prices, focusing on the impact of education amenities on this relationship. Specifically, we quantify how much of these endogenous changes in school performance are further capitalized into local housing markets as a percentage of housing price appreciation. We first quantify the impact of Asian immigrants on county-level school performance. Then, in a separate model, we estimate the capitalization rate of school performance improvement in housing prices at the county-level. Reconciling these two separate estimates enables us to decompose the housing price appreciation effect of Asian inflow into the school and non-school channels.

This study employs an Instrumental Variables (IV) approach to address potential endogeneity concerns when estimating the effects of Asian population shares and educational outcomes on housing prices. We use a Shift Share IV to tackle the selective location choice issue related to the Asian population, and the US state-level teacher accountability reform as another IV for county-level educational outcomes. These two IVs are arguably orthogonal to each other. The Shift Share IV, leveraging the cross-sectional variation in the historical Asian population shares and the temporal variation in nationwide visa issuance, provides both spatial and temporal exogenous variation. On the other hand, the state-level teacher accountability reform offers suitable spatial and temporal variation, addressing the endogeneity concerns with county-level educational outcomes. By employing these two orthogonal IVs, we aim to disentangle the education channel and non-education channel to obtain consistent estimates of the causal effects of interest.

Our results indicate that an increase in the Asian immigrant population share in a county has significant impacts on housing prices, as well as the educational outcomes for other racial groups, especially white students. We decompose the impact of increased Asian shares on the housing market into education and non-education channels. We conclude that about one-third of the housing appreciation effect is attributed to the capitalization of school performance improvement. The remaining two-thirds are due to non-education factors. We also find that these effects are more pronounced in the counties with a high percentage of Asians, highlighting the non-linear nature of the relationship between the Asian population share and housing market outcomes that are consistent with classical tipping model literature.

We find suggestive evidence that the displacement of less-affluent white families in these neighborhoods may partially explain the positive impact of the Asian immigrant influx on school performance. However, it is important to note that our results cannot be fully explained by this potential displacement effect, so there may exist possible positive education spillover effects from Asian immigrants on other ethnic groups. These spillovers could occur through various channels, such as peer effects or the investments and efforts of Asian parents in local schools. We do not directly test those spillover mechanisms, and we leave it for future research.

Our research makes a contribution to the literature by bridging two well-established fields: the impact of immigrants on local housing markets, and the valuation of endogenous amenities. The literature has extensively documented the impact of immigrants on housing markets, with studies such as Badarinza and Ramadorai (2018), Saiz and Wachter (2011), and Saiz (2007) examining the effects of immigration on the housing market. In contrast, the literature on the valuation of endogenous amenities, (Black, 1999; Bayer et al., 2007; Almagro and Dominguez-Iino, 2022), has explored how neighborhood characteristics endogenously affect local housing prices. Our findings align with the literature demonstrating that socio-demographic composition affects neighborhood characteristics endogenously (Böhlmark and Willén, 2020; Diamond, 2016; Guerrieri et al., 2013). As individuals with higher socioeconomic status are willing to pay more for local neighborhood amenities (Bayer et al., 2007; Handbury, 2021; Diamond, 2016; Diamond and McQuade, 2019), our findings suggest that immigration-induced demographic shifts can alter the availability and valuation of local amenities, thereby changing housing prices.

Our study contributes to these fields by investigating how the arrival of certain types of immigrants displaces natives and changes local characteristics in ways that traditional immigration literature has not documented. Specifically, we demonstrate that endogenous amenity changes, induced by alterations in racial or ethnic composition, serve as a crucial driver for housing price responses. This finding advances the growing literature examining the impact of Asian inflow on housing prices in the US and Canada (Pavlov and Somerville (2020), Li et al. (2020), Gorback and Keys (2020), and Kahn (2021)), which has become a recent policy debate in the US and other countries.

This paper is organized as follows: Section 2 provides background, data, and stylized facts related to Asian ethnic groups in the US; Section 3 presents our empirical strategy; Section 4 presents our main results and robustness checks; mechanisms are investigated in Section 5 and finally, Section 6 concludes with our future plans.

2 Background and Empirical Setting

2.1 Asian Immigration Histories in the US

The first Asian immigrants landed in Morro Bay, CA, in 1587 from a Spanish galleon (Trinidad, 2012). The first Asian settlement was established in Saint-Malo, LA, by 1763 (Carter, 2022). It was Chinese immigrants began arriving in the US during the 1800s[2], marking the start of a diverse group of people from over 40 countries across the Middle East and East Asia collectively referred to as "Asian." However, in the early 1900s, several waves of legislation aimed at limiting immigration from Asian countries were passed[3]. It wasn't until the Hart-Celler Act of 1965 that immigration law was liberalized, which had significantly increased the Asian population[4]. The US saw an increase in the Asian population from around 1 million in 1960 to around 16 million in 2009 (Hsu, 2016).

In recent decades, immigration from Asia to the US has risen dramatically. The Asian population in the US increased from 11.9 million in 2000 to 22.4 million in 2019[5]. It is projected that Asian immigrants will overtake Hispanic immigrants as the largest share of all immigrants. In 2015, 47% of all immigrants residing in the US were Hispanic, but that number is projected to fall to 31% by 2065, while the share of immigrants from Asian countries is projected to be 38% by 2065[6]. Compared to older generations of Asian immigrants from the 1980s, this influx of new generation Asian immigrants is well-educated and has higher incomes[7].

This paper focuses on the Asian population in the United States from mainly six countries of origin: China, India, the Philippines, Vietnam, South Korea, and Japan. These countries of origin represent the largest shares of the Asian population in the US in 1980, and Asian immigrants from these countries make up 89.6% of all Asian immigrants. Table A1 presents descriptive statistics by different Asian subgroups. The six countries of origin exhibit substantial heterogeneity, particularly in terms of the share of individuals with a college degree.

[2] Milestones: 1866-1898, US House of Representatives, accessed on 06/03/2023, Source (link).

[3] First Arrivals, First Reactions — US House of Representatives: History, Art & Archives, accessed on 06/03/2023, Source (link)

[4] Hart-Celler Legacies — US House of Representatives: History, Art & Archives, accessed on 06/03/2023, Source (link)

[5] Key facts about Asian Americans — Pew Research Center, accessed on 12/19/2022, Source (link)

[6] Modern Immigration Wave Brings 59 Million to the US — Pew Research Center, accessed on 12/19/2022, Source (link)

[7] Immigrants from Asia in the United States — migrationpolicy.org, accessed on 12/19/2022, Source (link)

2.2 Data

In this section, we describe the main sources of data used in this paper. All the variables are aggregated at the county-level[8] for the years from 2008 to 2018. Summary statistics of the main variables are presented in Table 1.

2.2.1 Population by Race 2008-2018

The Surveillance, Epidemiology, and End Results (SEER) dataset provides annual estimates of population by age, sex, race, and Hispanic origin at the county-level. Population estimates by race are available for white, black, and other race from 1969-2020, and information on 'Expanded Race (i.e., White, Black, American Indian/Alaska Native, Asian/Pacific Islander) by Origin (Hispanic, Non-Hispanic))' is available from 1990-2020. This paper constructs the annual county-level population share by race, defined as White, Black, Hispanic, and Asian.

2.2.2 Population Shares 1980s-2010s

The American Community Survey (ACS) is an ongoing survey that is collected yearly by the US Census Bureau. It contains socio-demographic information of households and individuals at a fine spatial scale. Demographic variables are downloaded from IPUMS NHGIS (Manson et al., 2021) for each decade from 1970-2000 and at the annual level from 2009-2018. We use 1980 population shares as a part of our instrumental variables strategy to provide cross-sectional variation.

2.2.3 Test Scores

The Stanford Education Data Archive (SEDA) serves as the source for school performance outcome variables. It offers comprehensive information on schools, communities, and student achievement at the county-level across the United States. The dataset encompasses detailed data on average academic achievement measured through standardized test scores in Mathe-

[8] We choose county-level as a unit of analysis considering the first-stage regression of our IV approach. The smaller the geographical unit, the lower the likelihood that the share of Asian immigrants in the 1980s is correlated with the propensity of Asian immigrants' location choices in the 2010s. Such a weak correlation would reduce the explanatory power of the first-stage and thus threaten our IV identification strategy. The correlation between census tract-level Asian population in 2018 and Asian population in 1980 is 0.378, whereas the county-level correlation is 0.7598. We believe that our estimates are likely to be lower bounds of the estimates with finer geographical units, such as census tracts or zip codes, due to the sorting of Asians within counties. We talk more about our identification strategy in Section 3.

matics and Reading Language Arts (RLA) for grades 3 to 8. The data covers the school years from 2008-09 to 2017-18, focusing on major metropolitan areas in the US.

The dataset provides county-level public school test scores in Mathematics and Reading, disaggregated by race and grade. However, due to privacy concerns, the scores are only available if there are more than 20 students who took the tests within a specific county, race, and grade combination. Moreover, the SEDA dataset incorporates various county-level covariates such as median income, poverty levels, and unemployment rates.

For our analysis, we compute the weighted average of math and reading scores at the county-level, considering the number of students taking each subject in each cohort as the weighting factor.

2.2.4 Zillow Home Value Index (ZHVI)

Zip code-level housing price indices can be obtained from Zillow Research starting from 1997. The Zillow Home Value Index (ZHVI) represents a smoothed and seasonally adjusted measurement of the average value of homes and market fluctuations within a specific region and housing category. It reflects the typical value of homes falling within the 35th to 65th percentile range. ZHVI provides monthly observations denoted by month and year for all available counties. To derive annual county-level price indices, we calculate the average value using all available months of data. Figure A3 shows the coverage and spatial distribution of ZHVI in 2009 and 2019.

2.2.5 Visa Statistics

Monthly immigrant and non-immigrant visa issuance are taken from the US State Department's Bureau of Consular Affairs. The State Department includes how many visas were issued by nationality and visa type, including immigrant and non-immigrant visas. A non-immigrant visa is for temporary stays such as tourism, business, family visits, study, work, or transit. An immigrant visa is for permanent residence in the United States. Note that on average, the total number of non-immigrant visas is 1,935,010 per year and the total number of immigrant visas is 244,983 per year. We use annual (non-immigrant) visa issuance for Asian countries as an exogenous source of temporal variation in the local number of Asian immigrants yearly, which we will discuss more detail in our empirical strategy session.

Table 1 provides the summary statistics of the county-level data.

2.3 Stylized Facts

Fact 1. The influx of Asian immigrants is affected by federal immigration policies. The influx of Asian immigrants to the US is affected by immigration policies, as demonstrated by Figure 1. Every President since 1952 has taken executive action on immigration[9]. As a result, the number of visas issued to Asians is closely related to the US immigration and geo-political policies, with the number of visas issued to Asians increasing significantly during the Obama Administration (2008-2016) and decreasing significantly during the Trump Administration (2017-2020).

Fact 2. Share of Asians increases over time, and it is geographically dispersed. Using county-level US census data between 1980 and 2019, we see that Asians have become more spread out throughout the US (Figure 2). Many more neighborhoods throughout the US might be exposed to higher Asian population shares. This sustained increase in the Asian population remains despite the fact that the number of immigrant and non-immigrant visas issued to East Asians has been trending downwards since 2016.

Fact 3. Asians are located in those counties with higher weighted test scores. Thirdly, there are school performance outcome differences across racial and ethnic groups. Counties with higher shares of Asians and Whites are associated with higher weighted average scores. However, this relationship does not necessarily imply causality and further analysis is required to investigate this relationship more deeply (Figure 3).

Fact 4. Asians in the 2000s are the most affluent racial group on average in the US In 2019, the median annual household income of households headed by Asians was $\$85,800$, compared with $\$61,800$ among all the US households. In addition, more than half of Asians have a bachelor's degree or higher educational attainment, compared to 33% of the rest of the US population (American Community Survey, 2010-2019).

[9]Source: "By the Numbers: Every President Since Eisenhower Has Taken Executive Action on Immigration". https://www.americanprogress.org/issues/immigration/news/2014/10/06/98321/by-the-numbers-every-president-since-eisenhower-has-taken-executive-action-on-immigration/

To better understand the income distribution of different races in the US, Figure A1 displays the median per capita income for each race since 1993, based on data from the US Census Bureau's Current Population Survey Annual Social and Economic Supplement. Notably, Asians have had the highest median income among all races since the early 2000s, surpassing the median income of White Americans.

Fact 5. The characteristics of Asian immigrants have changed since the 1980s. Table 2 provides a summary of the average characteristics of recent Asian immigrants to the US, in comparison to US natives. By comparing data from the 1980s and the 2010s, we observe the following trends: (1) Asian immigrants are more likely than US natives to be college-educated, and this gap has widened over time. (2) Initially, Asian immigrants were less likely than US natives to be employed in high-skill industries. However, by 2018, they were more likely than US natives to be employed in high-skill industries. (3) In the 1980s, Asian immigrants were equally likely as US natives to be employed in low-skill industries. However, by 2018, they were less likely to be employed in low-skill industries. (4) In the 1980s, Asian immigrants were equally likely to be employed in blue-collar or white-collar occupations as US natives. However, over time, they became much less likely to be employed in blue-collar occupations and more likely to be employed in white-collar occupations. These trends illustrate the changing characteristics of Asian immigrants in the US over time, particularly the new generation's increasing education levels and upward mobility in the job market.

3 Empirical Strategy

3.1 Two-Way Fixed Effects Model

The primary objective of this study is to disentangle the overall impact of the Asian population on the housing market, distinguishing between education and non-education channels. We employ two Two-Way Fixed Effects (TWFE) regression models to achieve this goal.

Consider county j at time t:

$$\log Price_{jt} = \alpha + \theta_1 ShareAsn_{jt} + \eta_j + yr_t + \iota_{jt} \tag{1}$$

$$\log Price_{jt} = \alpha + \beta_1 ShareAsn_{jt} + \delta_1 MeanScore_{jt} + \eta_j + yr_t + \epsilon_{jt} \tag{2}$$

$$MeanScore_{jt} = \alpha + \gamma_1 ShareAsn_{jt} + \eta_j + yr_t + v_{jt} \tag{3}$$

Herein, $\log Price_{jt}$ represents the natural logarithm of the housing price index, $ShareAsn_{jt}$ denotes the proportion of the Asian populace, and $MeanScore_{jt}$ is the weighted mean of math and reading scores. Both county fixed effects (η_j) and year fixed effects (yr_t) are incorporated in all regression models. The standard errors are clusetered at the county-level.

Figure 4 provides a visual representation of our decomposition approach. We designate θ_1 as the comprehensive effect of the Asian population on the housing market. δ_1 represents the capitalization rate of the weighted mean of math and reading scores. Additionally, the influence of the Asian population's proportion on the weighted average scores is captured by γ_1. We characterize the 'education channel' of the Asian population's impact on housing prices by examining the interaction between γ_1 and δ_1. The residual effect of the Asian population (β_1) is referred to as the 'non-education channel,' encompassing all other potential channels, such as the pure quantity effect in the absence of changes in education quality. For example, this may be due to increased housing demand (in the face of inelastic supply) resulting from greater global capital flow, among other factors. Should the decomposition exercise prove valid, the results will indicate that the estimated total effects are approximately equal to the sum of the education and non-education effects (i.e., $\hat{\theta_1} \approx \hat{\gamma_1 \delta_1} + \hat{\beta_1}$).

3.2 Instrumental Variables Approach

There exist potential identification threats in estimating θ_1, β_1, and γ_1 if the Asian population selectively resides in counties with high educational amenities. Moreover, the identification of δ_1 may be subject to bias in the TWFE framework if there are any omitted variables, such as county-specific economic fundamentals that could simultaneously influence housing prices and educational outcomes. This section outlines the Instrumental Variable (IV) strategy employed to address these endogeneity concerns. We utilize two instrumental variables (arguably orthogonal to one another) for the two endogenous regressors ($ShareAsn_{jt}$, $MeanScore_{jt}$).

IV for Asian Shares ($ShareAsn_{jt}$): The Asian population may preferentially select locations with attributes that are more appealing to them, such as social demographics, educational environment, and other amenities. This selective location choice can lead to both reverse causality and omitted variables issues. To address the potential endogeneity concerns, we employ a 'Shift Share' type of IV – by interacting the share of the Asian population in county j in 1980 ('the shares') with the total cumulative number of visas issued for Asian country origin in year t from 2009 ('the shift'). These two components are devised to offer spatial and temporal exogenous variations, respectively. To be specific, we construct the following instrumental variable ($Shif\hat{t}Shr_{jt}$) for county j, in year $t \geq 2009$;

$$Shif\hat{t}Shr_{jt} = AsnPop_{j,2008} + \Sigma_t ShrAsn_{j,1980} AsnFlow_t \tag{4}$$

where $AsnPop_{j,2008}$ indicates the Asian population in county j in year 2008, $ShrAsn_{j,1980}$ indicates the share of Asian living in county j relative to the total Asian population in the US in 1980; $AsnFlow_t$ indicates the total visa issuance to Asian by the US in year t[10].

The identifying assumption for the relevance condition posits that the historical Asian population share strongly predicts the current Asian population share. The historical ethnic composition of a location is frequently utilized to gauge the influx of new immigrants, as they are likely to settle in areas inhabited by their respective ethnic groups (Card and DiNardo (2000), Card (2001)). Since historical shares are time-invariant, we employ the nationwide total number of non-immigrant visas issued as a proxy for the annual entry of Asian immigrants into the US, providing temporal exogenous variation. Overall, as demonstrated in Table A2, the F-statistics shows strong first stage results.

Regarding the exclusion restriction assumption, our two outcome variables (current housing prices and mean test score at county-level) should not be influenced by the Asian population shares from 30 years prior or by national-level visa policy changes, except through the current share of Asians in the county. Although this assumption cannot be directly tested, we address the potential threat to identification with the following arguments. We first discuss why we believe that 'the Shares' in our context are exogenous. If 'the shares' component is exogenous, then this is a sufficient[11] condition for a 'Shift Share' IV to be exogenous, con-

[10] In particular, we utilize the number of non-immigrant visas issued as our measure of temporal variations for several reasons. Firstly, non-immigrant visas provide insights into the international relations between the United States and the countries of origin, serving as our source of temporal shocks, as illustrated in Figure 1. Secondly, the total number of non-immigrant visas is approximately nine times greater than the number of immigrant visas. Lastly, we consider non-immigrant visas to be a more suitable indicator of newly arrived population, as immigrant visas are typically granted to individuals already residing in the United States. It is worth noting that our results remain largely consistent when we combine non-immigrant and immigrant visas as a combined measure of temporal shocks.

[11] Cunningham (2021) mentions that "While exogenous shares are sufficient, it turns out they are not necessary for identification of causal effect"

ditional on the fixed effects (Goldsmith-Pinkham et al. (2020)[12]). Secondly, we argue that 'the shifts' are also exogenous in our context. Borusyak et al. (2022) demonstrate that if 'the shifts' are uncorrelated with the bias of 'the shares', the Shift Share IV identifies the causal effects.

First, we argue that 'the shares,' which utilize the 1980 Asian population shares, are exogenous, conditional on fixed effects. As observed in Section 2.3, the characteristics of Asians in the 1980s differ from those of Asians in the 2010s. In particular, Asian immigrants in the 1980s were more likely to be working-class and less privileged compared to their counterparts in the 2010s. Consequently, employing the 1980s' distribution of the Asian population as our spatial distribution somewhat mitigates the sorting issue of 2010s Asians, who tend to gravitate towards growing counties and areas with high-skilled, high-paid, white-collar jobs. Figure A4 supports our argument that the concentration of the Asian population in 1980 (Y-axis) does not necessarily correspond to growing counties in terms of median income growth during our sample periods (2009-2018, X-axis). Therefore, it is less probable that location choices in 1980 are directly correlated with the growth of counties in the 2010s[13].

IV for Mean Score ($MeanScore_{jt}$): In this section, we address the potential endogeneity issues with $MeanScore_{jt}$ in Equation 2. Suppose a county experiences a positive productivity shock, which can lead to housing price appreciation, increased financial resources invested in schools, and potentially attracting high-income residents who may invest more in their children's education. In this case, the causal identification using TWFE to examine the impact of county-level education on housing prices would be spurious. To address these endogeneity issues, we use state-level teacher accountability reform as an instrumental variable for county-level educational outcomes.

The teacher reform was initiated in 2012 as part of the 'Race to the Top (RTT)' grant competition[14]. The reform involved evaluating teachers using multiple measures, such as

[12] Goldsmith-Pinkham et al. (2020) mention "the Bartik instrument is 'equivalent' to using local industry shares as instruments, and so the exogeneity condition should be interpreted in terms of shares."

[13] Furthermore, we contend that 'the shift' component in our context is exogenous, conditional on county-fixed and year-fixed effects. Importantly, as observed in Figure 1, the total number of visas issued is primarily influenced by partisan and geopolitical issues the federal government addresses, which are orthogonal to any county-specific economic conditions. Consequently, 'the shifts' are uncorrelated with the bias of 'the Shares' in our setting, rendering the Shift Share IV sufficient to identify the causal effects (Borusyak et al. (2022)).

[14] Race to the Top (RTT) was a $4.35 billion United States Department of Education competitive grant designed to spur systemic reform to enhance teaching and learning in America's schools. RTT was launched in 2009. https://obamawhitehouse.archives.gov/issues/education/k-12/race-to-the-top

student achievement growth, and rating teachers on a scale with multiple categories. By 2016, 44 states had enacted legislation mandating significant teacher evaluation reform (NCTQ (2014)), and the implementation years varied (See Figure A5 for the policy implementation timing). Kraft et al. (2020) demonstrate that the reform improved new teachers' quality but also increased the likelihood of unfilled teaching positions, particularly in hard-to-staff schools, which might even negatively affect school performance.

It is unclear ex-ante how the teacher reform would impact county-level students' outcomes as the improved teacher quality would positively affect county-level public school students' academic outcomes; however, the trade-off comes with the decreased teacher supply (Hanushek and Rivkin (2006)), which could negatively affect the student's academic outcomes. We document there is a non-linear relationship between school reform and county-level student outcomes. Specifically, Table A2 shows that the non-linearity exists with respect to the states' pupil-to-teacher number. In low pupil-to-teacher states, the reform had negative effects on student outcomes, whereas in high pupil-to-teacher states, the effects were positive. To account for such non-linearity, we instrument county-level academic outcome variables using an indicator variable that equals one after the state adopted the reform in year t, interacted with the indicator whether the state is low (bottom 25%) vs. median (25-75%) vs. high (above 75%) pupil-to-teacher states prior to the policy reform. The policy adoption timing varies across states, providing suitable spatial and temporal variation as an instrumental variable.

The identifying assumption for the relevance condition is that the reform has a strong enough impact on county-level weighted average scores. Table A2 displays the first-stage result of teacher reform as an IV for the average weighted mean score. With F-statistics for the first stage greatly above 10, the relevance condition is validated. Lastly, the timing of policy implementation across states is arguably random (Kraft et al. (2020)), which confirms the exclusion restrictions assumption of the IV.

4 Main Results and Robustness Checks

4.1 Main Results

The main focus of this section is to examine the correlation between a higher Asian population and higher housing prices, and to determine the channels through which this effect occurs and to what extent. Specifically, we are interested in investigating the education channel, whereby Asians influence school performance, which in turn is capitalized into housing prices, as illustrated in Figure 4. We estimate both the total effect (θ_1 in Equation 1) and the school effect ($\gamma_1 * \delta_1$ in Figure 4), and attribute the remaining effect (β_1 in Figure 4) to the non-education channel. The latter includes various factors, such as the 'Chinese Money' story, where increased capital flow from Asia (particularly China) creates a higher demand for housing in the face of limited supply, resulting in housing price appreciation.

To assess the overall impact of the Asian population on the local housing market, represented as θ_1 in Equation 1, we employ a shift-share instrumental variable that captures the proportion of the Asian population. As shown in Column (1) of Table 3, a one percentage point increase in the Asian population share leads to a 17.36% increase in housing prices. In Column (2), we control for key factors, such as the logarithm of median income and the logarithm of the population, which may influence housing demand. The regression results exhibit minimal variation (a 16.33% increase in housing prices with a one percentage point rise in the Asian population), supporting our claim that higher Asian shares in counties contribute to housing price appreciation. Our preferred estimate is based on the regressions with the control variables in Column (2).

Considering that the average population share of Asians across US counties in 2009 was only 1.7%, our estimates imply that an increase from 1.7 to 2.7 percentage points (a 59% increase in the current Asian share) results in a 16.33% growth in housing prices. Therefore, a 1% rise in Asian shares is associated with a 0.28% increment in house prices. To provide context, between 2009 and 2018, the mean annual growth of Asian shares was 5.13%. In the fastest-growing (top 5%) counties, this number escalated to 22.62%. According to our estimates, in an average county experiencing growth in Asian shares, housing prices appreciate by 1.42% annually due to increased Asian presence. We observe a 6.33% annual growth in housing prices in those markets, suggesting that 22.4% (1.42 / 6.33) of the observed housing price appreciation can be attributed to the growth in Asian population shares. Our findings align closely with existing literature, although different studies use varying measurement units. For example, Gorback et al. (2020) found that housing prices increased by 6 to 9 percentage points more in US zip codes with higher foreign-born populations. Similarly, Li et al. (2020) discovered that a one standard deviation increase in real estate capital was associated with a

15% surge in housing prices.

Furthermore, we demonstrate that higher Asian shares contribute to higher educational quality by estimating γ_1 in Equation 3. As shown in Table 3, a one percentage point increase in the Asian share leads to a 0.0778 (Column (3)) standard deviation increase in the weighted average score. Controlling for median income and population in Column (4) does not significantly alter the regression results. We contend that our estimates fall within a plausible range based on other research in this field. For example, Hanushek et al. (2004) used data from the UTD Texas Schools Project and found evidence of "Tiebout sorting," where students who relocated to new counties experienced 0.025 standard deviations higher levels of school quality. Similarly, Hanushek et al. (2009) showed that a one standard deviation increase in average teacher quality per grade improved math scores by 0.11 standard deviations and reading scores by 0.095 standard deviations.

The main objective of this paper, based on the findings in Columns (1) to (4), is to decompose the total effect of increased Asian shares on the housing market into the education channel ($\gamma_1\delta_1$ in Equation 2, 3) and non-education channels (β in Equation 2). The estimated values for $\hat{\delta_1}$ and $\hat{\beta_1}$ in Equation 2 are presented in Column (5) (without controls) and Column (6) (with controls) of Table 3. Focusing on the preferred estimations without control variables (Column (5)), the instrumental variable results reveal that the non-education impact of Asian shares on housing prices is 12.0403% when the share of Asians increases by one percentage point. The capitalization rate of the education amenity (δ_1 in Equation 3) is estimated to be 0.8445. Using these estimates, the education channel of Asians is calculated to account for 6.57% (= 7.7802 in Column (3) * 0.8445 in Column (5)).

In summary, when the share of Asians increases by one percentage point, the estimated total effect (17.36%) of the increased Asian shares on the housing market aligns closely with the combined non-education (12.04%) and education (6.57%) effects. This calculation suggests that approximately one-third of the housing appreciation effect of Asians can be attributed to the capitalization of improved school performance, while the remaining two-thirds of the total effect is due to all other possible non-education effects.

Nonlinearities According to classical tipping models, the effects of immigrants are more pronounced when minority population concentrations are higher (Schelling (1971), Card et al.

(2008), Saiz and Wachter (2011), Moraga et al. (2019)). In this section, we explore the possibility of non-linear relationships.

To investigate this, we categorize counties into high Asian share counties (with county-level Asian shares in the top 1% or 5% in 2009) and the rest to examine if the impacts differ between these groups. The names of the top 1% and top 5% Asian counties are listed in Table A4. In line with existing literature, Table 4 reveals that housing appreciation effects of the Asian population are predominantly observed in counties with a high percentage of Asians (top 5% Asian concentrated counties). Again, for those high Asian share counties, approximately one-third of the housing price appreciation effect of Asians is due to the improvement in education quality, while the remaining two-thirds result from other residual effects. This finding highlights the non-linear nature of the relationship between the Asian population share and housing market outcomes.

4.2 Robustness Checks

In this section, we perform robustness checks to address potential threats to identification in our analysis. Firstly, we include controls for the non-Asian foreign-born population in our main specification to partially account for time-varying omitted variables at the county-level. This helps to mitigate potential confounding factors that may influence our results. Next, we construct a measure capturing differing parental attitudes towards education across various Asian countries of origin. This allows us to examine the heterogeneity in the relationship between Asian population shares and housing prices, taking into account the cultural and educational backgrounds of different Asian groups. Lastly, we conduct a sub-sample analysis by excluding counties with the highest Asian population shares, particularly counties, particularly counties in the states of Hawaii and California. This helps to assess whether our findings hold robustly across different county contexts, and it allows us to explore the sensitivity of our results to the presence of highly concentrated Asian populations. Overall, the results from our robustness checks align with our main findings, providing further validation for our empirical specifications and strengthening the reliability of our conclusions.

1. Controlling for non-Asian foreign-born population flows As a robustness check, we address the potential omitted variable bias resulting from time-varying county-specific factors related to the sorting of Asian immigrants. The location choices of immigrants depend on both 'push factors' (i.e., factors from the countries of origin that 'push' migrants to the US, and how the US Federal Government's visa policy facilitates this push) and 'pull factors' (i.e., factors in destination counties that 'pull' immigrants from various source countries) (Burchardi et al., 2019). The shift shares instrumental variables account for the push factors, as the contemporaneous visa issuances for Asians capture the overall incoming Asian immigrants pushed by all origin countries and the US Department of Homeland Security to all states and counties in the US. The cross-sectional landscape of the historical Asian population across US counties captures how these pushed Asian immigrants are pulled by various counties, resulting in the spatial distribution we observe. However, a crucial question for our identification is whether the pull factors of counties, such as better economic and labor market conditions, directly drive higher housing prices and better neighborhood quality. If that were the case, our main regression results could not be interpreted as causal. We argue that if this were true, the non-Asian foreign-born population would have similar effects on housing and educational outcomes, as they are likely attracted by similar locational attributes (refer to Figure A2). In fact, Figure A2 shows that Asian and non-Asian immigrants tend to co-locate to some extent.

To address the potential endogeneity issue arising from county-level pull factors, we include the share of non-Asian foreign-born in our regression as a control variable. To causally identify the impact of the share of non-Asian foreign-born on neighborhood characteristics, we adopt a similar instrumental variable approach. We construct an instrumental variable by interacting the county's non-Asian foreign-born share in 1980 with the annual number of visas issued for non-Asian immigrants.

Table 5 presents the results, including the share of non-Asian foreign-born. Firstly, the positive impacts of Asian immigrants on housing prices in Column (1) remain statistically significant. Conversely, the impacts of non-Asian foreign-borns on housing prices turn out to be negative. The decomposition of the channels in Column (2) and Column (3) reveals that around one-third (31%) of the housing price appreciation driven by Asian immigrants can still be explained by the improvement in education quality. However, the negative housing price effect from non-Asian immigrants appears to be driven by non-education factors. Overall, these results confirm that the housing appreciation resulting from the increase in the share of Asians is not driven by other economic conditions in counties that attract all types of immigrants.

2. Another shift-share IV considering different countries of origin In our original specification, we utilized self-identified race categories from the American Community Survey to construct a county-level measure of the Asian population. As an alternative IV construction, we now consider the countries of origin for the Asian population and examine the differences in their respective attitudes towards education.

Specifically, we construct the following 'shift shares' for county j in year t and origin country $c \in$ {China, Japan, Korea, Philippines, India, and Vietnam}[15]:

$$ShiftShr_{jt}^{spec} = AsnPop_{j,2008} + \Sigma_c \Sigma_t Educ_c ShrAsn_{c,j,1980} AsnVisa_{c,t} \tag{5}$$

Here, $AsnPop_{j,2008}$ indicates the Asian population in 2008 in county j, $ShrAsn_{c,j,1980}$ denotes the population in 1980 from country of origin c, $AsnFlow_{c,t}$ represents the total number of non-immigrant visas issued for country c in year t. We interact the shift share with the share of education spending in origin country c as a proxy for country-specific differences in educational outcomes ($Educ_c$)[16]. In this analysis, we investigate if accounting for origin-country heterogeneity in education increases our precision in estimating the impacts of immigration on education.

The regression results using this alternative IV construction are presented in Table 6. Overall, the findings are qualitatively similar to our main results in Table 3 and Table 4, which further validates our primary specifications and confirms the robustness of our findings.

3. Subsample Analysis: without top five counties To address concerns that the observed shock may be concentrated solely in the top counties with a high concentration of Asian population, we conducted a sub-sample analysis by excluding the counties with the highest Asian population shares. Specifically, we excluded three counties in Hawaii (Honolulu, Kauai, and Maui), which had over 58% Asian population shares in 2009 (mainly of Japanese origin), and two counties in California (San Francisco and Santa Clara), which had over 33%

[15]Source: NHGIS data set (https://www.nhgis.org/). We focus on China, Japan, Korea, the Philippines, India, and Vietnam since those are the countries of origin with a significant share of the Asian population in the US in 1980.

[16]Source: Nationmaster.com. We use 2011-2012 data.

Asian population shares in 2009.

Table 7 presents the results of the sub-sample analysis without the top five counties. Although the overall effects on housing prices diminish in Column (1) compared to the results obtained from the full sample in Table 3, the implications regarding the overall effect and decomposition remain the same. Specifically, an increase in Asian population shares still leads to housing price appreciation, and approximately 30-33% of the observed results can be attributed to housing price appreciation.

5 Mechanism: Displacement or Spillovers?

To investigate the potential mechanisms for the amenity and housing price changes associated with increased Asian shares, this section examines whether school performance improvement and resulted housing price appreciation is at least partially attributed to an increased presence of the Asian population and their possible positive spillovers to other students. Or, alternatively, those observed results are mainly due to a displacement effect, where students and their families with poorer test score outcomes get displaced by Asian families, which mechanically raises local school performance.

To provide suggestive evidence, this section examines how racial compositions, median household incomes, and weighted average academic scores of each racial group are affected when the Asian share increases. This analysis can help to shed light on whether the observed changes in educational outcomes are due to purely a displacement effect or a potential spillover effect.

5.1 Racial Composition Changes

First, we look at racial composition changes when the Asian share increases. Panel A in Table 8 presents the changes in ethnic composition when the share of Asians increases in a county. Instrumental variable estimates indicate that a one percentage point increase in the Asian population results in a 0.6 percentage point decrease in the White share (Column (1)), a 0.28 percentage point decrease in the Black share (Column (2)), and no statistically significant impacts on the Hispanic share (Column (3)). The relationship between Asian arrivals and White departures has been documented in recent urban economics literature.

For instance, Boustan et al. (2023) report that between 2000-2016 in high-SES suburban districts in California, the arrival of each Asian student is associated with 0.6 White student departure[17].

5.2 Median Household Income and Test Score Changes

To understand the sorting pattern of different types of households across different races, we examine the median household incomes by race as an outcome variable. Panel B of Table 8 shows that a higher Asian population in counties does increase the overall median household incomes (Column (1)). In Column (2), we show that most of the increased median household incomes effects come from the White households – a one percentage point increase in Asian shares raises the median income of White households by 3.33% (Column (2)). Combining this result with the findings in Panel A of Table 8, we argue that these are suggestive evidence that the inflow of Asian immigrants induces the out-migration of less affluent White neighbors.

The above results demonstrate that the positive impact of increased Asian shares on overall academic outcomes could be at least partly driven by the out-migration of the least affluent White families. If Asian families displace households with low-performing students, the county-level mean scores would become mechanically higher. To address this question, we first investigate how the academic outcomes of students of other races are affected by a high Asian population. Panel C of Table 8 presents the regression results with instrumental variables for test scores. A one percentage point increase in the Asian share leads to the increase in other ethnic students' weighted average score (Column (1)-(3)). Notably, the improved county-level educational results associated with increased Asian shares are not driven by improvements in Asian students' own academic outcomes (Column (4)).

5.3 Back-of-Envelope Calculation

The remaining question is whether the possible displacement effect we observe above can completely drive the improved academic scores or not, and if not, other channels may exist beyond displacement channel. Our back-of-the-envelope calculation shows that the academic improvement of the other ethnic population is much higher than the pure displacement effects

[17]Unlike previous papers examining the "white flight" phenomenon in the US (e.g., Boustan et al. (2023), Boustan (2010)), this paper's focus is not on the reasons for White departure, such as housing market channels or distaste for certain demographic groups.

resulting from the potential out-migration of the worst-performing students. Specifically, consider a representative county with a White share of 80.5% and a mean score of 0.155. Results in Panel A of Table 8 indicate that when the Asian share increases by one percentage point, the White share decreases to 79.9% (or by 0.6 percentage points). Suppose the displaced White population by Asians consists of households with the worst-performing students (e.g., with a standardized score of -4). If so, the overall grade due to the displacement effects would be 0.1862 (i.e., a 0.03 standard deviation increase), which is much less than the 0.0852 standard deviation increase found in Column (1) in Panel C of Table 8. This calculation indicates that other mechnisms are at play beyond the displacement effect, including the potential positive spillover effects.

In summary, the results are consistent with Hoxby (2000)'s finding that an increase in the share of a grade cohort that is Asian causes an increase in educational outcomes for different ethnic groups. We can also see that the size of this effect is much larger than the maximum size of the pure displacement effect. Unfortunately, due to the data constraint, we cannot directly test the peer spillover effect, and we leave that for future research.

6 Conclusion

This paper investigates the channels through which the inflow of Asian immigrants into US cities has been associated with local housing price appreciation. We decompose the impact of Asian immigrants on local housing markets into education and non-education channels using 2009-2018 annual county-level data. To account for the endogeneity issues in Asian immigrants' location choice, we construct an instrumental variable by interacting the Asian population share in 1980 with the annual number of visas issued for Asian nationalities in the US. To identify the capitalization rate of school performance in the housing market, we adopt the staggered roll-out of state-level teacher reforms as an instrumental variable for the changes in county-level test scores with a nonlinear relationship. We find, first, that the housing price appreciation triggered by Asian immigrants is mainly concentrated in counties with the top 5% of the Asian population share. Second, the increased percentage of Asians in neighborhoods leads to higher test scores for students of other races. Third, our model results show that around a third of housing price appreciation driven by a higher Asian share is attributed to the improvement in school performance in neighborhoods. Finally, we also explore the potential mechanisms behind the observed effects, specifically whether the effects were only due to a displacement mechanism. The results suggest that the improved educational outcomes associated with the arrival of the Asian population have a much larger effect size than the maximum possible displacement effect alone, and positive spillover effects may exist beyond displacement. This paper uncovers a significant channel through which this new wave of immigration affects the US housing market.

This research is not without limitations. Above all, our data consists of county-level observations due to identification reasons; however, we acknowledge that we are missing important micro dynamics that occur within counties and across school districts. Second, we overlook interesting mechanisms between students as well as parents across different races.

Future research could further investigate the mechanisms through which Asians improve the quality of education, including public finance channels, parent-teacher relationships, the role of public schools, and peer effects, among others. It may also be worthwhile to explore the impact of the Asian population on other aspects of the local economy, such as employment, business growth, public safety, and innovation. Additionally, future studies could examine the relationship between the Asian population and other urban and housing market outcomes, such as new construction, home wealth, and urban form.

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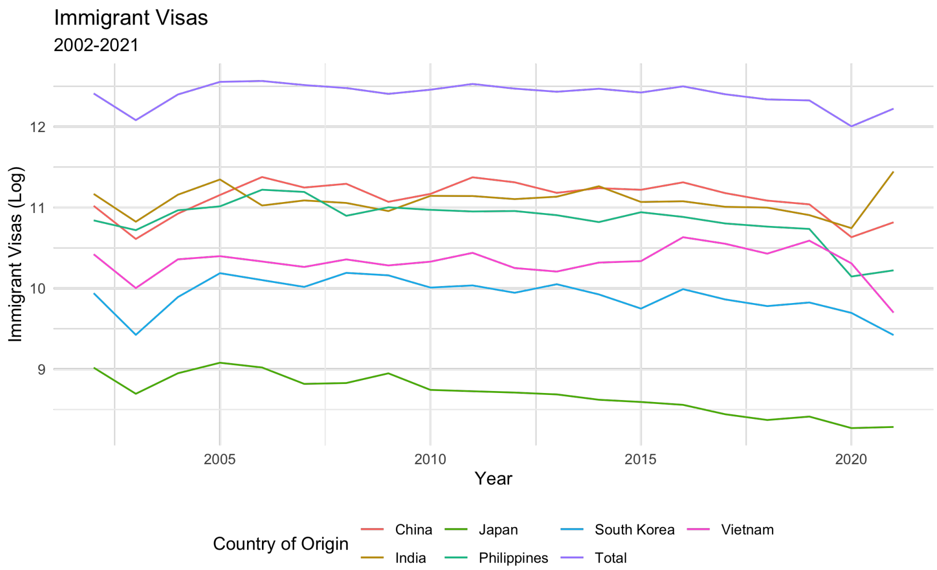
Figures and Tables



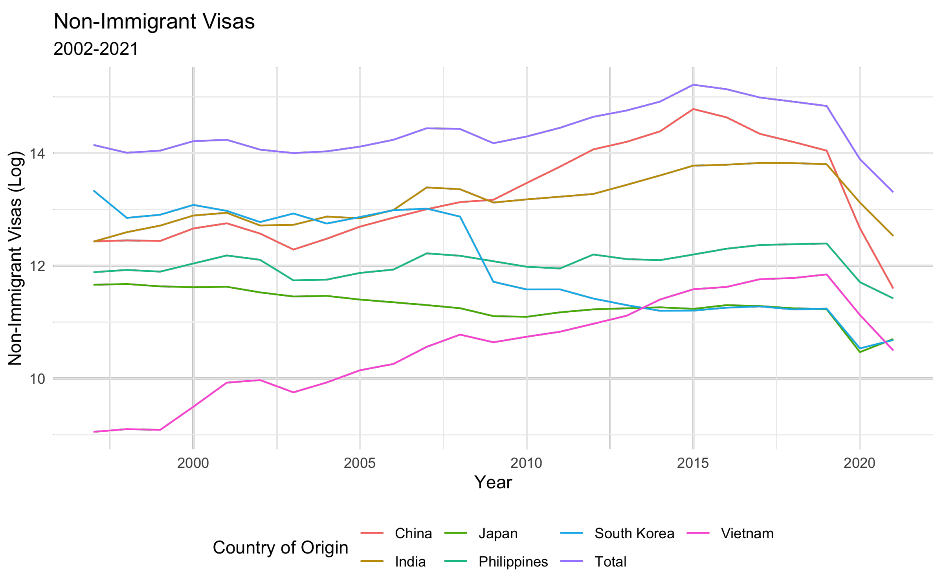


Figure 1: Non-immigrant and Immigrant Visas Issued
Main Asian Countries of Origin (2000-2021)

Notes: Monthly immigrant and non-immigrant visa issuances are taken from the US State Department's Bureau of Consular Affairs. On average, the total number of non-immigrant visas is 1,935,010 per year and the total number of immigrant visas is 244,983 per year. We use the annual number of non-immigrant visas issued for Asian countries at the national level as an exogenous source of variation in the number of Asian immigrants per county in each year.

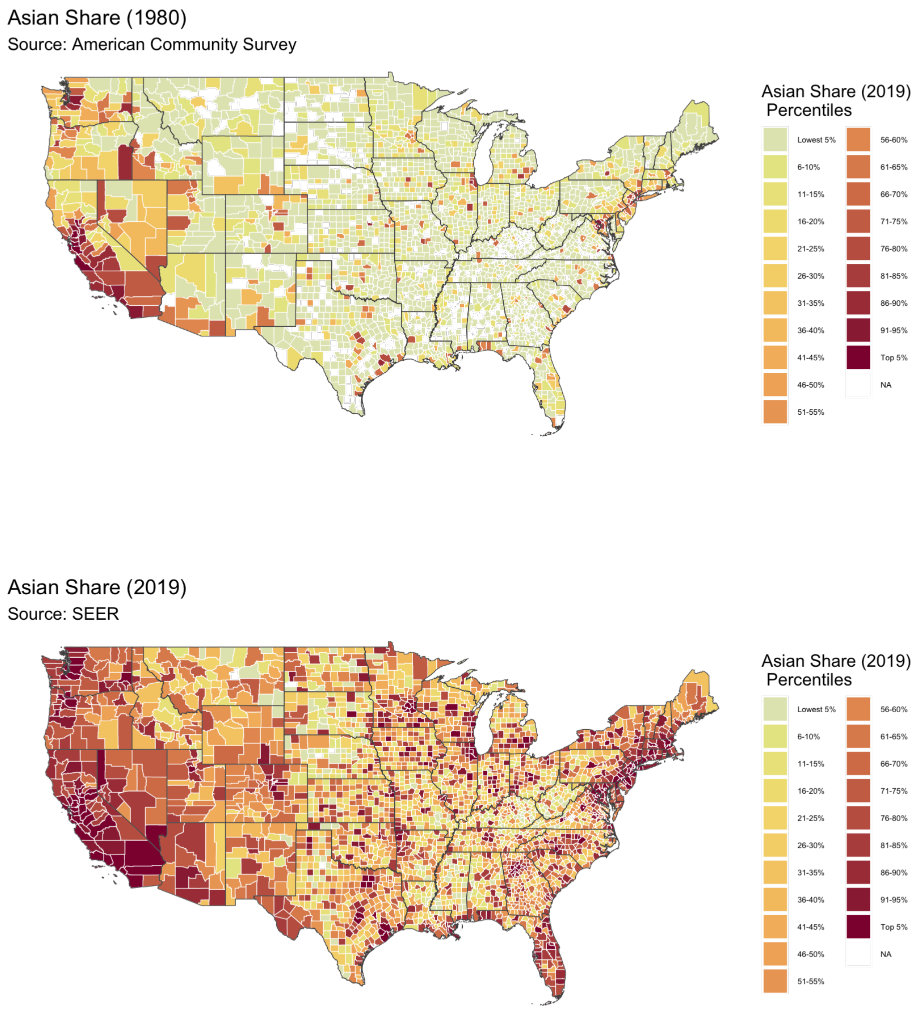
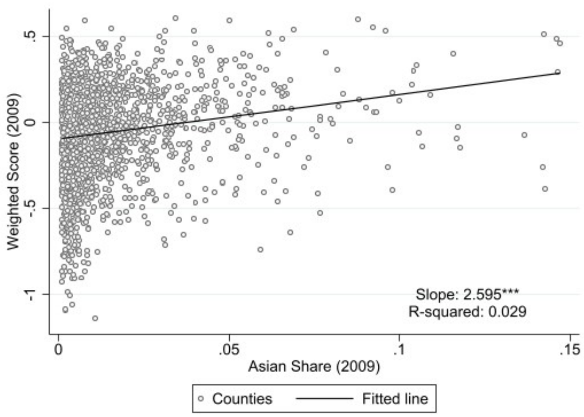
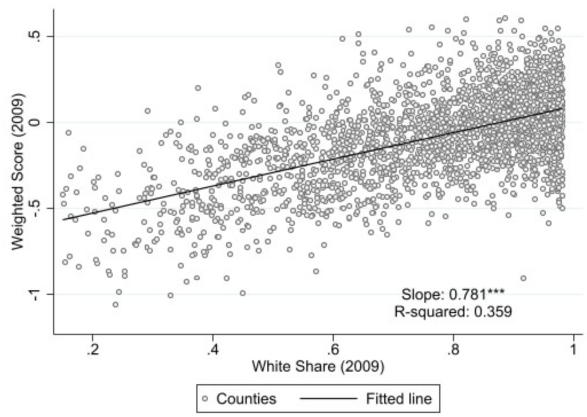


Figure 2: Asian Population Share across US Counties (1980 vs. 2019)

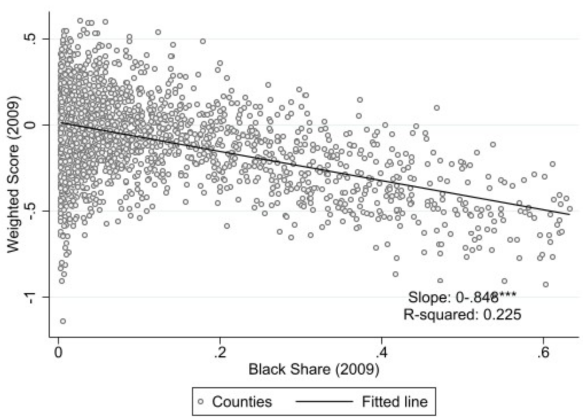
Notes: County-level shares of Asian residents in 1980 are obtained from the American Community Survey (Manson et al. (2021)). Survey respondents self-report being either White, Black / African American, American Indian or Alaska Native, Chinese, Japanese, Other Asian or Pacific Islander, Other Race, Two Major Races, or, Three or More Major Races. For this paper, we consider those who self-identified as Chinese, Japanese and Other Asian or Pacific Islander as Asian. This includes both foreign-born and US-born Asian respondents. County-level Asian shares for years 2009-2018 are taken from the Surveillance, Epidemiology, and End Results (SEER) dataset. We divide all US counties into 20 percentile groups based on the share of Asian residents in that county in that year and we use 2019 percentiles in both 1980 and 2019 in order to show how the US Asian population has both spread out across space and increased in quantity over time.



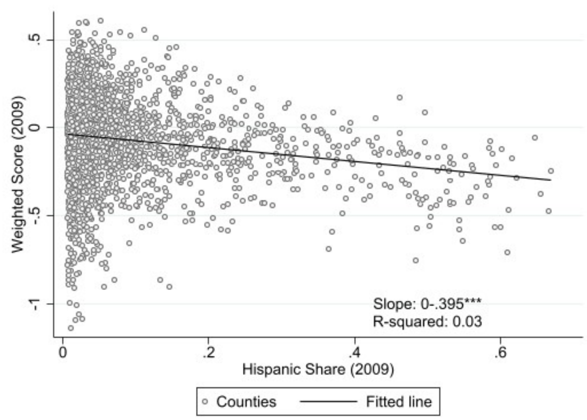
(a) Asian Shares



(b) White Shares



(c) Black Shares



(d) Hispanic Shares

Figure 3: Spatial Distribution of Race and County-level Weighted Scores

Notes: These graphs show the relationship between county-level weighted scores and the share of each race in 2010. The vertical axes represent county-level population shares of Asian, White, Black and Hispanic residents. Horizontal axes represents a county's weighted Math and Reading score. The red line in each graph is a non-parametrically fitted line for each scatter plot. Population shares and weighted scores are taken from the Stanford Education Data Archive.

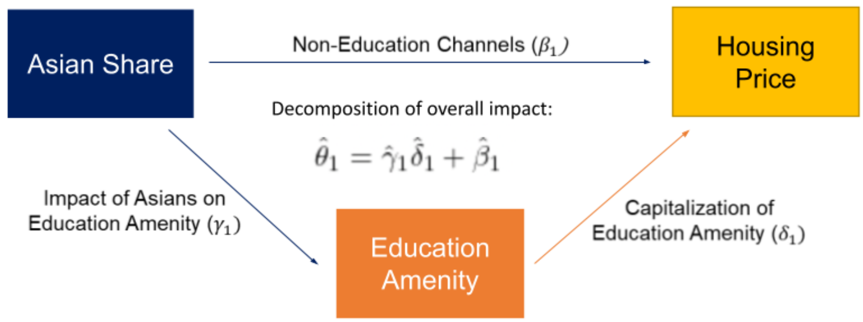


Figure 4: Channels through which Asians Affect Housing Market

Notes: This figure is a graphical depiction of our decomposition exercises, using the estimates from Equation (1), (2) and (3). The total impact of Asian immigrants on housing prices (θ_1 in Equation (1)) is decomposed into a non-education channel (β_1 in Equation (2)) and an education channel ($\delta_1 * \gamma_1$ in Equation (2), (3)). The non-education channel is captured when we regress housing prices on Asian population shares while explicitly controlling for educational outcomes. The educational channel is captured when we isolate the effect of Asian population shares on educational outcomes from the overall effect of educational outcomes on house prices.

Table 1: Summary Statistics

Variable	Obs.	Min.	Mean	Median	SD	Max.	Source
Reading							
Number of Students	32,140	2	6,733	1,788	22,232	729,471	SEDA
White	32,140	0	3,332	1,203	7,025	139,722	SEDA
Black	32,140	0	1,046	49	4,354	119,376	SEDA
Hispanic	32,140	0	1,581	74	11,466	467,533	SEDA
Asian	32,140	0	316	9	2,158	72,392	SEDA
Reading Score	32,140	-1.996	-0.042	-0.015	0.248	0.855	SEDA
White	32,140	-0.970	0.110	0.103	0.205	1.234	SEDA
Black	32,140	-1.483	-0.431	-0.443	0.225	0.436	SEDA
Hispanic	32,140	-1.068	-0.276	-0.284	0.217	0.532	SEDA
Asian	32,140	-2.932	0.354	0.366	0.367	1.461	SEDA
Math							
Number of Students	32,140	2	6,175	1,680	19,550	671,412	SEDA
White	32,140	0	3,091	1,072	6,630	139,677	SEDA
Black	32,140	0	963	40	4102.323	119,271	SEDA
Hispanic	32,140	0	1,441	77	9668.093	440,105	SEDA
Asian	32,140	0	290	7	1,952	68,622	SEDA
Math Score	32,140	-1.585	-0.040	-0.021	0.280	0.862	SEDA
White	32,140	-1.329	0.104	0.105	0.247	1.192	SEDA
Black	32,140	-1.616	-0.473	-0.477	0.249	0.453	SEDA
Hispanic	32,140	-1.069	-0.235	-0.228	0.222	0.647	SEDA
Asian	32,140	-2.461	0.515	0.526	0.411	2.138	SEDA
Population Shares (2009)							
White	3,139	0.000	0.434	0.368	0.396	0.998	SEER
Black	3,139	0.000	0.049	0.005	0.114	0.855	SEER
Hispanic	3,139	0.001	0.082	0.032	0.131	0.959	SEER
Asian	3,139	0.000	0.008	0.002	0.026	0.710	SEER
Population Shares (2019)							
White	3,142	0.004	0.427	0.352	0.381	0.983	SEER
Black	3,142	0.000	0.050	0.009	0.112	0.864	SEER
Hispanic	3,142	0.006	0.098	0.045	0.139	0.963	SEER
Asian	3,142	0.000	0.010	0.004	0.028	0.697	SEER

Notes: The SEDA database contains mean Reading and Language Arts (RLA) and Math scores at the grade by school district level for major metropolitan areas in the US. We aggregate scores from the school district level to the county-level. We weight reading and math scores by the total number of students who took the test. Population shares are taken from the Surveillance, Epidemiology, and End Results (SEER) dataset.

Table 2: Comparing Asian Immigrants and US Natives 1980-2018

Ratio of Asian Immigrants / US Natives			
Shares	1980	2010	2018
College-Educated	1.860	1.936	1.927
Industry			
High-Skill	0.865	0.941	1.097
Low-Skill	1.000	0.948	0.934
Occupation			
Blue-Collar	0.949	0.543	0.621
Services	0.863	0.750	0.733
White-Collar	1.060	1.211	1.372

Notes: In this table, Asian immigrants are defined as those who were born in Asian countries and who have been in the US for less than 5 years. We note that in our main analysis we do not distinguish between native- and foreign-born Asians in the US. We use recent Asian immigrants in this table to highlight changes in socioeconomic status in Asian immigrants from 1980-2018. We use ACS survey weights to generate the following shares for both Asian immigrants and those born in the US, for the years 1980, 2010 and 2018: college-educated, homeowners, working in specific industries and occupations. We generate this table by taking the ratio of Asian immigrants relative to US natives. We group industries and occupations using aggregated categories provided by the Bureau of Labor Statistics. High-skill industries are defined as those encompassing communications, utilities, transportation planning, finance, insurance, real estate, business and professional services. Low-skill industries are defined as transit operations, warehousing, fossil fuel extraction, wholesale trade, retail trade and services. White-collar occupations include technical support, managerial and specialty professions. Blue-collar occupations include mechanics, repairers, extractive occupations, metalworking, wood-working and machine operators. Service occupations include sales representatives and all other service occupations (e.g. dental assistants, janitors, hairdressers, etc.)

Table 3: Instrumental Variable Results

	(1) ln(price)	(2) ln(price)	(3) Mean Score (Reading & Math)	(4) Mean Score (Reading & Math)	(5) ln(price)	(6) ln(price)
Asian Share	17.3560***	16.3342***	7.7802***	8.1031***	12.0403***	11.2417***
	(1.4572)	(1.5792)	(1.5498)	(1.7201)	(1.7125)	(1.7604)
Mean Score					0.8445***	0.8159***
					(0.0524)	(0.0520)
Year FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Observations	22,419	22,419	22,419	22,419	22,419	22,419

Notes: *** p<0.01, ** p<0.05, * p<0.1. Columns (1) and (2) show the results from regressing the logarithm of the county-level Zillow house price index on Asian population share, with Asian population share instrumented using a shift-share instrumental variable. Columns (3) and (4) shows the results from regressing mean math and reading scores on Asian population share, with Asian population share instrumented using a shift-share instrumental variable. Columns (4) and (5) show the results from regressing the logarithm of the county-level Zillow house price index on Asian population share and mean math and reading scores, with the Asian population share instrumented using a shift-share instrumental variable and the mean score instrumented using the implementation of a state-level teacher reform. The standard errors are clustered at the county-level.

Table 4: IV Results (Non- linearity: Top 5% Asian Counties vs. Rest)

	(1) ln(price)	(2) Mean Score (Reading & Math)	(3) ln(price)
Asian Share × Top 5%	15.3618***	6.6009***	10.7048***
	(1.2254)	(1.3848)	(1.5834)
Asian Share × Non-Top 5%	2.7274**	-0.8702	4.4701***
	(1.2141)	(1.3720)	(1.5864)
Mean Score			0.8243***
			(0.0521)
Year FE	Y	Y	Y
County FE	Y	Y	Y
Observations	22,419	22,419	22,419

Notes: *** p<0.01, ** p<0.05, * p<0.1 We estimate separate coefficients for counties in the top 5% of the distribution of Asian population shares (Asian shares more than 5.6% in 2009) and those in the bottom 95% of the distribution. (1) shows the results from regressing the log of county-level Zillow house price index on Asian population share, with Asian population share instrumented using a shift-share instrumental variable (2) shows the results from regressing mean math and reading score on Asian population share, with Asian population share instrumented using a shift-share instrumental variable and (3) shows the results from regressing the log of county-level Zillow house price index on Asian population share and mean math and reading score, with the Asian population share instrumented using a shift-share instrumental variable and the mean score instrumented using the implementation of a state-level teacher reform. The standard errors are clustered at the county-level.

Table 5: Robustness Check: Asian vs. Non-Asian Foreign Born

	(1) ln(price)	(2) ln(price)	(3) Mean Score	(4) Mean Score
Asian Share	8.1476***	6.7944***	3.831**	3.631*
	(1.7919)	(1.9603)	(1.801)	(2.030)
Share Non-Asian Foreign Born	-4.8387***	-4.7546***	-1.531	-1.626
	(1.3610)	(1.3856)	(1.368)	(1.435)
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Control Variables	N	Y	N	Y
Observations	22,421	22,421	22,421	22,421

Notes: *** p<0.01, ** p<0.05, * p<0.1 In our main specification, we construct the shift-share instrumental variable as follows: $IV_{jt} = ShareAsian_j^{1980} \times VISA_t$, where $VISA$ is the total number of non-immigrant visas issued for Asian countries in each year t. In this specification, we want to rule out the explanation that places attracting more immigrants in general are also places which have higher school quality and higher housing prices. We control for both Asian population and non-Asian immigrants (share of non-Asian foreign-born in each county) to disentangle the effect. We instrument non-Asian foreign-born population share using the following IV: $IV_{jt} = ShareNonAsianFB_j^{1980} \times VISA_t$, where $VISA$ is the total number of non-immigrant visas issued for non-Asian countries in each year t. The standard errors are clustered at the county-level.

Table 6: Robustness Check: Alternative IV (Specific Countries of Origin)

	(1) ln(price)	(2) Mean Score (Reading & Math)	(3) ln(price)
Asian Share	12.1333***	5.2854***	8.4229***
	(0.8264)	(0.9321)	(1.0893)
Mean Score			0.8339***
			(0.0511)
Year FE	Y	Y	Y
County FE	Y	Y	Y
Observations	22,419	22,419	22,419

Notes: *** p<0.01, ** p<0.05, * p<0.1 In this paper, we present the results of our main specification using an alternative instrumental variable. In our main specification, we construct the shift-share instrumental variable as follows: $IV_{jt} = ShareAsian_j^{1980} \times VISA_t$, where $VISA$ is the total number of non-immigrant visas issued for Asian countries in each year t. In this specification, we construct an alternative shift-share variable as follows: $IV_{jt}^{1980,Country} = \frac{\Sigma_c Share_{jc}^{1980} VISA_{ct} Educ_c}{10000}$ for the countries which make up the largest share of incoming Asian immigrants: China, Japan, South Korea, Vietnam, India, and the Philippines. We include country-specific education spending as a measure of differential attitudes towards investing in education. The standard errors are clustered at the county-level.

Table 7: Sub-sample Analysis: without Top Five Counties

	(1) ln(price)	(2) Mean Score (Reading & Math)	(3) ln(price)
Asian Share	11.8470***	4.4894***	9.4073***
	(1.0285)	(1.1642)	(1.3268)
Mean Score			0.8291***
			(0.0517)
Year FE	Y	Y	Y
County FE	Y	Y	Y
Observations	22,371	22,371	22,371

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The results presented in this subsample analysis are the same regression results without the five counties with highest Asian shares (San Francisco, CA; Santa Clara, CA; Honolulu, HI; Kauai, HI; Maui, HI). Column (1) shows the results from regressing the logarithm of the county-level Zillow house price index on Asian population share, with Asian population share instrumented using a shift-share instrumental variable. Column (2) shows the results from regressing mean math and reading scores on Asian population share, with Asian population share instrumented using a shift-share instrumental variable. Column (3) shows the results from regressing the logarithm of the county-level Zillow house price index on Asian population share and mean math and reading scores, with the Asian population share instrumented using a shift-share instrumental variable and the mean score instrumented using the implementation of a state-level teacher reform. The standard errors are clustered at the county-level.

Table 8: Potential Mechanisms

Panel A: Displacement of Other Races					
		White Share	Black Share	Hispanic Share	
Asian Share		-0.6046***	-0.2841***	-0.0159	
		(0.1265)	(0.0810)	(0.0963)	
Year FE		Y	Y	Y	
County FE		Y	Y	Y	
Observations		22,419	22,419	22,419	
Panel B: Changes in Median Income By Race					
	All	White	Black	Hispanic	Asian
Asian Share	2.4872***	3.3283***	0.0215	1.7739	2.2710
	(0.8324)	(0.8592)	(2.3752)	(2.7113)	(4.3065)
Year FE	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y
Observations	22,419	22,366	10,786	12,101	5,480
Panel C: Peer Effect					
		White	Black	Hispanic	Asian
Asian Share		8.5282***	5.7764**	7.2607**	2.5509
		(2.0988)	(2.7995)	(2.8809)	(6.7943)
Year FE		Y	Y	Y	Y
County FE		Y	Y	Y	Y
Observations		21,904	11,650	12,860	5,463

Notes:*** $p<0.01$, ** $p<0.05$, * $p<0.1$. In these regressions, we look at the potential mechanisms governing the impact of higher Asian shares on county-level educational outcomes. In Panel A, we show the results of regressing county-level Asian population share on the shares of other races. In Panel B, we show the results of regressing county-level Asian population share on race-specific median incomes. In Panel C, we show the results of regressing county-level Asian population share on race-specific weighted test scores.

A Appendix

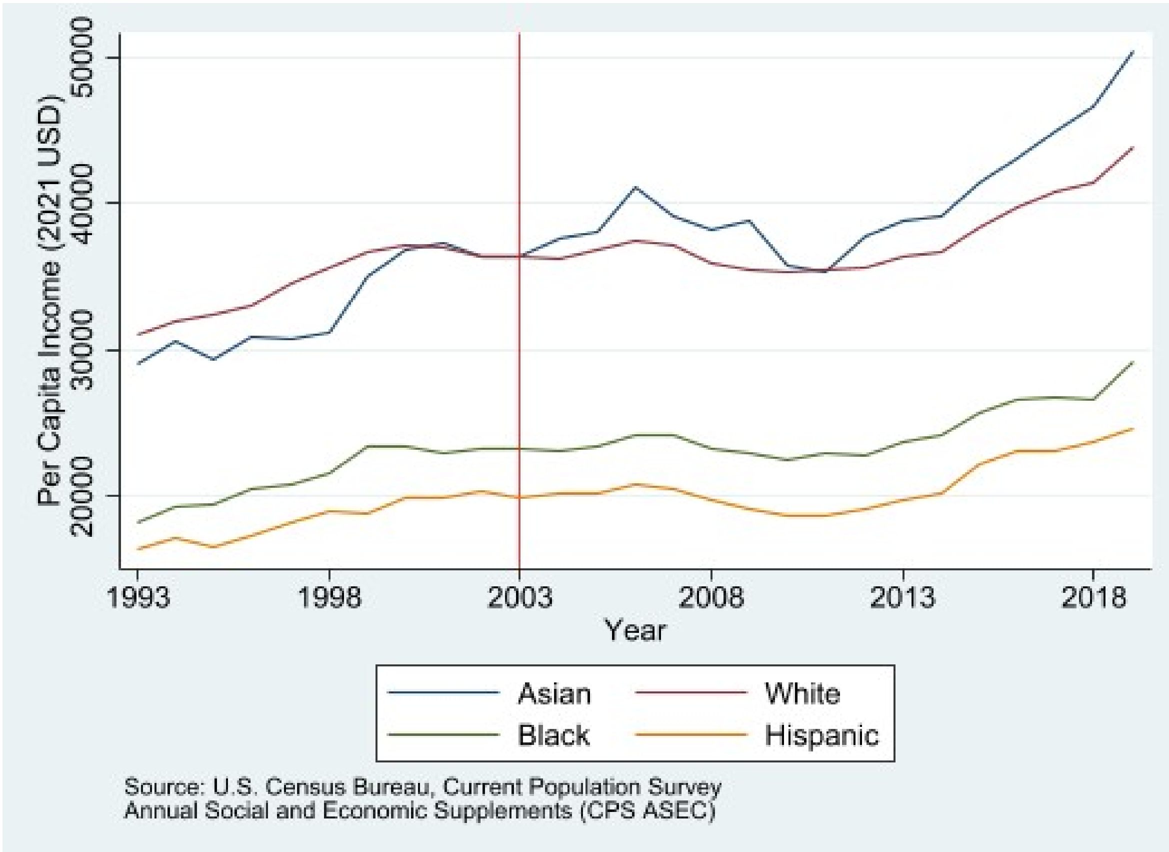


Figure A1: Historical Median Income by Race

Notes: The graph plots annual per capita income by race (2021 USD). The source of the data is US Census Bureau, Current Population Survey Annual Social and Economic Supplements. In the row data, the Asian category appears only after 1993.

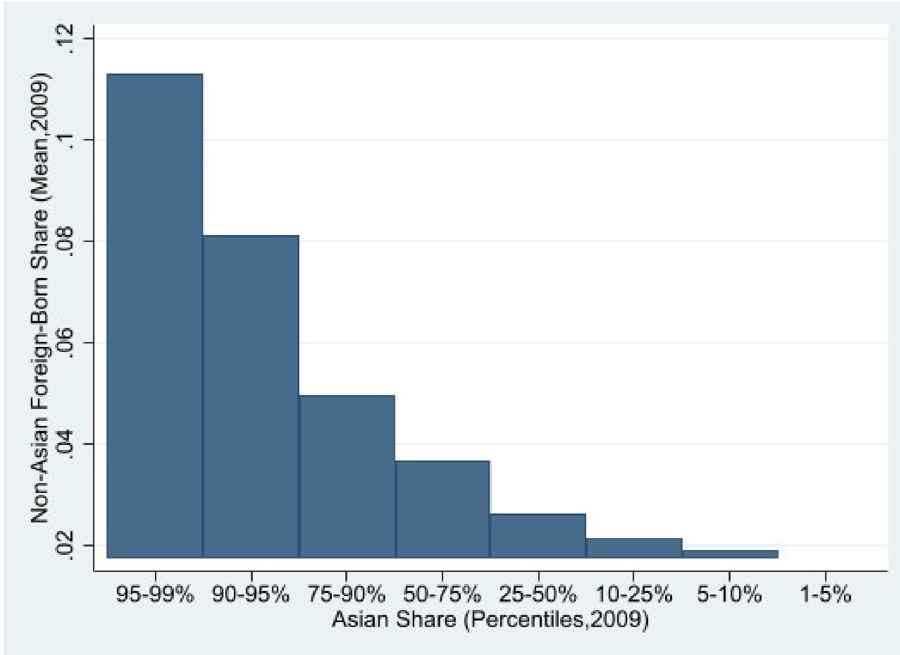
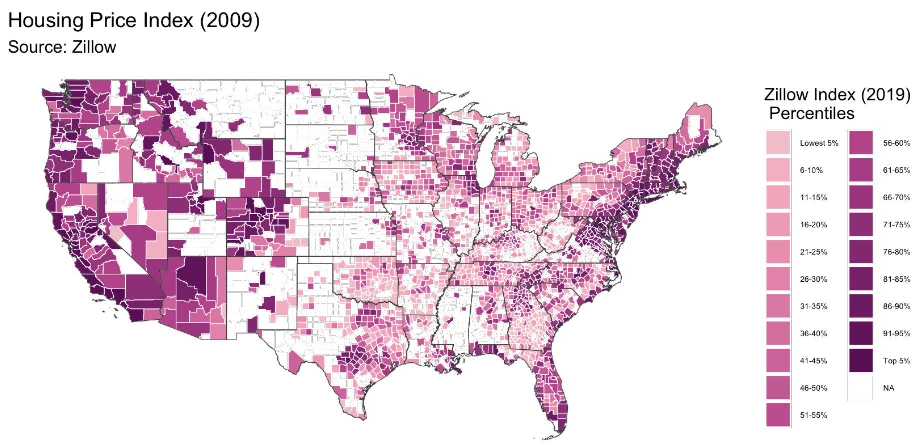


Figure A2: Relation Between Sorting of Asians and Non-Asian Foreign-Born (2009)

Notes: The graph plots the relationship between Asian Shares and non-Asian foreign-born shares based on 2009 statistics. The X-axis indicates counties with their Asian shares in each percentile. Y-axis indicates the mean of the non-Asian foreign-born share of the counties in each percentile. The source of the Asian Share is US Census Bureau, Current Population Survey Annual Social and Economic Supplements, and the source of non-Asian foreign-born is American Community Survey (ACS).



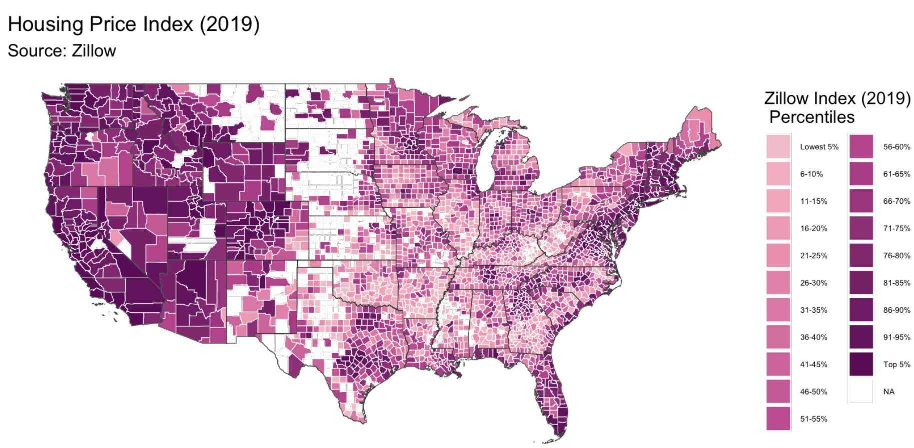


Figure A3: Zillow Housing Price Index across US Counties (2009 vs. 2019)

Notes: The Zillow Home Value Index is a measure of housing value for a given region across different home types. Data is available for a subset of locations across the US. To derive annual county-level price indices, we calculate the average value using all available months of data. We divide all US counties into 20 percentile groups and we use 2019 values in both 2009 and 2019 in order to show housing values across the US have changed over time.

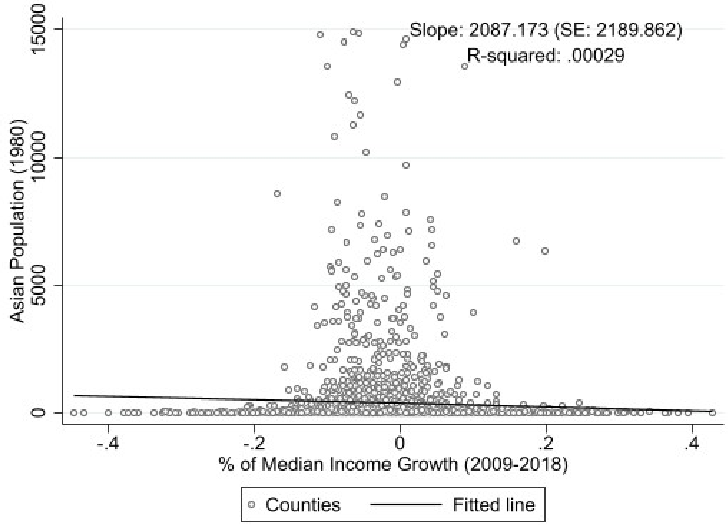


Figure A4: Relation Between 1980 Asian Shares and Median Income Growth (2009-2018)

Notes: The graph plots the relationship between Asian Shares and median income growth of counties (2009-2018). The X-axis indicates counties' median income growth from 2009 to 2018. Y-axis indicates Asian population in 1980.

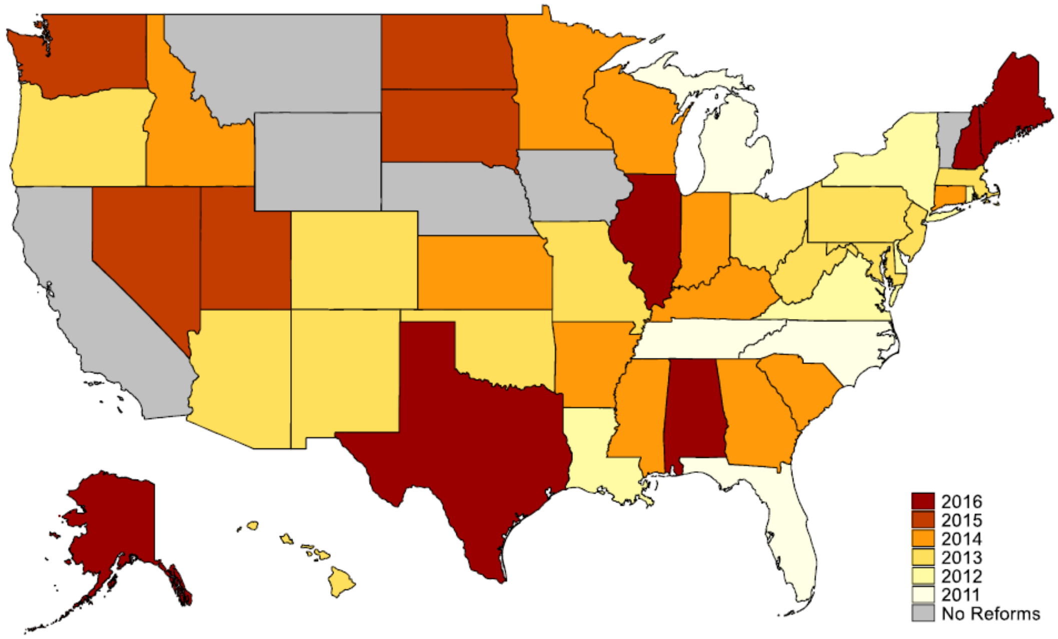


Figure A5: Implementation of Teacher Reform

Notes: The map is from Kraft et al. (2020). The colorsindicate the year when state-wide teacher accountability reforms were implemented.

Table A1: Summary Statistics By Country of Origin

					1980			
Variables	Whole Sample	Chinese	Indian	Filipino	Vietnamese	Korean	Japanese	Other Asians
Share of Asian Pop.	-	0.226	0.104	0.207	0.057	0.087	0.215	0.101
Education								
Share High School	0.348	0.197	0.155	0.200	0.284	0.289	0.342	0.323
Share College	0.140	0.321	0.465	0.315	0.092	0.279	0.238	0.133
Av. No. of Children	0.862	0.968	1.019	1.195	1.396	1.212	0.813	1.250
					2000			
Variables	Whole Sample	Chinese	Indian	Filipino	Vietnamese	Korean	Japanese	Other Asians
Share of Asian Pop.	-	0.237	0.153	0.181	0.103	0.102	0.084	0.137
Education								
Share High School	0.381	0.207	0.170	0.235	0.326	0.281	0.281	0.321
Share College	0.215	0.438	0.575	0.379	0.171	0.382	0.392	0.216
Av. No. of Children	0.751	0.796	0.893	0.943	1.049	0.796	0.575	1.174
					2019			
Variables	Whole Sample	Chinese	Indian	Filipino	Vietnamese	Korean	Japanese	Other Asians
Share of Asian Pop.	-	0.237	0.210	0.165	0.099	0.079	0.042	0.165
Education								
Share High School	0.347	0.183	0.120	0.220	0.309	0.210	0.225	0.291
Share College	0.304	0.545	0.713	0.456	0.297	0.547	0.519	0.343
Av. No. of Children	0.645	0.616	0.844	0.733	0.785	0.614	0.512	0.927

Notes: These summary statistics show how Asian immigrants from different countries of origin have educational outcomes. We use the “detailed race” variable from the American Community Survey to determine country of origin.

Table A2: First Stage of Instrumental Variables

VARIABLES	(1) Asian Share	(2) Mean Score	(3) Asian Share	(4) Mean Score
	(1 Endogenous Var, 1 IV)		(2 Endogenous Var, 2 IV)	
Shift Share IV	0.0719***		0.0705***	0.5165***
	(0.0034)		(0.0034)	(0.1075)
Teacher IV		-0.0097***	-0.0005***	-0.0092***
		(0.0020)	(0.0001)	(0.0020)
× Low Pupil-to-teacher States (2009)		-0.0603***	0.0007***	-0.0605***
		(0.0033)	(0.0001)	(0.0033)
× High Pupil-to-teacher States (2009)		0.0199***	0.0002***	0.0196***
		(0.0026)	(0.0001)	(0.0026)
F-Statistics	**442.59**	**181.21**	**131.29**	**141.83**
Observations	22,419	22,428	22,419	22,428

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table reports the first stage results using the two instrumental variables (i.e., Shift Share constructed for the share of Asians and teacher accountability reform constructed for the mean of scores). Column (1) and (2) shows the first-stage results when there is one endogenous variable and one instrumental variable, and column (3) and (4) show the first-stage results with two endogenous and two instrumental variables. The standard errors are clustered at the county-level.

Table A3: Top 5% Asian populated counties in 1980 and their Growth in the 2010s

	A. Growth of Share of Asian (2009-2018)	
	Non-top 5%	Top 5%
Counties w/ Top 5% Asian Shares (1980)	93 (62.00%)	57 (38.00%)

	B. Growth of Median Income (2009-2018)	
	Non-top 5%	Top 5%
Counties w/ Top 5% Asian Shares (1980)	148 (98.67%)	2 (1.33%)

Notes: This table shows the number of top Asian share counties in 1980 categorized into top 5% vs. non-top 5% counties in terms of their growth in the Asian population share (Panel A) and median income (Panel B), between 2009 and 2018. The source is US Census Population for the Asian shares in the 2010s; American Community Survey for the Asian shares in 1980; and Stanford Educational Data Archive (SEDA) for median income.

Table A4: List of Top 5% Asians Counties

County, State
Kodiak Island,AK*; Alameda,CA*; Contra Costa,CA*; Orange,CA*; Sacramento,CA*; San Francisco,CA*; San Mateo,CA*; Santa Clara,CA*; Solano,CA*; Sutter,CA*; Honolulu,HI*; Kauai,HI*; Maui,HI*; Middlesex,NJ*; Queens,NY*; Fort Bend,TX*; Fairfax,VA*; Loudoun,VA*; Fairfax City,VA*; King,WA*; Anchorage,AK; Juneau,AK; Ketchikan; Gateway,AK; Fresno,CA; Los Angeles,CA; Marin,CA; Merced,CA; Monterey,CA; Napa,CA ; Placer,CA; Riverside,CA; San Bernardino,CA; San Diego,CA; San Joaquin,CA; Stanislaus,CA; Ventura,CA; Yolo,CA; Yuba,CA; Alachua,FL; Forsyth,GA; Fulton,GA; Gwinnett,GA; Champaign,IL; Cook,IL; Dupage,IL; Lake,IL; Tippecanoe,IN; Buena Vista,IA; Jefferson,IA; Story,IA; Howard,MD; Montgomery,MD; Middlesex,MA; Norfolk,MA; Suffolk,MA ; Oakland,MI; Washtenaw,MI; Hennepin,MN; Olmsted,MN; Ramsey,MN; Scott,MN; Clark,NV; Washoe,NV; Atlantic,NJ; Bergen,NJ; Hudson,NJ; Mercer,NJ; Morris,NJ; Somerset,NJ; Los Alamos,NM; Kings,NY; Nassau,NY; New York,NY; Richmond,NY; Rockland,NY; Tompkins,NY; Westchester,NY; Orange,NC; Wake,NC; Benton,OR; Multnomah,OR; Washington,OR; Montgomery,PA; Philadelphia,PA; Brazoria,TX; Collin,TX; Denton,TX; Harris,TX; Travis,TX; Arlington,VA; Henrico,VA; Montgomery,VA; Prince William,VA; Alexandria City,VA; Charlottesville City,VA; Falls Church City,VA; Manassas Park City,VA; Virginia Beach City,VA ; Williamsburg City,VA; Island,WA; Kitsap,WA; Pierce,WA; Snohomish,WA; Thurston,WA; Whitman,WA

Notes: The top 5% of Asian share is based on data from 2009. The source data is US Census Population. Top 5% counties are those with the share of Asians great than 5.6%. Asterisk(*) symbol indicates counties with Asian share great than 20%.