An Analysis of Asian Housing Outcomes in the US

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1 Introduction

The literature examining racial bias against Black Americans in the United States is exhaustive. However, despite the abundance of literature surrounding the comparison between Black and White, or otherwise ”non-Black” households, there is a relative dearth of research into the comparison between Asian households and non-Asian households. This gap in housing inequity research is important as Asian households showcase an interesting cross-section of high-income, on average, as well as a growing section due to frequent migration to the United States.

This research analyzes how Asian households experience differing housing outcomes from other groups, particularly Black and White households, from 1980 until 2019. Using Census microdata on housing preferences like what houses to rent or buy and the decision of whether to rent or buy, the analysis finds large differences between Asian and White households. Estimation is done by using a dynamic equilibrium model, allowing for market segmentation by race, and then mapping the differences in housing preferences into economic welfare differences. This research has, thus far, produced interesting results which are mixed in terms of their compliance to previous research.

2 Literature Review

The primary literature to which this research attempts to contribute is the housing outcomes of Asian households in comparison to other groups. For now, there is literature which suggests that the trends seen in this research could potentially be explained by immigration patterns and spatial differences, as well as socio-economic and demographic attributes (DeSilva and Elmelech, 2012 [18]). There is other research which suggests that even within these high cost of living areas, subgroups of Asian households will concentrate into specific towns or neighborhoods (Walton, 2015 [44]). Other researchers focus more heavily on the price differences in the price differences in the housing market (Bayer, Casey, Ferreira, and McMillan, 2017 [4]). There has also been consideration paid to the mortgage market for Asian immigrants in the United States (Courchane, Darolia, Gailey, 2015 [15]). Finally, there is research which has focused specifically on home ownership factors for Asian groups, which draws the connection between home ownership and unobserved financial support (Painter, Yang, Yu, 2003 [38]).

There are four other literatures to which this paper adds. Firstly, the extensive literature studying racial differences in in the housing market. Muth (1969) [34] alongside Kain and Quigley (1975) [?] are among the earliest contributors to the literature which uses expenditure shares to estimate differences in rent when segmented by race. Others like Gyourko and Linneman (1996) [22], Gyourko et al. (1999) [23], Charles and Hurst (2002) [12], and Collins and Margo (2011) [14] documented and explained the massive gaps in ownership rates between races. There is a swath of literature which discuss the causes of geographic racial segregation. Examples include Schelling (1971, 1978 [40, 41] who contributes theoretical models of segregation. Cutler, Glaeser, and Vigdor (1999) [16] and Logan and Parman (2017) [32] measure indexes of segregation longitudinally. Card, Mas, and Rothstein (2008) [11] and Boustan (2010) [8] estimate tipping points and White flight, respectively. Mapping outcomes like the changes in index of isolation or white flight into economic welfare can be challenging, especially when there is interaction between these phenomena. As put forth by King and Mieszkowski (1971) [29], segregation's existence does not directly imply that housing prices for Black households would be different without differences in the housing supply in Black neighborhoods. This paper contributes to prior research by analyzing the effect geographic segregation has on the three primary housing outcomes -what house to purchase, what house to rent, and whether ownership is correct.

Next, the paper contributes to the broad literature on racial differences in income (Margo, 2016 [33]; Bayer and Charles, 2018 [5]; Chetty, Hendren, Jones and Porter, 2020 [13]), wealth (Blau and Graham, 1989 [6]; Kuhn, Schularick and Steins, 2020 [30]; Derenoncourt, Kim, Kuhn and Schularick, 2022 [17]) and welfare (Brouilette, Jones and Klenow, 2022 [10]) by analyzing the significance of gaps in the housing market for wealth gaps and welfare. Other papers have estimated the role of differences in returns and learning (Boerma and Karabarbounis, 2022 [7]) and income differences (Aliprantis, Carroll and Young, 2021 [2]). In terms of housing markets, Black households have seen worse returns on housing in recent decades, according to empirical evidence from Kahn (2021) [27] and Kermani and Wong (2021) [28], the latter of which shows that distressed home sales (such as foreclosures and short sales) are mostly to blame. As asserted by Gupta, Hansman, and Mabille (2022) [21], mortgage leverage limits may prevent Black households from relocating to areas with more income prospects because they tend to have higher levels of leverage. This work contributes by explaining racial variations in portfolios across the income distribution using a long run general equilibrium technique. Particularly, by breaking down the ways in which distortions in the relative pricing of housing quality and the cost of house ownership affect portfolios.

Thirdly, this research adds to the housing market assignment models by expanding the model to encompass both the rental and ownership sectors, as well as implementing a novel approach to racial inequalities. Early theoretical contributions came from Braid (1981) [9] and Sweeney (1974a,b) [42, 43]. Recently, researchers have employed quantitative assignment models to examine various aspects of housing markets, including buyer restrictions (Landvoigt, Piazzesi and Schneider, 2014) [31], the influence of income inequality on house prices (Maattanen and Tervio, 2014) [35], housing supply changes (Nathanson, 2020; Wang, 2022) [37,45], interest rate changes (Hacamo, 2021) [24], and the welfare effects of transaction taxes (Maattanen and Tervio, 2021) [36] and rental market evictions (Abramson, 2022) [1]. To estimate such models, Epple, Quintero, and Sieg (2020) [19] also provide a methodology based on GMM. This work is the first to combine an equilibrium assignment model of both the rental and ownership markets with the usual elements of a buy-rent decision (i.e., inside a life-cycle problem with mortgages). By creating a test of segmentation using variations in the arrangement of families according to race, it also offers a novel method for estimating the costs and welfare impacts of discrimination in the housing market.

Lastly, this paper has many similarities to the literature on misallocation (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009) [39] and related applications to the distribution of talent among racial and gender groups (Hsieh, Hurst, Jones and Klenow, 2019) [25]; misallocation resulting from spatial constraints imposed by zoning (Hsieh and Moretti, 2019) [26]; Babalievsky, Herkenhoff, Ohanian and Prescott, 2021 [3]); and rent control (Glaeser and Luttmer, 2003 [20]). Similarly, the pricing discrepancies in this study can be understood as quality-specific gaps that emerge naturally as a result of market segmentation and variations in the quality supply between the Black and White segments.

3 Data and Empirical Evidence

3.1 Data

This paper tests for differences in housing outcomes when controlling for racial differences. Therefore, to accomplish this aim, data on ownership, rent prices as well as housing values are needed for comparable Asian and White houses. IPUMS Census microdata is very useful for providing the necessary data and fits the desired time horizon of both before and after the Fair Housing Act of 1968. The time horizon which is being analyzed are 1960 and 2019. 1960, of course, is the Census before the Fair Housing Act and 2019 is used as the most recent available year in the original research. In 2024, it is a useful cutoff as to avoid the Covid shock of 2020.

The main dataset is constructed using the one and five percent samples from IPUMS USA for the decennial Census for years 1980-2000 and the one percent samples of the American Community Survey for years 2010 and 2019. Data is analyzed at the household level with group dwellings disregarded. Where household variables are not provided, the household head's data is used as a proxy. Household weights are used on estimates. Asian is both a dummy for the broader race as well as segmented into categories of Chinese, Japanese, Korean, Filipino, Vietnamese, and Korean.

3.2 Summary Statistics

The summary statistics paint an interesting picture of how Asian housing trends look when compared to non-Asian trends. When looking at the overall population in 1980 as compared to 2019, it would appear that Asian households are paying more for rent proportional to income than non-Asian households, with the percentage growing larger in 2019. Home value as a percentage of income, similarly, sees Asian households paying more for homes as a percentage of income, with the gap decreasing by 2019. Ownership rates have also become closer for Asian and non-Asian households, especially in the first income quintile.

Chinese households in 1980 paid very slightly more in rent as a percent of income than non-Chinese households, with the gap growing in 2019. the gap in home value as a percent of income remained similar between 1980-2019. Ownership rates for Chinese and non-Chinese households became very close, especially in the bottom two quintiles. Japanese, Korean, and Filipino households show similar trends when compared to non-Japanese, non-Korean, and non-Filipino households. Vietnamese households saw massive increases in ownership rates between 1980 and 2019, with the lowest income quintile even seeing higher ownership rates than non-Vietnamese households. The Inidan population sees an interesting trend in ownership rates, with the gap being completely inconsistent when compared to non-Indian households. With that said, the lowest income quintile is the closest to non-Indian ownership rate until the highest quintile.

4 Primary Results

4.1 Gap Ranking Analysis

Formulating the gaps into a linear regression is a useful way to analyze the difference between Asian and White households. Household i's price rank is modeled as a linear function of their income ranks allowing for differences in coefficients for Asian and White groups

$$p_i = \alpha_W + \beta_W y_i + \alpha_A Asian_i + \beta_A [Asian_i \times y_i] + X_i \Gamma + \epsilon_i, \tag{1}$$

in which $p_i \in [0, 100)$ is the rank of household i in the overall house price or rent distribution, $y_i \in [0, 100)$ is the rank of the same household in the overall income distribution, and $Asian_i$ is an indicator variable which is equal to one if the household is defined as Asian and 0 if it is non-non-Asian. Furthermore, X_i is a vector of control variables such as the age, sex and education level of the head of household, the household type (single or couple), the household's location (metropolitan area and state), as well as if the property is classified as a farm. α_W estimates the mean house price rank of a White household in the lowest income rank in the distribution ($p = 0$) and the slope variable β_W estimates the increase in the mean house price rank as income rank increases. The Asian indicator and its interaction with the income rank variable estimates the difference in the intercept and the slope coefficients for Asian households. The model is applicable to the subgroups within the Asian category, with an indicator variable delineating Chinese, Japanese, Korean, Vietnamese, Filipino, or Indian.

The primary coefficients of interest are α_W and β_A which estimate the average gap in the price distribution at each point in the income distribution. Using these coefficients, the rank gap at income rank y is defined as

$$\hat{p}_y^{gap} = \alpha_B + \beta_A \times y. \tag{2}$$

This rank gap is the estimated average difference in the home value rank of Asian households at the y-th rank in the income distribution relative to White households at the same income rank. This estimation is used for both rents and home values, as well as ownership rates.

Some interesting patterns arise when looking at the figures. Firstly, the households in the general Asian population are paying more than non-Asian households in both rent and home value when comparing at the same income levels. These gaps have remained relatively static, increasing and decreasing slightly throughout the time horizon. The ownership gap is also quite large, though it is shrinking in the most recent Census year sampled. For Chinese households, the rent gap is quite small, hovering around a 2 percentage point gap in 2019 while the home price gap is quite high, with Chinese households paying more for housing when compared to non-Asian households at the same income level. The ownership gap has dramatically decreased, even to the point of equal ownership rates to non-Asians. The rest of the populations follow the trend displayed in the overall population, paying more for rent and homes than non-Asians in the same income percentile, and having lower rates of ownership. The Vietnamese population is one which, seemingly, deviates. The group has come close to non-Vietnamese households in terms of rents, and even has higher ownership rates than non-Vietnamese households. They still pay more for housing, however. The Indian population is also interesting as ownership rates remain between 10 and 20 percentage points lower than non-Indian households, though it seems that all income levels are around the same ownership level.

4.2 Observable Quality Analysis

It is imperative to showcase evidence of how rent and price gaps are intertwined with lower quality housing. This is done via the following equation

$$y_i = \beta Asian_i + \sum_{j=1}^{10} \alpha_j \mathbf{1}\{\text{Income Decile} = j\}_i + \mathbf{X}_i \Gamma + \epsilon_i, \tag{3}$$

in which y_i is the measure of housing quality for household i, and $Asian$ is an indicator for the race of the household. This race is interchangeable with the subgroups Chinese, Japanese, Korean, Vietnamese, Filipino, and Indian and follows the same construction. Dummies for each income decile are included to control for the non-linear relationship between income and outcomes alongside a vector of controls, $\mathbf{X}$. The Census does not provide great measures of observable quality, but does include age of house and number of bedrooms. Neighborhood quality is not able to be assessed through the Census, such as school zones or crime rates. The key coefficient is β, estimating the difference between the group of interest and the rest of the population's households dependent on income, referred to as the gap.

It would be tedious to go race by race discussing yearly results, but there are some important outcomes to note. Firstly, households in the overall Asian population bought newer houses though with less bedrooms than other households. For instance, in 1980, Asian households live in a house 1.42 years newer than non-Asian households, but with 0.26 less bedrooms. All results were statistically significant for the overall group. The Chinese sample saw that only 2019 had statistically significant results for age of house, but the trend with bedrooms persisted. Japanese, Korean, Vietnamese, Filipino, and Indian households all showcase the same characteristics as estimated by the overall Asian population. For the overall Asian population, the divide between rich and poor households is approximately double that of the gap between Asian and non-Asian houses in 1980. The gap has also grown between 1980 and 2019.

This section would seemingly show that Asian households tend to settle into homes which are both newer and possess less bedrooms than the non-Asian population. This information, alongside the home price gaps, would show that Asian households are paying more for smaller and newer homes than non-Asian households. Without neighborhood information, it is difficult to report more without delving into the waters of speculation.

5 Future Plans

5.1 Segmentation

Asian, as a category, is not ideal. It is far too broad given the size of the continent. Therefore, being able to segment by region within Asia such as Middle Eastern, South Asian, and Southeast Asian. Beyond that, countries with large immigrant populations within America like China, India, or Vietnam would need to be segmented as well. There are also challenges in that race is typically defined how one is perceived rather than by self classification. This further segmentation is work which is key to be completed, though fell just outside of the scope of the class.

5.2 Geographic Analysis

In previous research, it has been found that Asian households tend to concentrate into specific geographic areas. This effect is very interesting, thus it appears worthwhile to investigate further if outcomes in a hotspot are better than those in a relatively less Asian populated city or region. Using IPUMS geographic information this should not be hard to implement, though it is outside of the time scope available to me.

6 Conclusion

This research shows how Asian households experience different housing outcomes compared to other groups. Importantly, it showcases that Asian households see very different outcomes in comparison to non-Asian households, typically seeing higher prices paid with lower ownership rates. While the ownership gaps are, for the most part, shrinking, there persists a gap for certain groups which warrants further consideration. There is still much work to be done to nail down a precise explanation for housing differences, but I look forward to ascertaining the answers.

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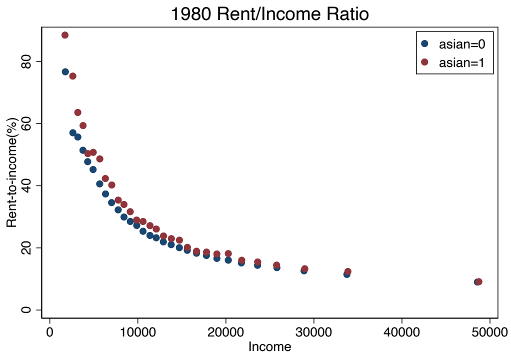
Table 1: Summary Statistics (Overall Asian Population)



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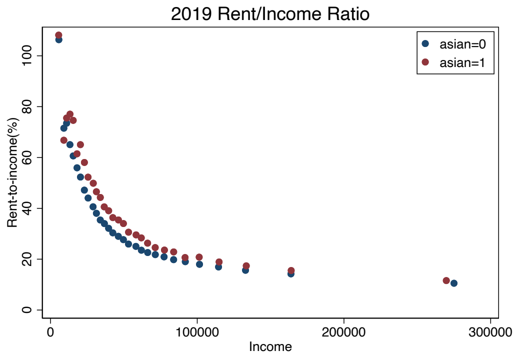

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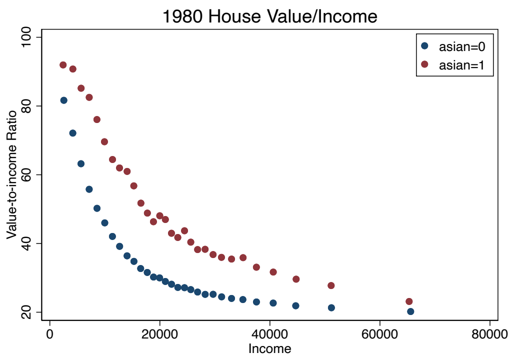

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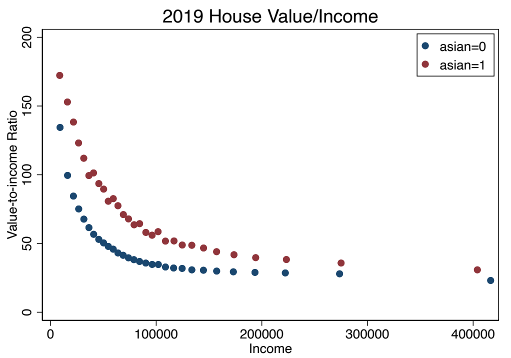

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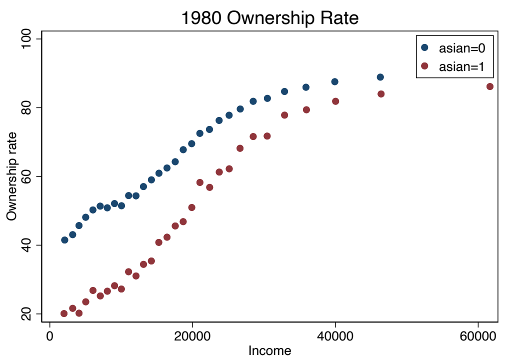

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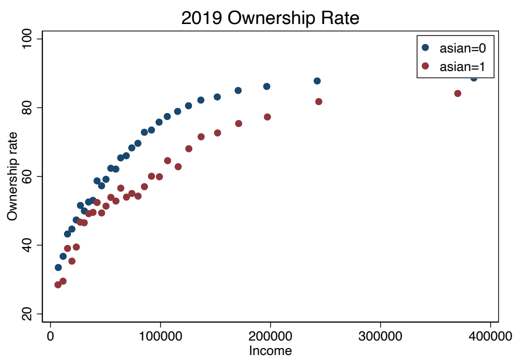

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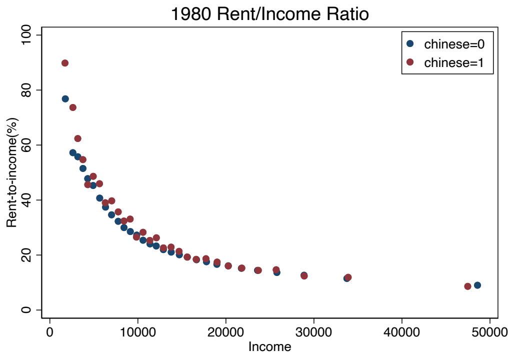

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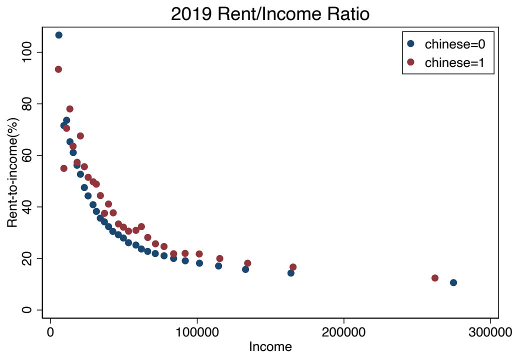

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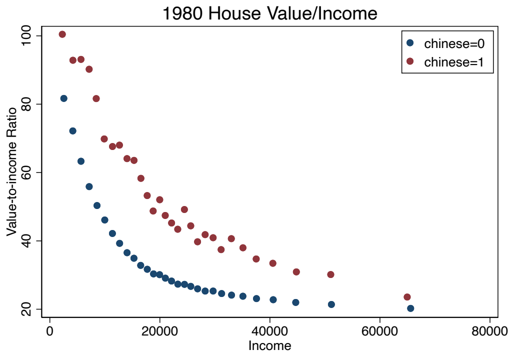

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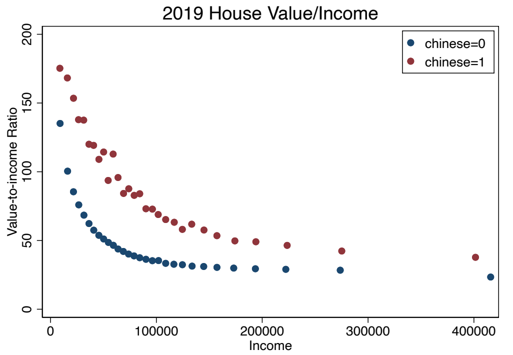

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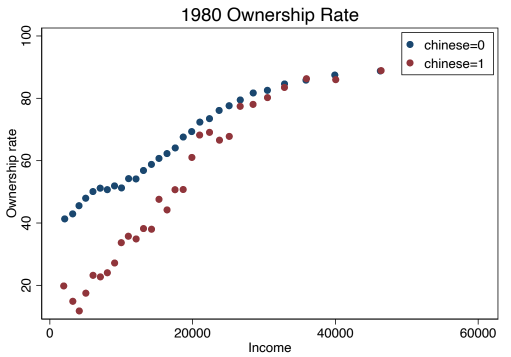

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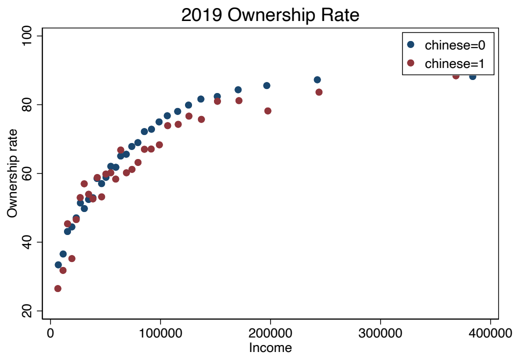

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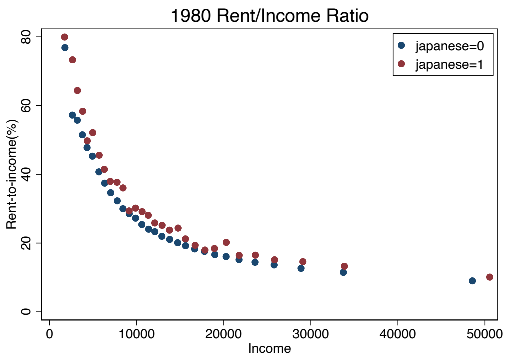

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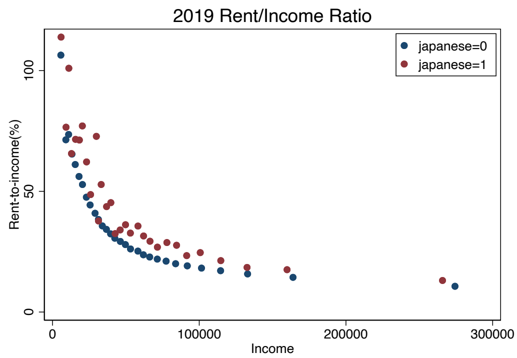

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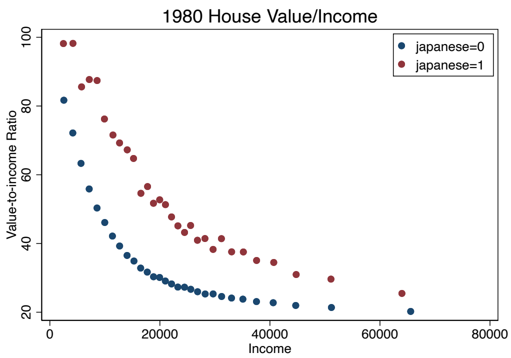

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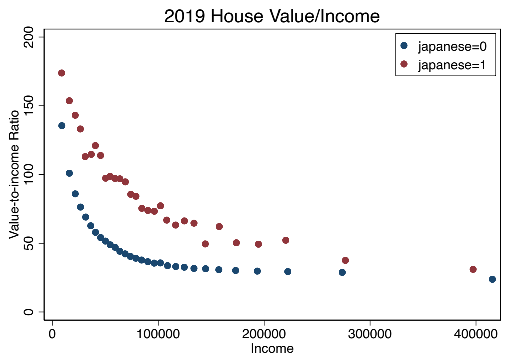

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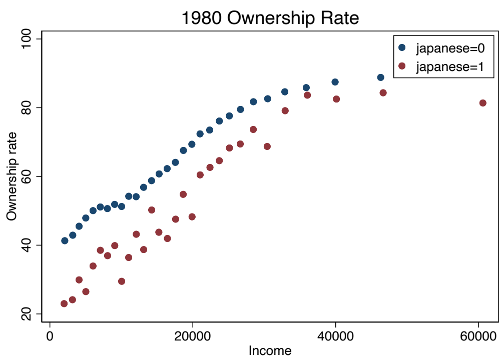

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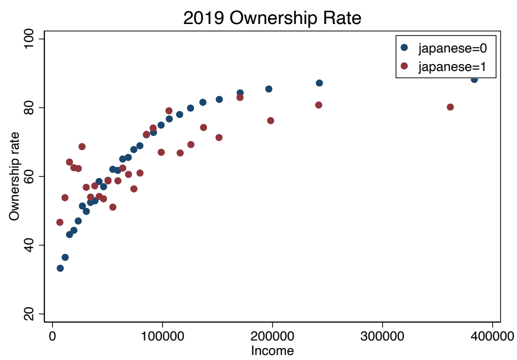

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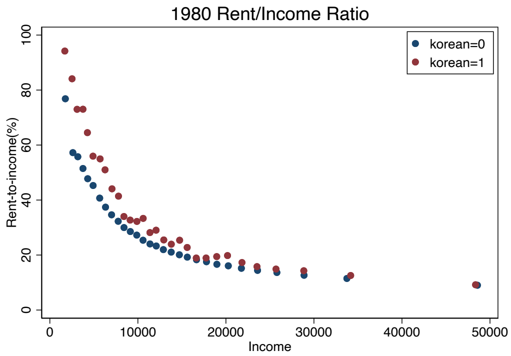

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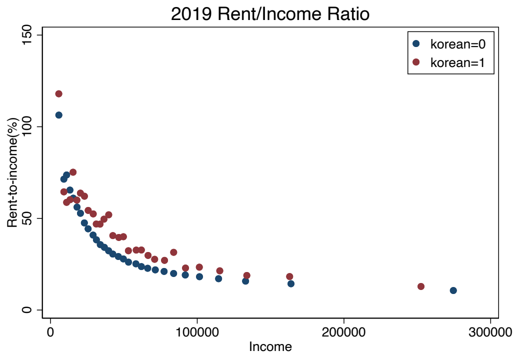

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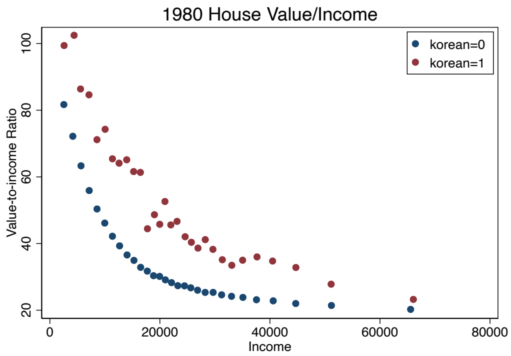

Figure 21: c

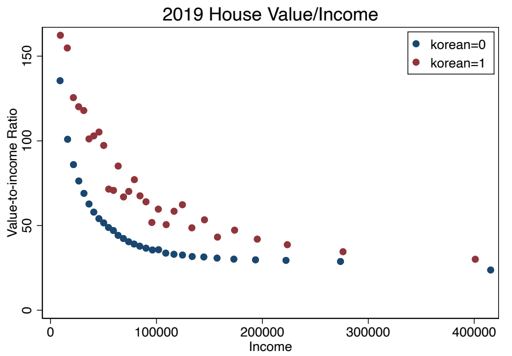

Figure 22: d

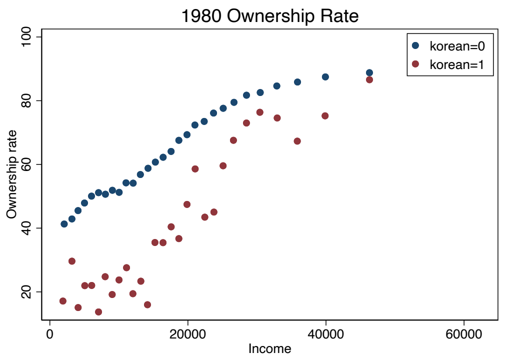

Figure 23: e

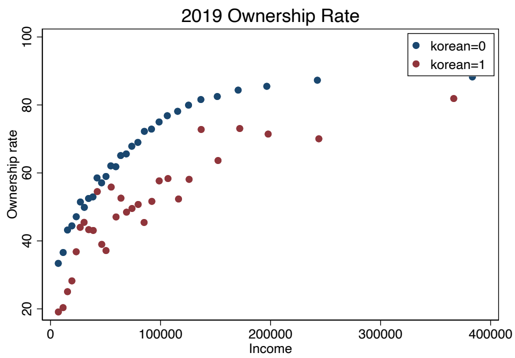

Figure 24: f

Table 5: Summary Statistics (Vietnamese Population)

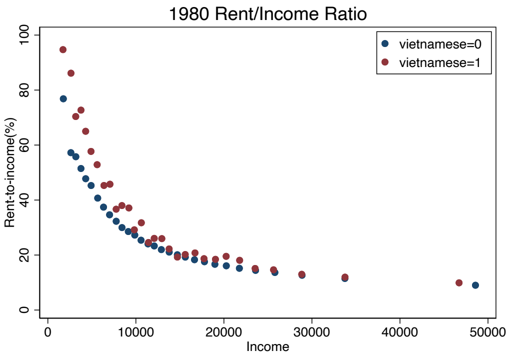

Figure 25: a

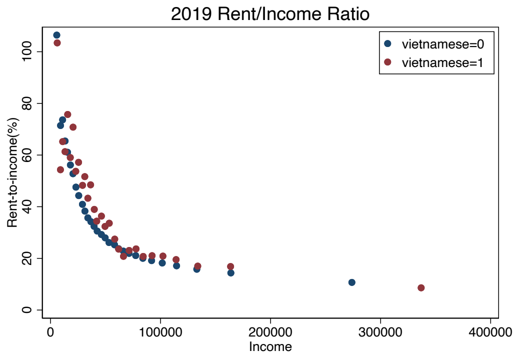

Figure 26: b

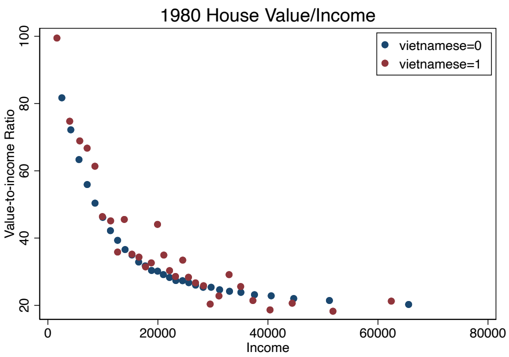

Figure 27: c

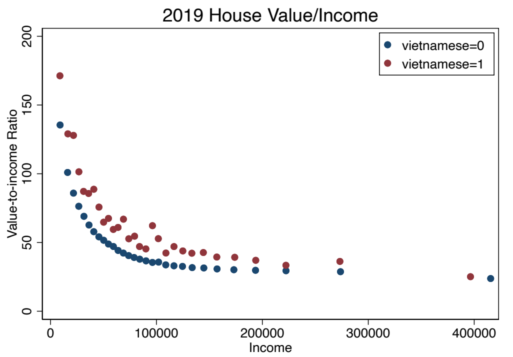

Figure 28: d

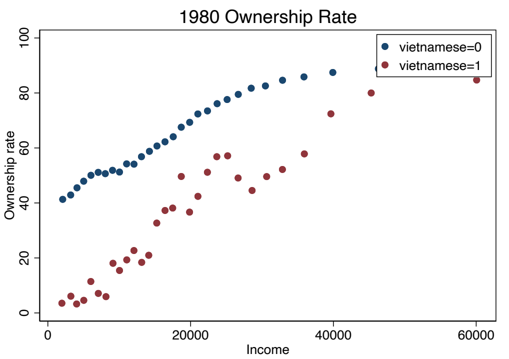

Figure 29: e

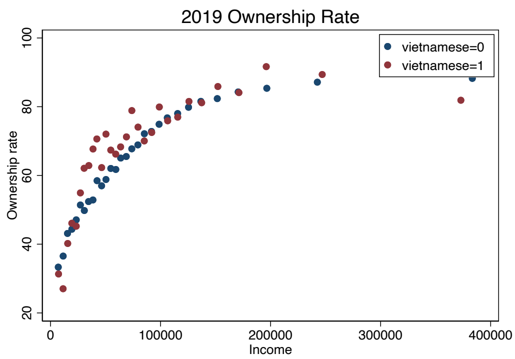

Figure 30: f

Table 6: Summary Statistics (Filipino Population)

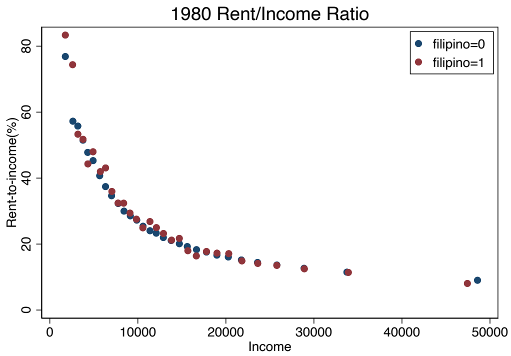

Figure 31: a

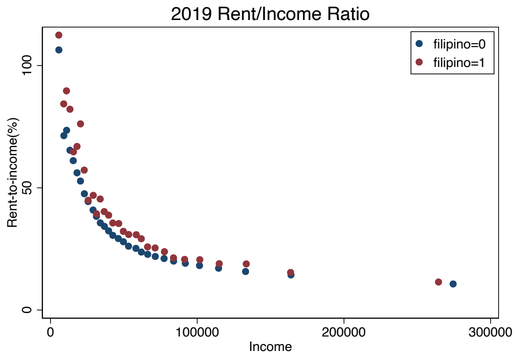

Figure 32: b

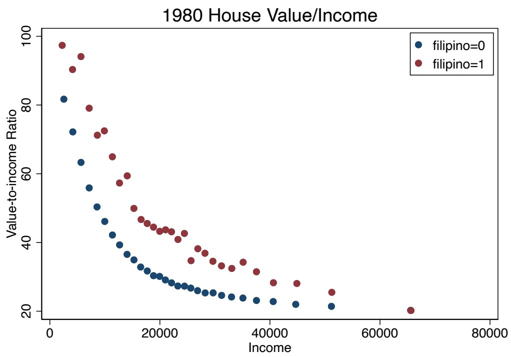

Figure 33: c

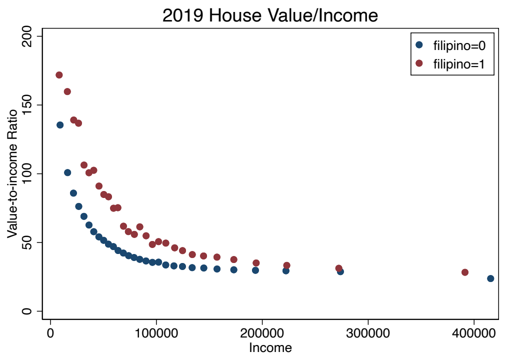

Figure 34: d

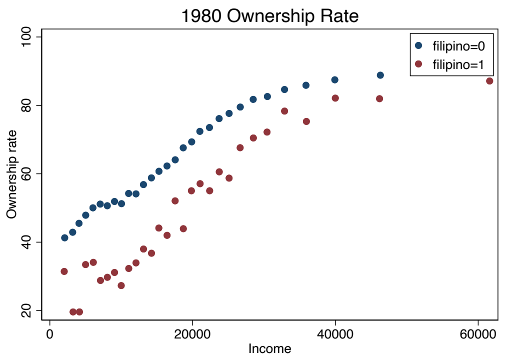

Figure 35: e

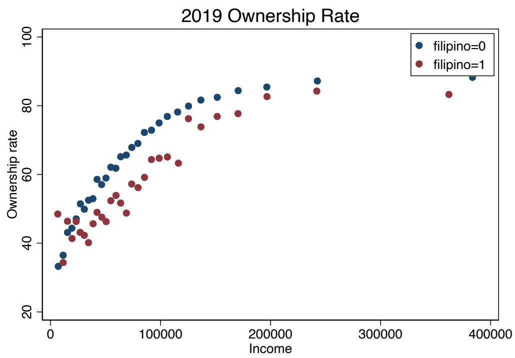

Figure 36: f

Table 7: Summary Statistics (Indian Population)

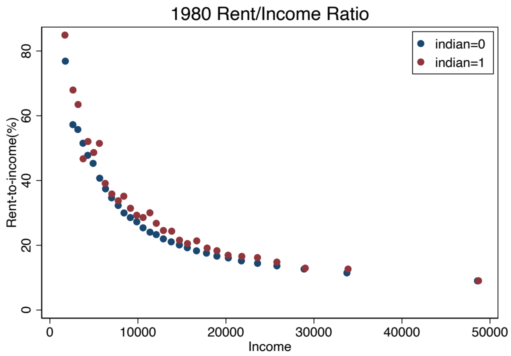

Figure 37: a

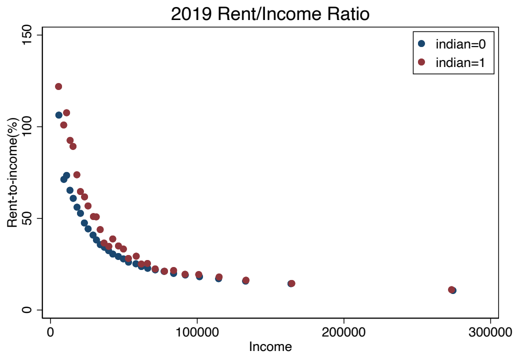

Figure 38: b

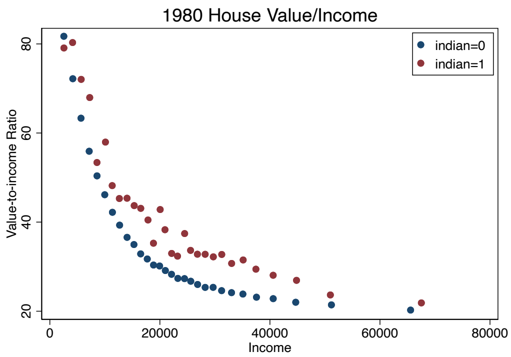

Figure 39: c

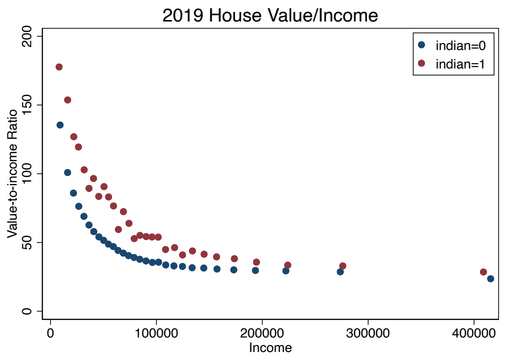

Figure 40: d

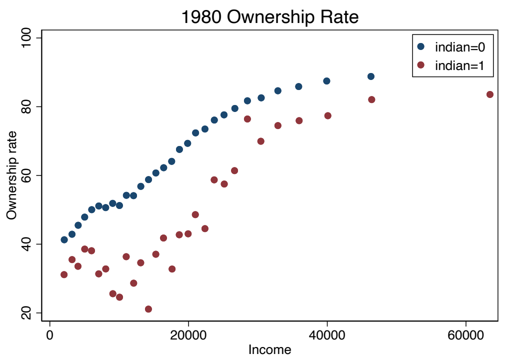

Figure 41: e

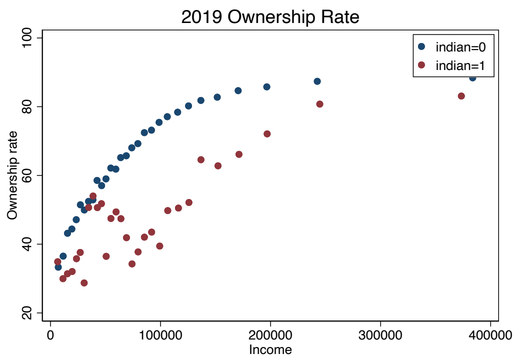

Figure 42: f

Table 8: Rank Gap Analysis (Overall Asian Population)

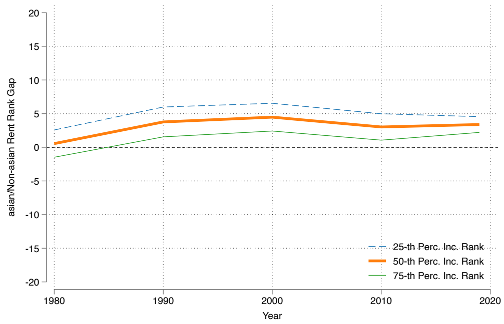

Figure 43: a

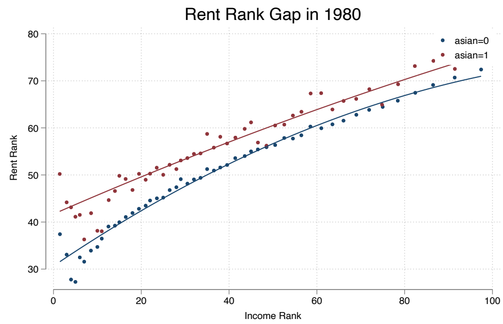

Figure 44: b

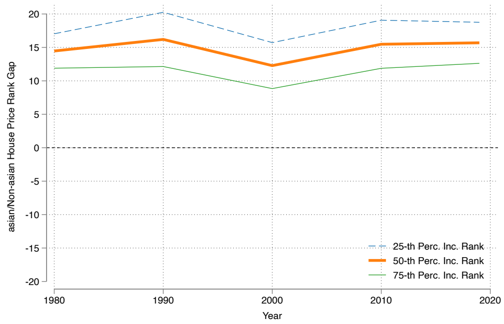

Figure 45: c

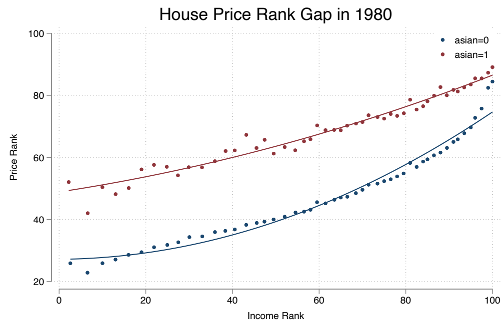

Figure 46: d

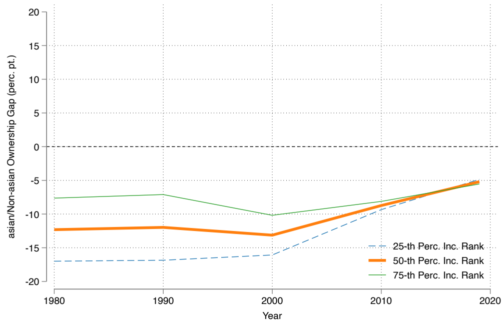

Figure 47: e

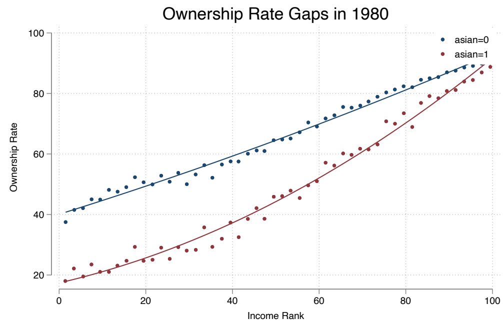

Figure 48: f

Table 9: Rank Gap Analysis (Chinese Population)

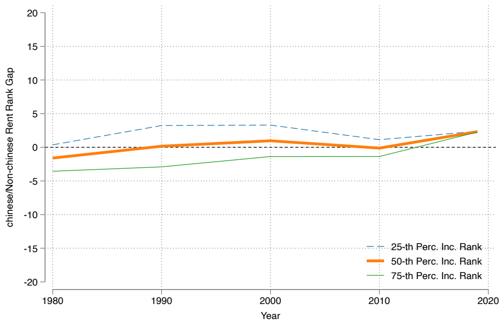

Figure 49: a

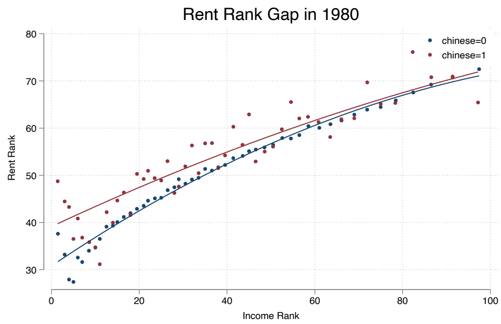

Figure 50: b

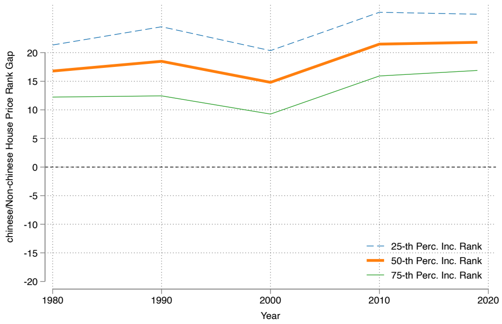

Figure 51: c

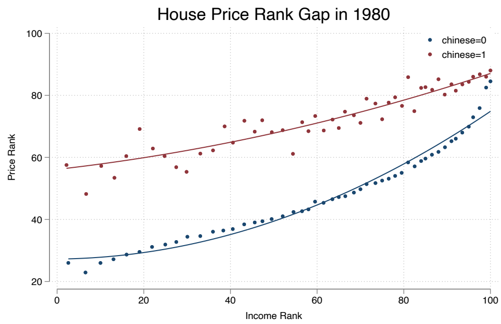

Figure 52: d

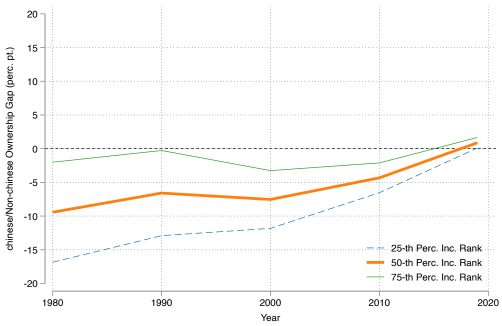

Figure 53: e

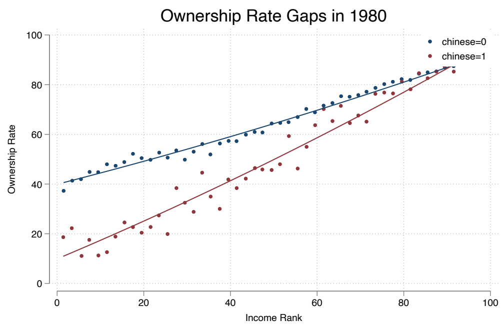

Figure 54: f

Table 10: Rank Gap Analysis (Japanese Population)

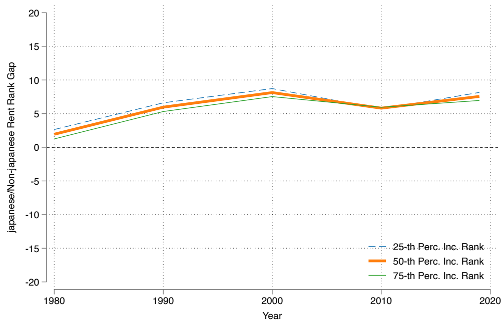

Figure 55: a

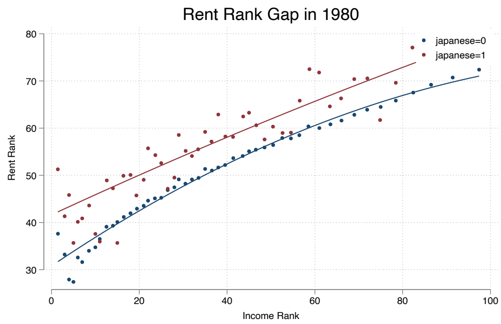

Figure 56: b

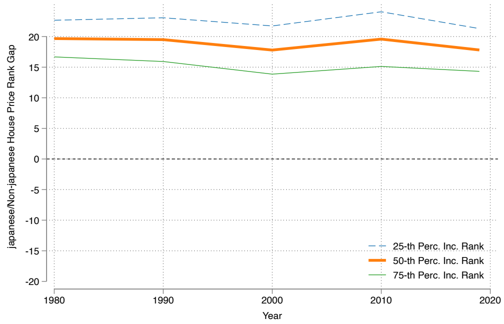

Figure 57: c

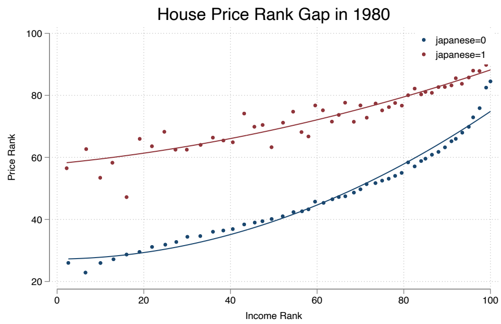

Figure 58: d

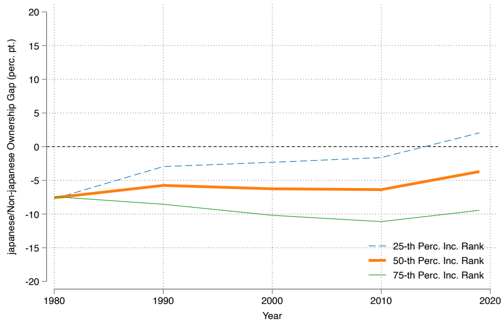

Figure 59: e

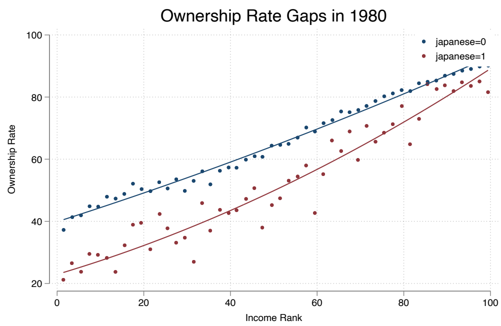

Figure 60: f

Table 11: Rank Gap Analysis (Korean Population)

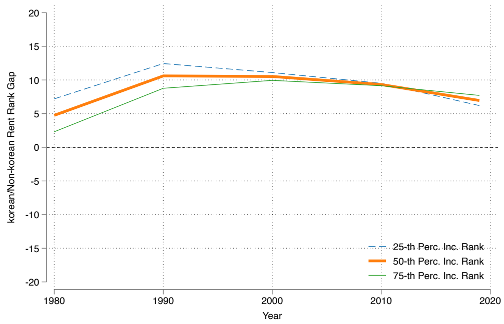

Figure 61: a

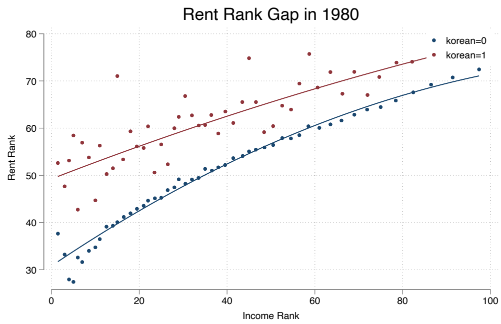

Figure 62: b

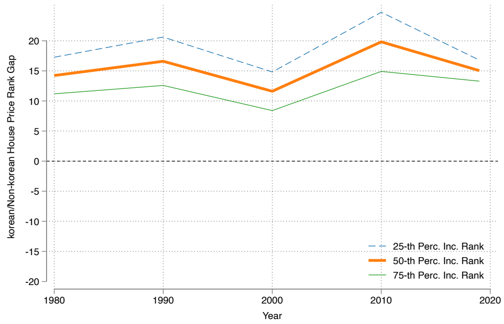

Figure 63: c

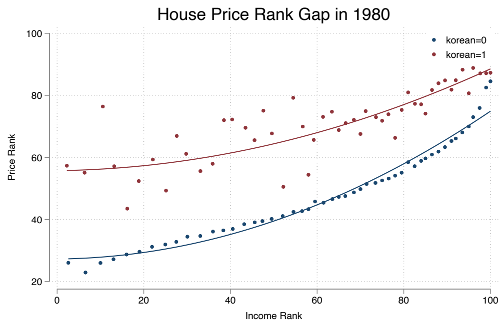

Figure 64: d

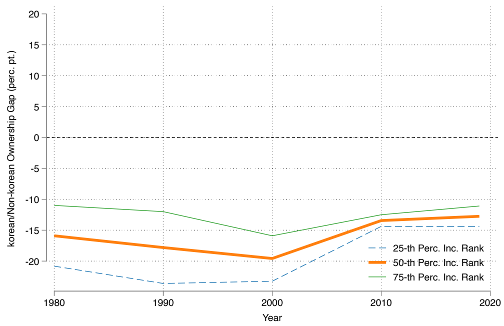

Figure 65: e

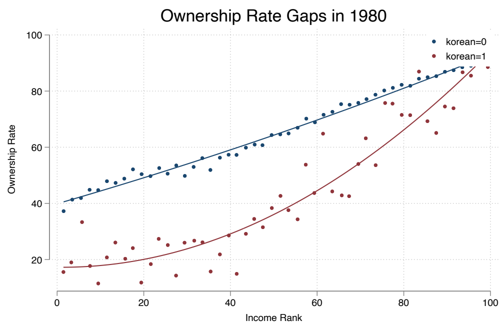

Figure 66: f

Table 12: Rank Gap Analysis (Vietnamese Population)

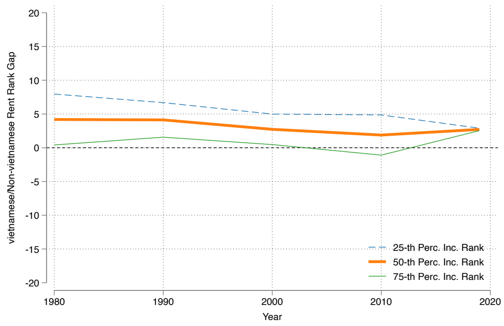

Figure 67: a

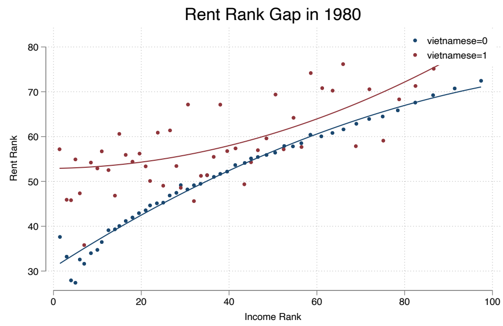

Figure 68: b

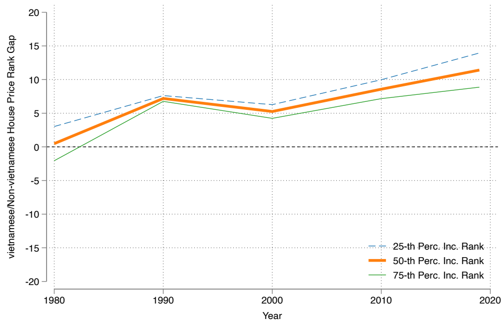

Figure 69: c

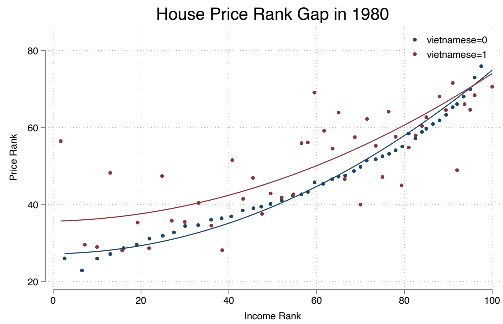

Figure 70: d

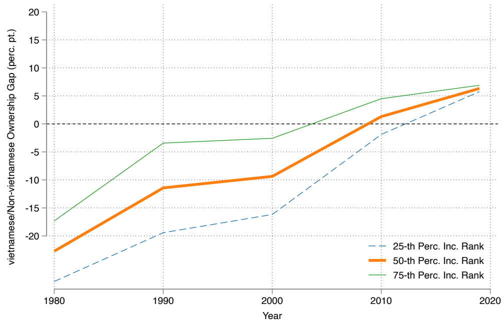

Figure 71: e

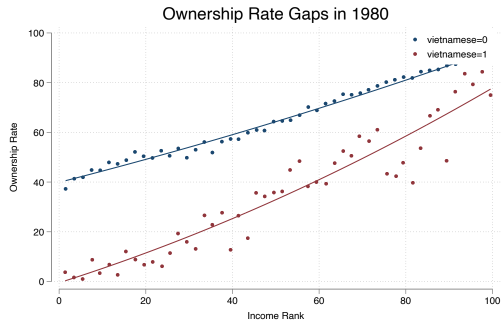

Figure 72: f

Table 13: Rank Gap Analysis (Filipino Population)

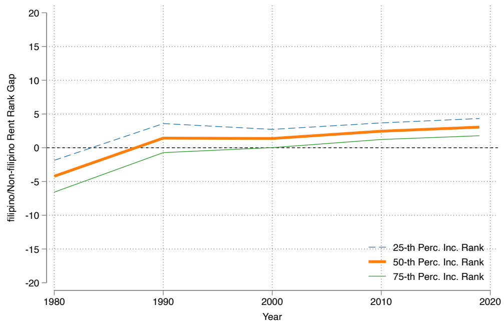

Figure 73: a

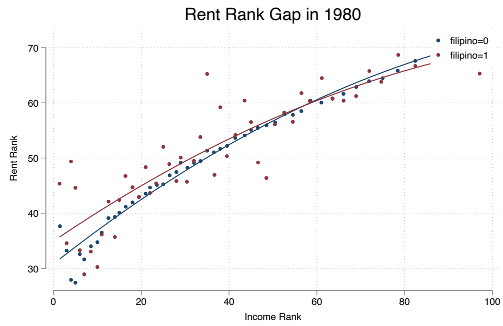

Figure 74: b

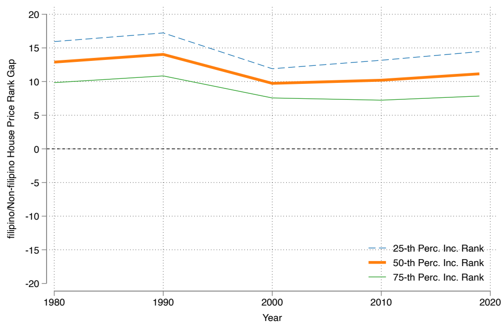

Figure 75: c

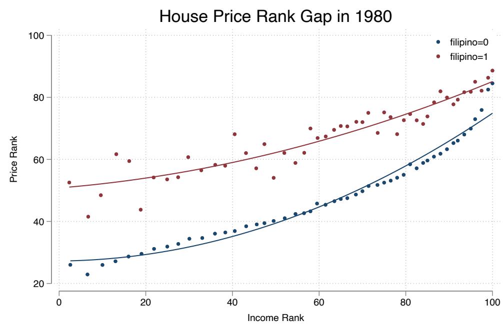

Figure 76: d

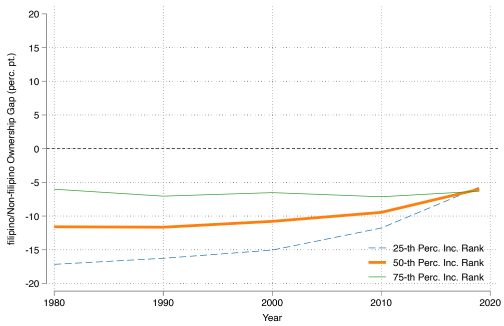

Figure 77: e

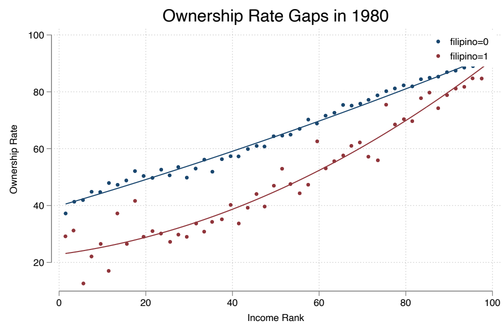

Figure 78: f

Table 14: Rank Gap Analysis (Indian Population)

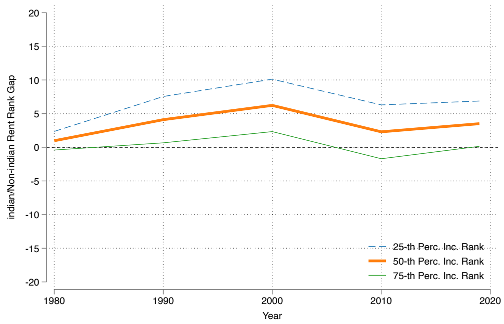

Figure 79: a

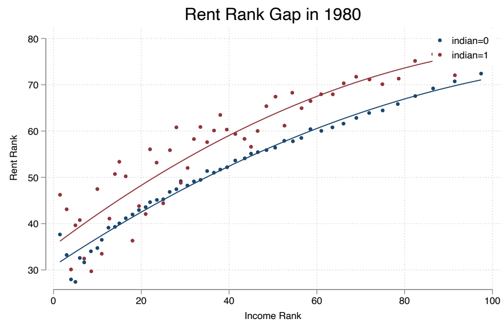

Figure 80: b

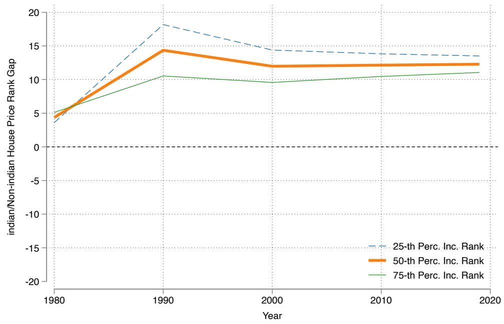

Figure 81: c

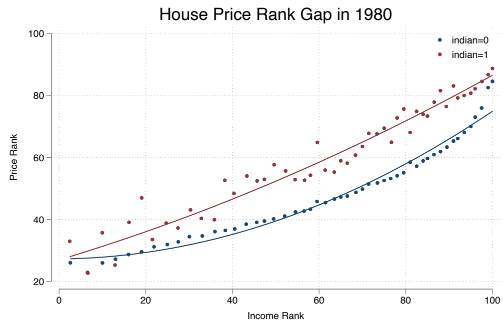

Figure 82: d

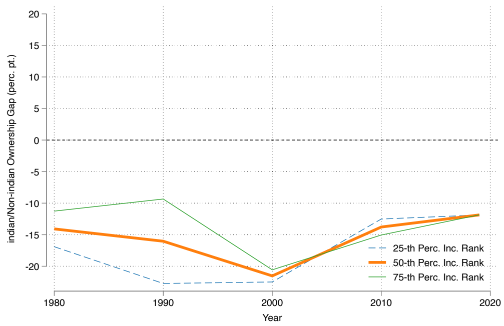

Figure 83: e

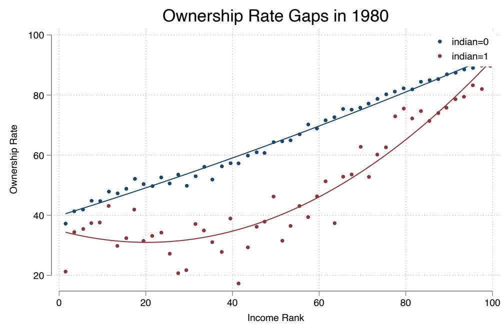

Figure 84: f

Housing Quality Indicators (Overall Asian Population)

Panel (a)	Age of House				
	1980	1990	2000	2010	2019
Asian	-1.42***	-1.64***	-1.84***	-2.80***	-2.79***
	(0.065)	(0.130)	(0.053)	(0.098)	(0.084)
Highest income decile	-3.68***	-2.27***	-3.99***	-4.94***	-4.29***
	(0.002)	(0.09)	(0.039)	(0.092)	(0.086)
Adjusted R^2	0.086	0.052	0.036	0.043	0.032
Panel (b)	No. of bedrooms				
	1980	1990	2000	2010	2019
Asian	-0.257***	-0.352***	-0.378***	-0.072***	-0.086***
	(0.004)	(0.007)	(0.002)	(0.004)	(0.004)
Highest income decile	0.984***	1.14***	1.12***	1.15***	1.18***
	(0.002)	(0.005)	(0.002)	(0.004)	(0.004)
Adjusted R^2	0.262	0.227	0.207	0.199	0.194
Observations	3,975,903	906,531	6,236,850	1,189,942	1,262,476
Income Deciles	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Table reports estimates from regression equation (3). The coefficient ”Asian” reports the average difference in observable quality for Asian and White households conditional on income. To interpret the magnitude, the coefficient on the highest income decile shows the average difference between rich and poor households. The table includes two measures of observable housing quality: age of house (panel a) and number of bedrooms (panel b). Data are from IPUMS.

Housing Quality Indicators (Chinese Population)

Panel (a)	Age of House				
	1980	1990	2000	2010	2019
Chinese	0.149	0.318	0.098	0.008	-0.342**
	(0.134)	(0.256)	(0.097)	(0.189)	(0.157)
Highest income decile	-3.68***	-2.27***	-3.99***	-4.96***	-4.34***
	(0.037)	(0.09)	(0.039)	(0.090)	(0.086)
Adjusted R^2	0.081	0.052	0.039	0.042	0.032
Panel (b)	No. of bedrooms				
	1980	1990	2000	2010	2019
Chinese	-0.221***	-0.349***	-0.324***	-0.066***	-0.069***
	(0.008)	(0.007)	(0.012)	(0.009)	(0.008)
Highest income decile	0.984***	1.14***	1.12***	1.15***	1.18***
	(0.002)	(0.005)	(0.002)	(0.004)	(0.004)
Adjusted R^2	0.261	0.225	0.204	0.199	0.194
Observations	3,975,903	906,531	6,236,850	1,189,942	1,262,476
Income Deciles	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Table reports estimates from regression equation (3). The coefficient ”Chinese” reports the average difference in observable quality for Chinese and non-Chinese households conditional on income. To interpret the magnitude, the coefficient on the highest income decile shows the average difference between rich and poor households. The table includes two measures of observable housing quality: age of house (panel a) and number of bedrooms (panel b). Data are from IPUMS.

Housing Quality Indicators (Japanese Population)

Panel (a)	Age of House				
	1980	1990	2000	2010	2019
Japanese	-1.29***	-1.04***	-0.74***	0.655*	1.38***
	(0.136)	(0.320)	(0.147)	(0.337)	(0.340)
Highest income decile	-3.67***	-2.27***	-3.99***	-4.96***	-4.34***
	(0.037)	(0.092)	(0.040)	(0.092)	(0.086)
Adjusted R^2	0.081	0.052	0.039	0.042	0.032
Panel (b)	No. of bedrooms				
	1980	1990	2000	2010	2019
Japanese	-0.131***	-0.184***	-0.166***	-0.120***	-0.129***
	(0.008)	(0.007)	(0.007)	(0.015)	(0.016)
Highest income decile	0.985***	1.14***	1.12***	1.15***	1.18***
	(0.002)	(0.005)	(0.002)	(0.004)	(0.004)
Adjusted R^2	0.261	0.225	0.204	0.199	0.194
Observations	3,975,903	906,531	6,236,850	1,189,942	1,262,476
Income Deciles	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Table reports estimates from regression equation (3). The coefficient ”Japanese” reports the average difference in observable quality for Japanese and non-Japanese households conditional on income. To interpret the magnitude, the coefficient on the highest income decile shows the average difference between rich and poor households. The table includes two measures of observable housing quality: age of house (panel a) and number of bedrooms (panel b). Data are from IPUMS.

Housing Quality Indicators (Korean Population)

Panel (a)	Age of House				
	1980	1990	2000	2010	2019
Korean	-3.22***	-3.41***	-4.13***	-4.82***	-4.12***
	(0.236)	(0.421)	(0.153)	(0.306)	(0.276)
Highest income decile	-3.68***	-2.28***	-4.00***	-4.98***	-4.35***
	(0.037)	(0.092)	(0.040)	(0.092)	(0.086)
Adjusted R^2	0.081	0.052	0.039	0.042	0.032
Panel (b)	No. of bedrooms				
	1980	1990	2000	2010	2019
Korean	-0.509***	-0.661***	-0.612***	-0.222***	-0.301***
	(0.014)	(0.022)	(0.007)	(0.014)	(0.013)
Highest income decile	0.983***	1.14***	1.12***	1.15***	1.18***
	(0.002)	(0.005)	(0.002)	(0.004)	(0.004)
Adjusted R^2	0.261	0.226	0.205	0.199	0.194
Observations	3,975,903	906,531	6,236,850	1,189,942	1,262,476
Income Deciles	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Table reports estimates from regression equation (3). The coefficient ”Korean” reports the average difference in observable quality for Korean and non-Korean households conditional on income. To interpret the magnitude, the coefficient on the highest income decile shows the average difference between rich and poor households. The table includes two measures of observable housing quality: age of house (panel a) and number of bedrooms (panel b). Data are from IPUMS.

Housing Quality Indicators (Vietnamese Population)

Panel (a)	Age of House				
	1980	1990	2000	2010	2019
Vietnamese	-1.77***	-3.64***	-2.77***	-4.31***	-3.81***
	(0.301)	(0.483)	(0.159)	(0.304)	(0.270)
Highest income decile	-3.68***	-2.27***	-4.00***	-4.96***	-4.34***
	(0.037)	(0.092)	(0.040)	(0.092)	(0.086)
Adjusted R^2	0.081	0.052	0.039	0.042	0.032
Panel (b)	No. of bedrooms				
	1980	1990	2000	2010	2019
Vietnamese	-0.431***	-0.335***	-0.386***	0.140***	0.169***
	(0.018)	(0.025)	(0.007)	(0.014)	(0.013)
Highest income decile	0.984***	1.14***	1.12***	1.15***	1.18***
	(0.002)	(0.005)	(0.002)	(0.004)	(0.004)
Adjusted R^2	0.261	0.225	0.204	0.199	0.194
Observations	3,975,903	906,531	6,236,850	1,189,942	1,262,476
Income Deciles	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Table reports estimates from regression equation (3). The coefficient ”Vietnamese” reports the average difference in observable quality for Vietnamese and non-Vietnamese households conditional on income. To interpret the magnitude, the coefficient on the highest income decile shows the average difference between rich and poor households. The table includes two measures of observable housing quality: age of house (panel a) and number of bedrooms (panel b). Data are from IPUMS.

Housing Quality Indicators (Filipino Population)

Panel (a)	Age of House				
	1980	1990	2000	2010	2019
Filipino	-2.18***	-2.80***	-2.44***	-3.64***	-2.18***
	(0.147)	(0.301)	(0.117)	(0.237)	(0.211)
Highest income decile	-3.67***	-2.26***	-3.98***	-4.94***	-4.33***
	(0.037)	(0.092)	(0.040)	(0.092)	(0.086)
Adjusted R^2	0.081	0.052	0.039	0.042	0.032
Panel (b)	No. of bedrooms				
	1980	1990	2000	2010	2019
Filipino	-0.276***	-0.374***	-0.367***	-0.019***	-0.064***
	(0.009)	(0.016)	(0.006)	(0.014)	(0.010)
Highest income decile	0.984***	1.14***	1.12***	1.15***	1.18***
	(0.002)	(0.005)	(0.002)	(0.004)	(0.004)
Adjusted R^2	0.261	0.225	0.204	0.199	0.194
Observations	3,975,903	906,531	6,236,850	1,189,942	1,262,476
Income Deciles	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Table reports estimates from regression equation (3). The coefficient ”Filipino” reports the average difference in observable quality for Filipino and non-Filipino households conditional on income. To interpret the magnitude, the coefficient on the highest income decile shows the average difference between rich and poor households. The table includes two measures of observable housing quality: age of house (panel a) and number of bedrooms (panel b). Data are from IPUMS.

Housing Quality Indicators (Indian Population)

Panel (a)	Age of House				
	1980	1990	2000	2010	2019
Indian	-1.85***	-3.12***	-3.48***	-5.59***	-6.70***
	(0.182)	(0.382)	(0.121)	(0.226)	(0.178)
Highest income decile	-3.68***	-2.27***	-3.99***	-4.93***	-4.26***
	(0.037)	(0.092)	(0.040)	(0.092)	(0.086)
Adjusted R^2	0.081	0.052	0.039	0.042	0.033
Panel (b)	No. of bedrooms				
	1980	1990	2000	2010	2019
Indian	-0.309***	-0.266***	-0.439***	-0.176***	-0.134***
	(0.011)	(0.020)	(0.006)	(0.010)	(0.009)
Highest income decile	0.984***	1.14***	1.12***	1.15***	1.18***
	(0.002)	(0.005)	(0.002)	(0.004)	(0.004)
Adjusted R^2	0.261	0.225	0.205	0.199	0.194
Observations	3,975,903	906,531	6,236,850	1,189,942	1,262,476
Income Deciles	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Table reports estimates from regression equation (3). The coefficient ”Indian” reports the average difference in observable quality for Indian and non-Indian households conditional on income. To interpret the magnitude, the coefficient on the highest income decile shows the average difference between rich and poor households. The table includes two measures of observable housing quality: age of house (panel a) and number of bedrooms (panel b). Data are from IPUMS.