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School and neighborhood: residential location choice of immigrant parents in the Los Angeles Metropolitan area

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Abstract This paper studies how immigrant parents value education for their children in the United States when making residential decisions. Parent valuation of education is examined through the differential effects of school quality on the residential location choices of households with and without children. The analysis relies on data from the 2000 Census and focuses on the Los Angeles Metropolitan Area. The results suggest that immigrant parents place a positive weight on school quality when choosing residences. The weight assigned to school is positively associated with household income and householder's education. The paper further explores variation across immigrants to get at the potential economic mechanisms for differential valuation of school quality. Number of school-aged children in the household, selective migration, and potential returns to education may explain variation in the emphasis immigrant parents place on school quality in residential location choices.

Keywords School quality · Residential location choice · Immigrant household · Discrete choice model · Selective migration · Returns to education

JEL Classification J61 · I2 · R2

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1 Introduction

Economic migrants are individuals who have emigrated from one region to another primarily because of their own economic opportunities. One of the standard propositions in the migration literature is that economic migrants are favorably self-selected for labor market success (Chiswick 1978; Borjas 1987; Chiswick 2000).

However, besides pursuing higher income themselves, some economic migrants may also migrate for better opportunities of their offspring. When examining the labor market performance of second-generation immigrants,[1] earlier literature finds that the second generation experiences high educational attainment and labor market achievement in the receiving economies whereas substantial heterogeneity exists by parental region of origin (Chiswick 1988; Boyd and Grieco 1998; Chiswick and Deb-Burman 2004; Card 2005). Most studies link education and earning advantages as well as cross-origin discrepancies among the second generation to intergenerational transmission of human capital (Card et al. 2000; Bauer and Riphahn 2007). Very few papers look at the human capital investment by immigrant parents for their children. If immigrants migrate partly for the economic well-being of their decedents, they might emphasize children's education more and be more willing to invest in school than the stayers if resources allow.

Correspondingly, this paper investigates how immigrants value education for their children and the economic mechanism for differential evaluation of school. The value placed on education is assessed through households' residential location choices. Parents have long exercised choice of their children's schools through residential location choices in what is often referred to as Tiebout sorting.[2] About half of the parents in the 1993 National Household Education Survey reported that the schools their children would attend influenced their decision of where to live (McArthur et al. 1995). The close link between school quality and residential location has been verified by a number of studies (Barrow 2002; Clapp et al. 2008; Hasting and Weinstein 2008).

This paper explores where immigrant households choose to live within the Los Angeles Metropolitan Area and how location characteristics, including school quality, neighborhood sociodemographics, house features, and other local amenities affect their decisions. Immigrant households are defined by the migration status of household heads. The analysis then compare the choices of immigrants to native-born Americans' and examines decisions cross immigrants by parent characteristics. The main dataset employed is the 2000 Census. The 1999 Academic Performance Index (API)[3] is used to measure public school quality.

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[1] A second-generation immigrant is someone who was born and raised in the destination but either one or both parents were foreign born.

[2] Tiebout (1956) suggests that competition among local jurisdictions would lead to the efficient provision of a series of local public goods, and individuals reveal their preferences by voting with their feet.

[3] API scores are produced by the California Department of Education to evaluate school accountability and the API Reports are publicly available to parents and guardians.

Residential location choice is modeled as a conditional logit model, which enables the researcher to examine immigrant household preferences over a broad range of housing and neighborhood characteristics and how these preferences vary by household characteristics. Since the unobserved characteristics of jurisdictions may be correlated with local school quality, I follow the identification strategy of Barrow (2002) and compare the role of public schools in the location choices of households with and without children, reasoning that unobservable non-school attributes affect both types similarly, while households with children care more about public schools. Specifically, an interaction term between the API and an indicator for having a child under 18 years of age[4] is included in the model to capture the differential effects of school quality on the residential location choices of the two types of households.

Regression results suggest that school quality is positively and significantly related to location choices of immigrant households with children. The importance of school quality in residential locations increases with household income and householder's education. These results are robust to addressing the omission of private school choices, unobserved constraints on choice sets, differential preferences toward non-school amenities, heterogeneity in mobility, and alternative school quality measure. Relative to their native counterparts, the weight allocated to school quality by immigrant parents is of similar magnitude. Yet low-income immigrant households appear to value school quality more than low-income native households.

To understand the underlying mechanisms that drive the heterogeneity in the emphasis on school quality, I compare the behaviors of immigrant parents. First, both the age and the number of children matter to the weight placed on school quality. Parents of school-aged children value school more than parents of children under six. The number of school-aged children is positively associated with the weight assigned to school quality, and the relationship is more evident among financially restricted immigrant households. Second, favorable self-selection among immigrants by origin could be another source of heterogeneity in weights. Motivation appears to play a positive role in how immigrant parents value schools. That is, immigrants who have overcome longer distances and more language barriers tend to value education more for their offspring. Last, potential returns to education may be an economic driver for immigrant parents to invest on their children's school quality in residential locations. The origin-specific returns to education for immigrants in Los Angeles are positively related to the probability that immigrant parents select areas with better public schools.

The remainder of the paper is organized as follows: Section 2 presents the empirical model and the identification strategy; Section 3 describes the data used to estimate the model; Section 4 examines the weight placed on school quality by immigrants; Section 5 compares immigrants and natives; Section 6 further explores the economic mechanism for immigrants to value school for their children; and Section 7 concludes the paper and discusses the policy implications.

[4] In the U.S. education system, the common high school finishing age is 18.

2 A model of residential choice

2.1 Conditional logit model

The residential location decision of each household is modeled as a discrete choice of a single residence. The conceptual experiment motivating this analysis considers a household moving into the Los Angeles Metropolitan Area and deciding where to live. The household may compare house features, local amenities, and community demographics, and select the location that best matches its ideal.

Because households who have lived at the same location for years may have a disincentive to move and their residential location may not well reflect their current demand for public education and other local amenities, I examine the location choices of households that recently moved from outside of Los Angeles to the current location. Given the high cost of moving, movers from out of the area are more likely to undergo some exogenous move-inducing shocks, such as job relocation, and re-sort when they move to the area.

More formally, I assess households' residential location choices using the conditional logit model introduced by McFadden (1974). Suppose that each household selects its residential location from N mutually exclusive alternatives to maximize its utility. The indirect utility function of household h that resides in location j is of the form:

$$U_{hj} = V_{hj} + \varepsilon_{hj}, \tag{1}$$

where V_{hj} stands for the component of indirect utility of household h that depends on the location characteristics observed by the household, such as characteristics of houses (e.g., size, age, and type), public goods (e.g., public school quality, crime rate and number of metro stations), neighborhood sociodemographics (e.g., ethnic composition, age structure, fraction of immigrants, and socioeconomic status), as well as housing price that accounts for the cost to live in location j. ε_{hj} represents household h's unobservable tastes in choosing where to live.

The probability that household h selects location j is

$$p_{hj} = \Pr\left(U_{hj} \geqslant U_{hk}\right), \forall k = 1, 2, ..., N. \tag{2}$$

Assuming that the error term ε_{hj} is independently and identically distributed with a standard Type I extreme value distribution[5] across alternatives, the probability that household h chooses location j can be derived as:

$$p_{hj} = \frac{\exp\left(V_{hj}\right)}{\sum_{n=1}^{N} \exp\left(V_{hn}\right)}. \tag{3}$$

I further assume that the observed component V_{hj} can be approximated by a linear function of choice-specific attributes:

$$V_{hj} = \beta_h Y_j. \tag{4}$$

[5]The density function is $f(e) = \exp\left[-e^{-\exp(-e)}\right]$.

Y_j denotes location characteristics, and β_h is the set of household-specific parameters. As different types of households may demand different bundles of public goods, β_h may be formulated as

$$\beta_h = \beta_0 + \sum_{r=1}^{R} \beta_r X_{hr}. \tag{5}$$

$X_{hr}, r = 1, 2, ..., R$ represents the characteristics of household h that do no vary across communities, such as household income, householder's education, and family composition.[6] That is, household characteristics are assumed to affect residential location choices through their influence on households' valuation of location attributes.

2.2 Identification strategy

I first examine how immigrant households value school quality in residential location choices. One major problem arising is that local school quality is potentially correlated with unobserved location characteristics. If this is the case, the coefficient on school quality may capture the effects of some non-education factors.

To address this problem, I compare the residential location choices of immigrant households with and without children following the identification strategy exploited by Barrow (2002). Having young children in a household indicates a direct demand for schooling services, whereas households without children are only indirectly affected by neighborhood schools. At the same time, location attributes other than schools may influence the two types of households similarly. Therefore, the differential effect that school quality has on the residential location choices of households with and without children potentially identifies the value parents place on school quality.

Accordingly, I rewrite Eq. 4 as

$$V_{hj} = \alpha_{1h} S_j + \alpha_2 S_j \cdot chd_h + \beta_h Z_j + \gamma_h e_j. \tag{6}$$

S_j measures the school quality of location j. chd_h is a binary indicator taking on value of one if household h has children under 18 years of age and zero if not. So the weight placed on school quality by households without children is α_{1h}, and that by households with children is $\alpha_{1h} + \alpha_2$. Z_j stands for attributes of location j which are observed by both households and econometricians, and e_j stands for the location attributes that are only observed by households but not observed by econometricians. The household-specific parameters are assumed to take the form of a linear function of household characteristics as Eq. 5.

The estimate of α_{1h} is biased if the unobserved neighborhood characteristics included in e_j are correlated with school quality S_j. But α_2 will be consistent as long as any unobservable attributes are equally valued by households with and without

[6] The household characteristics are included in the regression by interacting them with location characteristics. In a conditional logit model, variables such as household characteristics that do not vary across alternatives would be automatically dropped in the regression if included directly. However, their effects can be controlled for by interacting these variables with the characteristics of the alternatives.

children.[7] In particular, if households without children put no value on school quality per se, the estimated coefficient on the interaction term between school quality and presence of children provides an unbiased estimate of the true valuation of school quality by households with children. The estimate of the direct effect of school quality only captures the effects of unobserved amenities that are correlated with school quality.

To further assure that the two types of households have similar tastes for non-school location attributes, I use the method of propensity score to trim the sample. The propensity score for having children under 18 is estimated from a series of household sociodemographic characteristics and householder individual characteristics that may be correlated with demand for local public goods and residential location choices. Compared to restricting the sample by a certain household characteristic, such as age, the method of propensity score takes more household characteristics into consideration and balances their effects.

The propensity score is estimated using a probit model:

$$\Pr\left(chd_h = 1\right) = \Phi\left(\lambda X_h + \epsilon_h\right). \tag{7}$$

X_h represents the characteristics of household h, such as household income, linguistic isolation, family size, cross-state mover status, race, and householder's age, gender, educational attainment, and marital status. ϵ_h denotes the unobserved characteristics that are relevant to having children. I eliminate the observations with a predicted propensity score lower than 0.1 or higher than 0.9, and conduct the analysis on the remaining sample of more comparable households with and without children.[8]

In addition, to precisely capture the heterogeneity among parents with children in different age range, I generate three binary indicators: 1) chd_h^{0-6} which is unity if household h has children less than 6 years of age, and zero otherwise; 2) chd_h^{6-12} which is unity if there are children aged 6–12, and zero otherwise; and 3) chd_h^{12-18} which is unity if there are children aged 12–18, and zero otherwise. Usually, children under 6 do not utilize grade schooling service; children aged 6–12 go to elementary schools; and children aged 12–18 have a need for secondary school quality. It is possible that when migrating to a new area, households with children below school age do not care about school district as much since they may intend to move again when the children get older and school choice become more relevant. The value placed on elementary school and secondary school may also vary due to parents' beliefs about how different level of education determine one's future economic success.

[7] A short proof is as follows. Suppose e_j is a function of S_j. For simplicity, they are assumed to be linearly related, i.e., $e_j = f\left(S_j\right) = cS_j + u_j$, where c is a constant, and u_j is an error term that is uncorrelated with school quality. Equation 6 could be rearranged as $V_{hj} = \alpha_{1h}S_j + \alpha_2 S_j \cdot chd_h + \beta_h Z_j + \gamma_h \cdot cS_j + \gamma_h u_j = \left(\alpha_{1h} + \gamma_h \cdot c\right) S_j + \alpha_2 S_j \cdot chd_h + \beta_h Z_j + \gamma_h u_j$. So the estimated main effect of school quality may be biased, but the estimate on the interaction between school quality and having children in the household is not.

[8] More details about the effectiveness of the propensity score trimming approach are discussed in Appendix A.1.

Accordingly, I interact the three indicators with the school quality measure, and estimate the following equation on the trimmed sample:

$$V_{hj} = \alpha_{1h} S_j + \alpha_{21} S_j \cdot chd_h^{0-6} + \alpha_{22} S_j \cdot chd_h^{6-12} + \alpha_{23} S_j \cdot chd_h^{12-18} + \beta_h Z_j + \gamma_h e_j. \quad (8)$$

Now the differential weights that parents assign to school quality for children of different age range relative to childless households are captured by α_{21}, α_{22}, and α_{23}.

2.3 Potential mechanisms

To better understand the impacts of immigration on provision of public education in host societies, it is essential to know the economic mechanisms explaining why immigrant parents value school quality for their children.

One hypothesis to test is that the number of children matters to the priority parents place on schools in residential decisions. Immigrants in general have higher fertility rate than natives. The number of children can be related to the evaluation of school quality in a few ways. First, larger family size results in less resource available per child. If the number of children affects residential choices through income constraints, households with more children may be less able to afford to live in good school districts. Second, parents make trade-offs between the quantity and quality of children when they make fertility and human capital investment decisions (Hanushek 1992). The households with more children are likely to be the ones who value education less. Third, given the housing price a household has to pay to live in a neighborhood, more school-aged children in a household may indicate that moving to a location with good public schools is more cost-efficient.

The second hypothesis is that the weight assigned to school quality by parents is associated with a selection model of migration. When migrating to seek labor market success, immigrants face different costs for migration, such as physical distance, language barriers, cultural shocks, and skill mismatches. Therefore, the ones overcome more obstacles are supposedly more motivated. The discrepancies in motivation may also apply to how immigrant parents value the future success of their offspring. If so, more motivated immigrants may emphasize school quality more.

The third hypothesis is that parents are more willing to invest in children's schooling if the future returns are high. The heterogeneity in education and earning across immigrant groups have long been observed (Chiswick 1988; Bratsberg and Terrell 2002; Card 2005). It is possible that when immigrant parents expect high future returns to education, they have a stronger incentive to pay the premium in housing price so as to send their offspring to better public schools.

Given the established patterns using the estimation strategy in the previous sections, I conduct supplementary analysis to test the above hypotheses among immigrants with children only. The linear indirect utility of household h for the conditional logit model is formulated as follows:

$$V_{hjc} = \alpha_{1h} S_j + \varphi S_j \cdot A_{hc} + \beta_h Z_j + \gamma_h e_j. \quad (9)$$

V_{hjc} is the utility of immigrant household h from country c living in area j that depends on observed location attributes. A_{hc} is a measure based on the hypothesis tested, namely, measures for number of children in the first case, origin country characteristics relevant to selective migration in the second, and returns to education in the last. The definitions of other notations are the same as before.

Specifically, I assume A_{hc} to be the log number of children under 18 and/or the log number of school-aged children in the first case because the attention and economic resources allocated to each additional (school-aged) child usually diminish with the total number of (school-aged) children in a household.

Measures of self-selection include distance to the U.S., if English is an official language, percent of refugees, income inequality, and GDP per capita in the origin country. Earlier studies show that immigration is larger, *ceteris paribus*, when the source country and the destination country are geographically adjacent or the language and culture in the destination country is familiar (Lewer and Van den Berg 2008). Yet the story may not hold for those who migrated to the U.S. as refugees (Cortes 2004). The classical literature of migration (Chiswick 1978; Borjas 1987) also argues that self-selection among immigrants depends on the income distribution in their home countries relative to the United States or other destinations. That is, less dispersed income in the origin predicts that individuals at the right tail of home country income distribution migrate to the U.S., and vice versa. The quality of immigrants may matter to their school and residential location choices. In addition, I include the relative share of national origins among immigrants and the years since migration. Though the representation of origin countries could be result from selective migration, it may serve as a pull factor as well. The origin representation may also link to ethnic network and thus affect immigrants' labor market outcomes (Borjas 1995b; Damm 2009). While the years spent in the U.S. may shape immigrants' preferences toward education over time, they are correlated with waves of migrations of different set of countries.

Accordingly, α_{1h} stands for the base weight household h assigns to school quality in residential location choice, and the economic incentive among immigrant parents is reflected by φ. Since the school quality S_j may be correlated with unobserved location characteristics e_j, it is likely that the main effect of school quality α_{1h} is biased. However, if all households with children value e_j equally, φ is more likely to be unbiased as it captures the variation related to school quality in location choices across households or across origins.

3 Data

3.1 Main samples

The main dataset employed in this paper is the 5 % Integrated Public Use Microsample Series (IPUMS) version of the 2000 Census. In the public use Census data, household location is identified at the Public Use Microdata Area (PUMA) level. I examine the households in the Los Angeles Metropolitan Area. This area covers two counties - Los Angeles County and Orange County, and is divided into 84 PUMAs. I further restrict my sample to households that earn a positive income and have moved to their current location, from outside of the Los Angeles Metropolitan Area, within the past five years.

I study the population in the Los Angeles Metropolitan Area for three reasons. First, unlike many other states, school spending is not directly related to local property taxes in California. The State Supreme Court's decision in the case *Serrano v. Priest (1971)* mitigates the problem of controlling for the effective tax rate as it relates to school expenditure across regions. In this case, spending on public education in a district is less endogenous to the composition of households. Second, the smallest geographic area in the public version of the Census is the PUMA which generally follows county or city boundaries and consists of 100,000+ residents. Since Los Angeles is densely populated, all the PUMAs in this area are geographically small so that the choice of residing in a certain PUMA is less constrained by the location of employment. Third, the area has a diverse population with a high proportion of immigrants and high discrepancy in school quality across districts.

The above criteria were met by 11,821 immigrant households in the 2000 Census. Summary statistics of household characteristics of the entire immigrant population in the Los Angeles Metropolitan Area and the immigrant movers are reported in the first two columns in Table 1. Relative to the whole population, the movers are younger, slightly better educated with smaller family size, and migrated to the U.S. more recently. The reported adjusted household income is the total household income divided by the family equivalent scale (Citro and Michael 1995). The racial composition of the movers is similar to that of the whole population: more than half of the immigrant households are Hispanic, and Asians make up the second largest group. About 34 % of the movers have children under 18 in the household.

For the main analysis on immigrant households, I restrict the sample of immigrant movers by the propensity score to have children so that the preferences toward location characteristics other than school quality are more likely to be equal. Table 2 shows the estimates from the regression of having children on observed household characteristics and Fig. 1 depicts the distributions of the propensity score for households with and without children respectively. Among all the variables, marital status appears to be the strongest predictor for having children. Family size and the number of families in the household also explain a sizable proportion of variation in having children.[9]

I further compare the distribution of household characteristics that may be key determinants for both the fertility and the residential location decisions, namely, household income, householder's age, marital status, and family size by propensity score. Figure 2 depicts the averages of these characteristics within propensity score neighborhoods by group. Except the left tail of adjusted household income and the right tail of marital status, households with and without children with similar

[9]Marital status, family size, and number of families in household may explain the spike in the propensity score distributions among households without children. When excluding the three variables from the regression, the distribution is much smoother and more bell-shaped.

Table 1 Summary statistics on the census sample

Variables	Immigrant Households		
	All	Mover	Trim.
Household Income ($1000)	51.8 (59.3)	43.6 (54.9)	49.8 (58.3)
Adjusted Household Income ($1000)	68.9 (99.5)	68.6 (110)	60.5 (84.2)
Householder's Age	38.6 (11.6)	32.9 (10.6)	35.6 (11.0)
Female Householder (=1)	.326 (.469)	.305 (.461)	.312 (.463)
Householder's Education	11.0 (4.90)	11.6 (4.98)	11.7 (4.96)
Number of Children	1.11 (1.36)	.573 (1.03)	.767 (1.09)
School Attendance (=1)	.102 (.303)	.143 (.350)	.113 (.316)
Linguistic Isolation (=1)	.336 (.472)	.432 (.495)	.450 (.498)
Family Size	3.65 (2.30)	3.11 (2.34)	3.73 (2.03)
No. of Families	1.47 (.962)	1.76 (1.25)	1.45 (.986)
Children under 18 (=1)	.518 (.500)	.343 (.475)	.439 (.496)
Children under 6 (=1)	.227 (.219)	.157 (.363)	.199 (.399)
Children aged 6–12 (=1)	.285 (.451)	.156 (.363)	.202 (.401)
Children aged 12–18 (=1)	.252 (.348)	.142 (.348)	.177 (.382)
No. of Children under 18	1.25 (1.66)	.721 (1.30)	.915 (1.39)
No. of Children aged 6–12	.484 (.928)	.254 (.690)	.328 (.767)
No. of Children aged 12–18	.429 (.888)	.236 (.689)	.296 (.755)
Private School (=1)	.065 (.246)	.059 (.235)	.060 (.248)
Home Ownership (=1)	.294 (.456)	.221 (.415)	.236 (.425)
Years Migrated	16.9 (10.2)	8.27 (9.11)	8.72 (9.48)
White (=1)	.129 (.335)	.152 (.359)	.131 (.338)
Black (=1)	.013 (.115)	.019 (.135)	.025 (.157)
Asian (=1)	.237 (.425)	.287 (.453)	.308 (.462)
Hispanic (=1)	.612 (.487)	.528 (.499)	.518 (.500)
Move Within State (=1)	.023 (.148)	.154 (.361)	.173 (.378)
No. of Obs.	80,732	11,821	8,371

Reported are the means of variables with standard deviations in parentheses among different groups. The first column is for all immigrant households in the Los Angeles Metropolitan Area; second column is for immigrant households that moved to the area within the past five years; and the last column is for the movers adjusted for the propensity scores for having children under 18. Adjusted household income is total household income divided by family equivalent scale

Table 2 Propensity to have children under 18 in the household

Variables	1(child<18) (1)	(2)
Adjusted Household Income	−.000 (.000)	−.000 (.000)
Householder's Age	.010*** (.001)	.009*** (.001)
Marital Status (=1)	.885*** (.027)	.871*** (.028)
Family Size	.150*** (.007)	.148*** (.007)
Female Householder (=1)		.087*** (.029)
Householder's Education		.015*** (.003)
School Attendance (=1)		−.181*** (.041)
Linguistic Isolation (=1)		.054* (.029)
No. of Families in Household		−.084*** (.014)
Home Ownership (=1)		−.198*** (.033)
White (=1)		−.165 (.110)
Black (=1)		.053 (.141)
Asian (=1)		−.065 (.108)
Hispanic (=1)		−.019 (.108)
Employed (=1)		−.013 (.032)
Moved within State (=1)	.302*** (.035)	
No. of Obs.	11,821	11,821
Log-likelihood/1000	−6.29	−6.18
Pseudo R-square	.172	.186

*significant at 10 %; ** significant at 5 %; *** significant at 1 %.

Regressions are estimated using a probit model. The dependent variable is an indicator for having children under 18. The sample of immigrant households who migrated from outside the Los Angeles Metropolitan Area to the current location in the past 5 years are examined. Robust standard errors are reported in parentheses

propensity scores appear analogous. The householder's age of parents deviates from that of non-parents to a certain extent in the middle range of propensity score, yet there is no consistent trend.[10] These figures may indicate the propensity score matches the characteristics of households with and without children effectively.

[10]The bandwidth in the figure is 0.04. When narrower bandwidth is employed, all the lines show the same pattern but more noise.

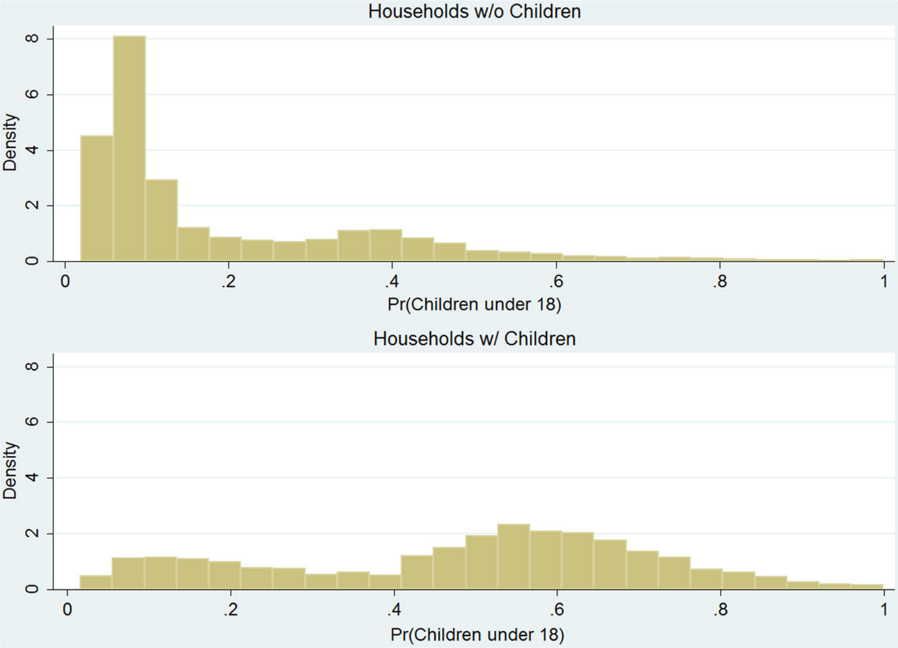


Fig. 1 Propensity score for having children under 18 years of age

Column 3 Table 1 reports the summary statistics for the sample of immigrant households trimmed by the propensity score. The trimmed sample accounts for approximately 70 % of immigrant movers and 10 % of all immigrant households. The trimmed sample has lower adjusted income and larger number of children, but resembles the untrimmed sample in most of the other respects.

3.2 School quality

The school quality measure employed is the 1999 Academic Performance Index (API) of public schools from the California Department of Education. The API Report is part of California's Accountability Progress Reporting which starts in 1999. The report measures the academic success of California's nearly 10,000 public schools in over 1,000 school districts and local educational agencies. A school's API is a number that ranges from 200 to 1,000 and is calculated from the results for each school's students on statewide tests. The API Reports are publicly available to parents and guardians as indicators of school performance.

I employ the APIs of high schools as a measure for local school quality. Since the number of high schools in each school district is much smaller than the number of elementary or middle schools, using high school quality largely mitigates problems related to discrepancies of school quality within a district. Also, since school quality

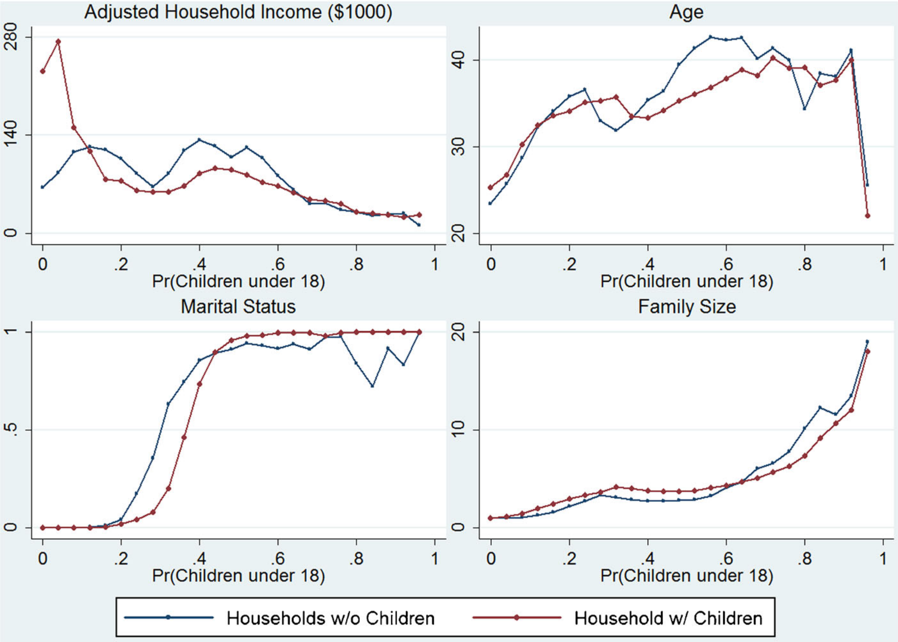


Fig. 2 Family characteristics by propensity score

is highly correlated across levels,[11] high school quality well represents the school quality of all grade levels in a district.

Admittedly, some households in my sample moved to their current location prior to 1999. When they evaluated location attributes and made a decision about where to live, school quality may have been different from that measured by the 1999 APIs. Nevertheless, school quality is likely to be stable over a five-year period.[12] As earlier data are not collected, the APIs in 1999 are the best available indicator for school quality when households chose their current locations.

According to the data obtained from the California Department of Education, there are 233 public high schools in 67 school districts in the Los Angeles Metropolitan Area. However, the PUMAs defined in the public use Census data do not tend to line up with school district or attendance zone boundaries. It is possible that several small school districts are contained in one PUMA, while a large school district like the Los Angeles Unified School District consists of several PUMAs.

[11]For the Los Angeles Metropolitan Area, the correlation between the district mean APIs (weighted by student enrollments) of elementary schools and those of high schools is .94, and the correlation between the district mean APIs (weighted by student enrollments) of middle schools and those of high schools is .95.

[12]As the APIs prior to 1999 are not available, I compare the district average APIs in the Los Angeles Metropolitan Area in the subsequent five years. The correlation between the district mean APIs (weighted by student enrollment) in 1999 and those in 2004 is over .95, indicating that school quality is quite stable over time.

Table 3 Summary statistics on the neighborhood characteristics

Variables	Mean	Std. Dev.	Min	Max
API	588	102	400	803
Housing Price ($)	682	145	402	1093
% White	34.6	23.8	.600	82.3
% Black	8.09	11.5	.400	55.4
% Asian	12.3	10.7	.300	53.6
% Hispanic	42.2	23.4	6.30	97.0
% Urban Population	99.0	6.35	42.7	100
Density/1000,000	37.5	31.2	.361	215
% Under 18	28.0	5.68	13.4	40.4
% Over 62	11.5	3.33	5.30	20.9
% Immigrants	34.7	12.3	12.9	69.8
% Unemployed	7.88	3.24	3.20	18.2
Median Household Income ($1000)	47.2	15.0	20.0	83.4
Median Educational Attainment	12.0	.928	10.5	14
% Private School Enrollment	16.7	7.11	4.06	49.0
% Homeownership	48.2	17.1	18.3	94.4
Avg. House Age (Years)	36.1	7.53	15.6	50.0
Avg. No. of Bedrooms	2.14	.515	.663	3.08
Crime Rate (%)	1.82	1.15	.110	5.06
Avg. Commute Time (Min.)	21.7	3.41	15.0	30.0
No. of Metro Stations	.881	1.68	0	9
No. of Parks	14.4	12.9	0	60
No. of Colleges	.786	.879	0	4
No. of Hospitals	1.30	1.36	0	6
No. of House Units/1000	2.55	.843	1.43	5.35
SAT Score	945	113	691	1158
No. of Obs.				84

The aggregation of the individual school API to the PUMA level proceeds as follows. First, except for the Los Angeles Unified School District,[13] the mean API of each school district weighted by school enrollments is calculated. Second, I average the district mean APIs to the PUMA level weighted by the population in the intersections of each PUMA and overlapping school districts. Third, lacking data for attendance zone for each school, I simply calculate the mean API weighted by school enrollment for every PUMA within the Los Angeles Unified School District. Table 3 reports the summary statistics for PUMA mean APIs.

[13]The Los Angeles Unified School District is very large and covers a number of PUMAs, while other school districts are usually smaller than or of similar size as PUMAs.

3.3 Housing prices

The Census has collected an array of measures related to housing: a binary variable whether the unit is owned or rented, the corresponding rent or owner-reported value, property tax payment, number of rooms, number of bedrooms, type of structure, the age of the building, and etc. Because house values are self-reported, it is difficult to ascertain whether these prices represent the current market value of the property, especially if the owner purchased the house many years ago. A second deficiency of the house values reported in the Census is that they are top-coded at $500,000. In the Los Angeles Metropolitan Area, it is not unusual that the top-code is binding. Therefore, I employ the reported monthly rent instead. Presumably, rents are subject to less misreporting than house values, even though renters who have occupied a unit for a long time may receive some sort of tenure discount (Bayer et al. 2007).

In order to get a more accurate measure for market rent that is comparable across PUMAs, I first run a hedonic price regression on all the households with cash rent in the Los Angeles Metropolitan Area in the 2000 Census. Specifically, I regress the reported gross rent on the tenure of the current renter, a full set of PUMA dummy variables, and a series of house characteristics, including number of rooms, number of bedrooms, number of units in the structure, whether there is a kitchen, and the age of the building. I utilize the estimated PUMA fixed effect as a measure for overall housing price of each PUMA.

There may be two empirical issues related to the housing price measure to address. First, the housing price measure derived from reported rents may suffer from the problem of endogeneity. An analogous problem is commonly discussed in the empirical industrial organization literature in which market shares and prices are simultaneously determined while consumer level data is often unavailable (Berry 1994). Relative to a market-level analysis, the use of household level data reduces the simultaneity problem (Barrow 2002). Also, as my sample accounts for only less than 5 % of all the households dwelling in Los Angeles, it is likely that the sample is not representative of net market demand shifts. Second, housing price not only accounts for the cost to live in a certain neighborhood, it also capitalizes the value of local amenities to the marginal homebuyer. This may lead to a positively biased estimate of price and complicates the interpretation of the coefficient on school quality, since the difference in the value across marginal residents should already be reflected in the price. Yet in both cases, the approach of netting out the weights estimated for households without children mitigates the problem, and the interaction between school quality and having children under 18 may not be biased. The question studied is thereby interpreted as, given the price a household has to pay to live in a community, whether households with children sort to expensive communities where the public bundle is skewed toward good schools.

3.4 Neighborhood characteristics

The data for neighborhood characteristics, including sociodemographic characteristics, house features and local amenities are from various sources.

The sociodemographic characteristics of each PUMA, including the racial distribution, age structure, percentage of immigrants, percentage of urban areas, percentage of unemployed, and median household income, are extracted via the Missouri Census Data Center's Dexter Data Extractor. Some other characteristics which are not covered by Dexter Data Extractor, such as median educational attainment, fraction of private school enrollments among households with children, percentage of owned houses, density, and total number of house units are directly calculated from the 2000 Census. Similarly, the PUMA average house characteristics, including the age of the building and the number of bedrooms are also calculated from the 2000 Census data.

The conventional monocentric urban model assumes all employment is located at the center of a circular city encompassed by a suburban ring (Straszheim 1987). Previous literature on residential location choices often uses the distance to the city center, or the Central Business District (CBD) , to proxy for access to employment. However, with the decline of central cities and the growth of suburbs, more than one CBD has emerged in populous metropolitan areas like Los Angeles. Hence, I measure the job access of different PUMAs using the average commute time to work among all employed individuals in each PUMA.

The data of crime rates for Los Angeles County and Orange County are from the Criminal Justice Statistics Center Databases of California. Other local amenities data, including parks, metro stations, hospitals, and colleges are derived from the Geographic Information System documents provided by the Cal-Atlas Geospatial Clearinghouse.

The summary statistics for the neighborhood characteristics are also reported in Table 3.

3.5 Selective migration

Six origin-level characteristics are employed to measure selective migration: distance to the United States,[14] whether English is an official language,[15] fraction of refugees, income inequality relative to the U.S., per capita GDP, and the relative share of national origin among immigrant population in the Los Angeles Metropolitan Area.[16]

As the Census does not collect information about immigration status, I use the fraction of refugees among migrants from each national origin instead so as to incorporate the distinction in motivation for migration between refugees and economic immigrants (Cortes 2004). The data of refugees and asylums granted lawful permanent residents are from the 2000 Yearbook of Immigration Statistics provided by the U.S. Department of Homeland Security.[17]

[14] Distance to U.S. is calculated as the number of air kilometers between home country's largest city and the nearest U.S. gateway (Los Angeles, Miami, or New York). The data are from www.timeanddate.com.

[15] The information about nations' official languages is from en.wikipedia.org/wiki/List_of_official_languages.

[16] The national origin shares are calculated from the 2000 Census.

[17] Data source: www.dhs.gov

I calculate the ratio of occupational income at the 90th percentile to the 10th percentile in each country as a measure for income inequality. The ratios are obtained from the Occupational Wages around the World (OWW) Database by Freeman and Oostendorp. The dataset collects occupational wages for 161 occupations in 171 countries and regions from 1983 to 2008. To capture the persistent dispersion by nation relative to the U.S., I estimate the country fixed effects from a regression of the ratio on a specification that includes year effects.[18] I also include the origin country GDP per capita so as to control for the mean of the income distribution of each country. The GDP data are from the Statistics on World Population, GDP and Per Capita GDP by Maddison.

Table 4 Panel A presents the summary statistics for these factors.[19]

3.6 Returns to education

Because an individual's return to education is endogenous to the quality of the school he or she attends (Card and Krueger 1992; 1996), I use the returns to education among the parental generation, i.e. first-generation immigrants and link these to how immigrant households value schools when choosing residences. It is possible that immigrant parents' perceptions of potential future earnings of their children come from their own experiences in the labor market.

Since the local labor market in the Los Angeles Metropolitan Area is unique compared to other parts of the U.S., I derive the static "local" returns to education in the area by immigrants' country of origin. The "local" returns to education are estimated from the 2000 Census data based on the same regression function proposed by Bratsberg and Terrell (2002).[20] Table 4 Panel A presents the summary statistics.

It is worth mentioning that variation in returns to education of first-generation immigrants could partly result from self-selection. Table 4 Panel B displays the relationship between returns to education and the measures for selective migration. Distance from the source country to the U.S. is positively correlated with the returns to education, indicating that more motivated immigrants enjoy better labor market achievements in the U.S. Immigrants who have English as their native language and who are from wealthier countries also tend to earn more. The share of national origin shows a negative relationship with the returns to education, perhaps as a result of the high fraction of Hispanic immigrants in the Los Angeles Metropolitan Area. The six selection measures together explain about 53 % of the cross-origin variation in the returns to education among first-generation immigrants. Some other factors, such as origin-specific attitudes toward education and the demand side of the U.S. labor market, may also be a determinant. Therefore, I also test controlling for the factors that

[18] I first calculate the ratio of the 90th percentile to the 10th percentile occupational income by year and country. Then I regress the year by country ratio on a set of country dummies and year dummies, using the U.S. and year 1990 as the omitted country and year.

[19] Only national origins that have no less than five observations in the sample of immigrant households with children under 18 are included.

[20] More details about the estimation of "local" returns to education among immigrants are in the Appendix A.2.

Table 4 Summary statistics on the origin characteristics of immigrants

PANEL A: Summary Statistics

Variables	Origin	Mean	Std .Dev.	Min	Max
Distance to the U.S. (1000km)	59	7.97	4.31	.315	14.5
English as Official Language (= 1)	59	.220	.418	0	1
% Refugees	59	15.0	25.5	0	98.1
Income Inequality Relative to the U.S.	41	1.15	1.60	−.860	5.91
GDP Per Capita ($1000)	41	6.90	5.92	.559	19.3
Returns to Education in the U.S.	59	.057	.016	.025	.104
Share of National Origin (%)	59	1.57	5.68	.045	43.1

PANEL B: Returns to Education and Selective Migration

Variables	Returns to Education (1)	(2)	(3)
Distance to the U.S.	.893** (.447)	.902* (.502)	.667 (.518)
1(EnglishOfficial)	10.4** (5.08)	9.56* (4.94)	9.72** (4.83)
%Refugees	−.083 (.073)	.182 (.136)	.173 (.131)
Income Inequality Relative to the U.S.		−1.76 (1.52)	−1.81 (1.46)
GDP Per Capita		.992*** (.358)	.938** (.355)
Share of National Origin (%)			−.488*** (.146)
No. of Origins	59	41	41
R-Square	.190	.483	.526

* significant at 10 %; ** significant at 5 %; *** significant at 1 %

Regressions in Panel B are estimated by the OLS with robust standard errors. The dependent variable is the measure for returns to education times 1000 may affect selective migration when studying the role of returns to education in how parents value school quality.

4 Immigrant values on school quality

4.1 The role of school quality

Table 5 presents the results for different specifications of the conditional logit model. The dependent variable is an indicator for residential location choice among 84 PUMAs.

The first regression includes only school quality as measured by the API score, the interaction term between the API and the child indicator, adjusted rent as the proxy for the cost of living in a given location, and the number of house units in each PUMA to account for size differences across neighborhoods. Estimates from this parsimonious specification imply that immigrant households without children assign negative weight to school quality in residential location choices while households with children value school quality significantly more. Both types of households tend to avoid areas where housing price is high. As discussed above, it is possible that both the rent and API are correlated with other neighborhood characteristics, and thereby capture households' preferences over those characteristics.

The second regression takes more location attributes into account, including neighborhood sociodemographics, average house characteristics, and local amenities. When other location characteristics are controlled for, both coefficients on the API and the rent become positive. The parent-non-parent difference in the weight placed on the API stays positive and significant, implying immigrant parents value school quality in choosing where to live.

To rule out the possibility that the API-child interaction picks up differential preferences toward non-school characteristics between households with and without children, column 3 include the interactions between the child indicator and other location attributes in addition. The estimated main effects of location characteristics resemble those in column 2, and so is the interaction effect of the API on households with children. The estimates being insensitive to including additional interaction terms may support the validity of the assumption for identification that parents and non-parents view unobserved non-school attributes similarly.

Moreover, the fourth column assumes that the set of weights assigned to location characteristics vary by household income and householder's educational attainment. I add a series of interactions between these two household characteristics[21] and the location attributes, including the API score, to the regression. The estimate on API-child interaction is not affected.

[21] The household income employed here is the income adjusted by household size. Both household income and householder's educational attainment are standardized to have mean of 0 and standard deviation of 1 when interacting with location characteristics from now on. Hence, the estimated main effects of location attributes represent the weights assigned by an immigrant household with mean income and mean education.

Table 5 Conditional logit model of residential location choices

Variables	(1)	(2)	(3)	(4)	(5)
API/1000	−1.75*** (.196)	.620** (.287)	.406 (.347)	.631** (.294)	.510 (.348)
API/1000 × 1(child<18)	1.50*** (.220)	1.13*** (.232)	1.68*** (.487)	1.24*** (.242)	1.57*** (.486)
Housing Price/100	−.024* (.013)	.191*** (.031)	.192*** (.031)	.175*** (.032)	.175*** (.032)
White (=1) × % White		.029*** (.002)	.029*** (.002)	.025*** (.002)	.025*** (.002)
Black (=1) × % Black		.042*** (.004)	.042*** (.004)	.044*** (.004)	.045*** (.004)
Asian (=1) × % Asian		.050*** (.002)	.050*** (.002)	.051*** (.002)	.051*** (.002)
Hispanic (=1) × % Hispanic		.026*** (.001)	.026*** (.001)	.018*** (.001)	.018*** (.001)
Density/1000		−1.41*** (.461)	−1.34*** (.463)	−1.72*** (.321)	−1.64*** (.491)
% Urban Population		.012*** (.004)	.012*** (.004)	.014*** (.004)	.014*** (.004)
% Under 18		.011* (.006)	−.001 (.008)	.001 (.007)	−.012 (.008)
% Over 62		−.046*** (.008)	−.057*** (.011)	−.061*** (.008)	−.071*** (.011)
% Immigrants		.018*** (.002)	.018*** (.002)	.017*** (.002)	.017*** (.002)
% Unemployed		−.050*** (.013)	−.072*** (.017)	−.066*** (.014)	−.091*** (.018)
Median Household Income/1000		−.034*** (.006)	−.033*** (.007)	−.039*** (.007)	−.039*** (.007)
Median Educational Attainment		.065** (.027)	.032 (.034)	−.005 (.027)	−.045 (.035)
% Homeownership		.019*** (.003)	.024*** (.004)	.011*** (.004)	.017*** (.005)
Avg. House Age (Years)		.003 (.004)	.004 (.005)	.003 (.004)	.004 (.005)
Avg. No. of Bedrooms		1.02*** (.137)	1.07*** (.167)	.823*** (.147)	.882*** (.174)
Avg. Commute Time		.013*** (.004)	.008 (.005)	.009* (.005)	.004 (.006)
Crime Rate (%)		−.010 (.015)	.011 (.019)	−.009 (.016)	.011 (.020)
No. of Metro Stations		.027*** (.010)	.041*** (.013)	.019* (.011)	.033** (.013)
No. of Parks		.001 (.001)	.000 (.002)	.002 (.001)	.001 (.002)
No. of Colleges		.020 (.017)	.028 (.022)	.029* (.018)	.039* (.023)
No. of Hospitals		.033*** (.010)	.027** (.013)	.040*** (.011)	.034** (.014)
No. of House Units/1000	.283*** (.014)	.388*** (.022)	.335*** (.022)	.354*** (.024)	.350*** (.024)
× Income & Education	No	No	No	Yes	Yes
× 1(child<18)	N/A	No	Yes	No	Yes
No. of Obs.	7,039	8,371	8,371	8,371	8,371
Log-likelihood/1000	−31.0	−34.7	−34.7	−34.4	−34.3

Table 5 (continued)

Variables	(1)	(2)	(3)	(4)	(5)
Marginal Effect					
% Point Change	.163 (.044)	.153 (.079)	.228 (.099)	.168 (.091)	.214 (.095)
% Change	13.7 %	12.9 %	19.3 %	14.2 %	18.0 %

*significant at 10 %; **significant at 5 %; ***significant at 1 %

Regressions are estimated by the conditional logit model. The dependent variable is an indicator for residential location choice among 84 PUMAs. Robust standard errors are reported in parentheses. The reported marginal effects are the average percentage point change and the average percentage change in parent-non-parent difference in choosing a PUMA given a 1 S.D. increase in API of that PUMA

Again, column 5 includes a series of interactions between location characteristics and the child indicator when adjusting for effects of household income and householder's education. Similar estimates are produced.

To quantify the implications for choice of residence (Ai and Norton 2003), I calculate the difference in the probability change to live in a certain PUMA between a hypothetical household with children and a hypothetical household without children if the API of that PUMA increases by one standard deviation based on the estimates in column 4. The adjusted household income and householder's education are assumed to be at the sample means. The APIs of other PUMAs and all the non-school location attributes are held constant. The parent-non-parent difference is calculated repeatedly for all the 84 PUMAs. Table 5 displays the average and standard deviation in percentage points. The average percentage change is also reported. The simulated results suggest that a one standard deviation increase of the API in a PUMA raises the probability that an immigrant household with children select that PUMA relative to an immigrant household without children by .17 percentage points on average, representing a 14 % change.

4.2 Different effects by socioeconomic status

A selection model of migration (Chiswick 1978; Borjas 1987) suggests that migrants are highly inspired for labor market success regardless of their socioeconomic background. If so, household income or householder's education should not be predictive for how immigrants evaluate education.

However, despite the value on schools, both household income and householder's education play a pivotal role in residential choices through budget constraint. Low-income households have more restricted choice sets compared to their wealthier counterparts. Householder's education may also capture the parental tastes for education - better educated individuals may favor education more.

As these two household characteristics may lead to heterogeneity in the parent-non-parent difference in the weight assigned to school quality, I examine the sample by households' socioeconomic status.

Table 6 School quality and residential location choices by group

	$API/1000$	API/1000 $\times 1(\text{child}<18)$	No. of Obs.	Marginal Effect % Pts.Δ	Marginal Effect %Δ
Income					
Q1	−1.33 (1.31)	.461 (.399)	3,300	.049 (.039)	4.17 %
Q2	−.797 (2.46)	.973** (.470)	2,231	.113 (.072)	9.53 %
Q3	−.814 (.762)	2.37*** (.592)	1,280	.295 (.156)	24.9 %
Q4	1.68 (2.03)	3.62*** (.729)	899	.611 (.475)	52.0 %
Q5	2.33 (1.76)	3.65*** (.892)	661	.655 (.589)	56.0 %
Education					
H.S. Dropout	1.29** (.656)	−.108 (.555)	2,784	−.015 (.010)	-1.23 %
H.S. Grad.	−.431 (.659)	.148 (.549)	2,112	.017 (.009)	1.44 %
Some College	1.98** (.783)	1.11* (.656)	1,029	.170 (.109)	14.4 %
Bachelor	.018 (.632)	2.86*** (.548)	1,460	.396 (.253)	33.5 %
Postgrad.	.683 (.858)	2.97*** (.712)	986	.441 (.306)	37.4 %

*significant at 10 %; **significant at 5 %; ***significant at 1 %

Regressions by income quintiles are estimated using the full model specification in column 4 Table 5. A three way interaction term of the API, child indicator, and adjusted income is added in the estimations by education. Robust standard errors are reported in parentheses. The reported marginal effects are the average percentage point change and average percentage change in parent-non-parent difference in choosing a PUMA given a 1 S.D. increase in API of that PUMA

First, I split the trimmed sample into five household income quintile[22] groups and run separate regressions using the specification presented in column 4 Table 5 on each group. Table 6 reports the results. The base effect of the API score is not significant in all income quintiles. The API-child interaction exhibits a monotonic relationship with income: the importance of school quality grows as household income grows. The interaction effect of the API on households with children is all positive, and it is statistically significant in the upper four quintiles. Admittedly, the difference in value placed on school quality across income quintiles is more likely to reflect the de facto choice sets of immigrant households of different income levels instead of differential tastes for children's education.

Second, I examine how the value placed on school quality varies by the educational level of the householder. Five categories are generated: 1) high school

[22]The income quintiles are formed among all the households in the Los Angeles Metropolitan Area based on the household income adjusted by family equivalent scale. The cutoffs would be same in all the analysis related to income quintiles in this paper.

dropouts, 2) high school graduates, 3) attended some college, 4) college graduates, and 5) postgraduates. To isolate the effect of education from that of income constraints, I include an additional three-way interaction of the API, the child indicator, and the standardized adjusted household income in each regression. The weights allocated to other location characteristics are assumed to vary only by household income within each educational level. Table 6 displays the regression results by education. Consistent with the findings of Barrow (2002) and Bayer et al. (2007), the magnitude of the parent-non-parent difference in value on school quality is positively associated with educational attainment of householders.

4.3 Robustness

I explore modifying the benchmark regressions in Table 5 in various ways to test whether the finding that immigrant parents value education is robust.

First, to address the concern that the private school options may partly break the link between residential location and school to attend, I test including the percentage of households who send children to private schools in each PUMA as a proxy for households' propensity to choose private schools over public schools. Second, in case the choice sets of certain immigrant groups are mischaracterized, I focus on naturalized immigrant households who resemble natives more and are probably better informed in residential selection, and exclude households with household heads themselves are in school so that the residential choices of the remaining sample are not restricted by the school location of household heads. Third, to assure that immigrant households with and without children have homogenous preferences toward unobserved non-school location attributes, I test two subsamples: households with householders aged 35 to 54, and households who rent. I also test accounting for the difference between households who would potentially have children in the near future and other households without children. Fourth, to address the potential differences in mobility, I examine out-of-state movers and movers who moved within Los Angeles Metropolitan Area. Last, I employ an alternative school quality measure, the SAT score. All robustness checks produce reassuring results. More details are provided in Appendix A.3.

5 Immigrant v.s. native value on school quality

Earlier studies find that second-generation immigrants outperform the children of natives in education and wages. Even children of the least-educated immigrant origin groups have closed most of the education gap with the children of natives (Chiswick and DebBurman 2004; Card 2005). One relevant hypothesis to test is whether immigrant parents emphasize schools more in residential locations than native parents. If so, this may shed light on the higher labor market achievements of the second generation.

Immigrant and native households are distinct in many aspects. The two groups may not share the common preferences over the unobserved location attributes or face the same choice set of residential locations. For instance, immigrants may prefer to cluster with immigrant households, but native households do not. Compared to the native-born, some immigrant households are more constrained by limited English skills and lack of access to public goods.

Therefore, instead of contrasting immigrant parents with native parents directly, I compare the parent-non-parent difference among the two groups. Presumably, the households with and without children within each group have similar unobserved preferences over non-school location attributes. I again employ the propensity score trimming method to balance the two groups.

The sample of native households is drawn based on the same criterion for the immigrant sample. That is, only households who earn a positive income and moved to the Los Angeles Metropolitan Area within the past five years are included. I estimate the propensity score for being an immigrant household from observable household and householder characteristics, and remove observations with estimated propensities below 0.1 or above 0.9 from the sample.[23,24] Then I run the regression in column 4 Table 5 on the two groups separately.

Table 7 reports the weight assigned to school quality by immigrant households versus native households as a whole, by income quintile, and by educational level.[25] In general, the interaction effects of the API are of similar size on immigrants and natives. The weight on school quality is positively associated with household income and householder's education for both groups. Yet among the households in the lowest income quintile and the households with household heads who attended some college, immigrant parents place significantly higher weight than their native counterparts.

I also explore disaggregating the sample of immigrant and native households with both parents present into smaller groups by the migration status of the household head and the spouse.[26] No significant differences are detected across these smaller groups.

6 Mechanisms for differential values on school quality

This section investigates the potential economic mechanisms that drive differential evaluation of education among immigrant parents. Three aspects are examined: age and number of children in the household, selective migration, and future returns to education.

[23] To balance the preferences toward non-school location characteristics of households with and without children, I first estimate the propensity for having children under 18 among the sample of immigrant and native movers in the manner discussed in the previous section and trim the sample using this propensity score. Then I estimate the propensity score for being an immigrant household and further trim the sample.

[24] More details are discussed in the Appendix A.4.

[25] Immigrant households generally have lower household income than natives. It is important to compare the location choices of the two groups when they face the same budget constraints.

[26] Four groups are considered: 1) both parents are immigrants; 2) the household head is an immigrant but the spouse is not; 3) the household head is native-born, but the spouse is not; and 4) both parents are native-born.

Table 7 Residential location choices: immigrants vs. natives

	Native			Immigrant			$t-stat$
	$API/$ 1000	$\times 1$ (child <18)	Marg. Effect	$API/$ 1000	$\times 1$ (child <18)	Marg. Effect	$\beta^{\text{Immig}}_{\text{API-child}} > \beta^{\text{Native}}_{\text{API-child}}$
All	−.124 (.432)	1.30*** (.392)	.164 [13.8 %]	.805* (.442)	1.23*** (.351)	.170 [14.4 %]	−.133
Income							
Q1	17.2*** (5.57)	−2.01** (.787)	−.814 [98.1 %]	−2.44 (.478)	−.264 (.680)	−.243 [20.6 %]	1.68**
Q2	4.51 (3.88)	.819 (.685)	.153 [13.5 %]	1.52 (3.82)	1.03 (.699)	.149 [12.8 %]	.216
Q3	.100 (.916)	2.75*** (.599)	.382 [32.2 %]	−.933 (1.04)	2.36*** (.782)	.290 [24.5 %]	−.396
Q4	−6.11*** (2.18)	3.50*** (.643)	.274 [23.0 %]	1.68 (2.56)	3.39*** (.871)	.564 [48.1 %]	−.102
Q5	.007 (2.14)	2.53*** (.787)	.342 [29.0 %]	.243 (2.34)	2.70** (1.11)	.376 [32.0 %]	.125
Education							
H.S. Dropout	−2.31 (2.18)	−.168 (.157)	−.025 [2.11 %]	2.74** (1.34)	−1.80* (1.01)	−.259 [21.9 %]	−.876
H.S. Grad.	−.558 (.758)	.755 (.564)	.089 [7.49 %]	−1.18 (.934)	.065 (.782)	.070 [.589 %]	−.716
Some College	.832 (.768)	.860 (.573)	.117 [9.85 %]	1.04 (1.09)	2.52*** (.861)	.379 [32.1 %]	1.61*
Bachelor	.327 (.919)	2.17*** (.694)	.299 [25.3 %]	1.02 (.888)	1.98*** (.741)	.288 [24.4 %]	−.193
Postgrad.	2.44* (1.46)	1.92** (.955)	.318 [27.3 %]	.645 (1.12)	2.62*** (.887)	.379 [32.2 %]	.532

*significant at 10 %; ** significant at 5 %; *** significant at 1 %

Regressions are estimated using the full model specification in column 4 Table 5 immigrant and native households separately. Robust standard errors are reported in parentheses. The reported marginal effect is the average percentage point change in parent-non-parent difference in choosing a PUMA given a 1 S.D. increase in API of that PUMA. The percentage changes are reported in brackets

6.1 Age and number of children

In this section, I examine the differential demand for the level and quantity of schooling services of immigrants due to the age and the number of children in the household.

I start with estimating Equation 8 using the trimmed sample of immigrant households as a whole and by income quintiles. This model specification allows the weight placed on school quality vary by the age structure of children. Similar to column 4 Table 5, I control for household income and householder's education. The regression results are presented in Table 8.

For households with lower income, having children under six lowers the weight assigned to school quality. It is likely that children of this age range have no direct needs for schooling services but leads to tighter budgets. Households with school-aged children, no matter in elementary or secondary schools, basically value school quality more than households having no children or very young children.

Table 8 Value on school quality and age of chidren

	All	Income				
	Immig.	Q1	Q2	Q3	Q4	Q5
API/1000	.904*** (.286)	−1.00 (1.28)	−.065 (2.46)	−.610 (.747)	1.82 (2.02)	2.67 (1.75)
×1(child<6)	−.643** (.302)	−1.38*** (.476)	−.035 (.605)	−.146 (.726)	1.78* (1.04)	1.10 (1.27)
×1(child:6–12)	.718** (.302)	−.043 (.478)	.974* (.591)	2.93*** (.732)	2.89*** (1.00)	1.91 (1.22)
×1(child:12–18)	1.41*** (.306)	1.47*** (.485)	.760 (.620)	1.70** (.786)	3.00*** (.960)	3.08** (.122)
F-stat						
$\beta_{API-1(0-6)}=\beta_{API-1(6-12)}$	8.24***	1.60	1.11	7.74***	0.53	0.17
$\beta_{API-1(0-6)} = \beta_{API-1(12--18)}$	25.1***	19.0***	0.93	3.38*	0.90	1.31
$\beta_{API-1(6--12)} = \beta_{API-1(12--18)}$	2.19	6.57***	0.05	1.15	0.01	0.36
All API-interactions=0	35.4***	20.4***	5.36	23.8***	22.0***	12.4***
No. of Obs.	8,371	3,300	2,231	1,280	899	661
Log-likelihood/1000	−34.4	−13.4	−9.21	-5.32	−3.59	−2.59
Marginal Effect						
1(child<6)	−.082 [6.88 %]	−.139 [11.8 %]	−.039 [.330 %]	−.016 [1.37 %]	.278 [23.6 %]	.180 [15.3 %]
1(child:6–12)	.097 [8.22 %]	−.045 [3.81 %]	.114 [9.69 %]	.383 [32.4 %]	.476 [40.5 %]	.325 [27.7 %]
1(child:12–18)	.198 [16.7 %]	.170 [14.4 %]	.088 [7.48 %]	.209 [17.6 %]	.496 [42.3 %]	.552 [47.4 %]

* significant at 10 %; ** significant at 5 %; *** significant at 1 %

Regressions are estimated by the conditional logit model on the trimmed sample of immigrant households. The dependent variable is an indicator for residential location choice among 84 PUMAs. Robust standard errors are reported in parentheses. The reported marginal effects are the average percentage point change in probablity to choose a PUMA given a 1 S.D. increase in API of that PUMA of parents with children in certain age range relative to non-parents. The percentage changes are reported in brackets

In the highest two income quintiles, households with children of all ages assign positive weight on school quality with no significant difference observed across the age groups. This may suggest that parents do not take children's age into calculation to choose where to live when the resources are abundant.

Though the above analysis provides interesting insights into the heterogeneity across the age structure of children, one caveat is that the three age groups are not mutually exclusive. Households with multiple children may belong to more than one category. It is difficult to disentangle the values over education for children of different ages in such households. Also, the number of categories that households fall into is related to the number of children in the households. So a household fits into more categories may also face a tighter budget constraint.

Accordingly, I move on to study the relationship between differential values on school quality and the number of children.

I focus on households with children only and replace the API-child interaction in the specification in column 4 Table 5 with an interaction term between the

Table 9 Value on school quality and number of chidren

PANEL A: All Immigrant Parents

	(1)	(2)	(3)
API/1000	2.98*** (.828)	3.54*** (.422)	
×ln(no.ofchildren)	−.594 (.547)	−2.54*** (.422)	−2.26*** (.443)
×ln(no.ofchildren:6–12)		1.45*** (.498)	1.47*** (.552)
×ln(no.ofchildren:12–18)		2.10*** (.475)	1.84*** (.484)
×Household Income	.843 (.604)	.836 (.586)	.219 (.550)
×Householder's Education	−.357 (.342)	.408 (.349)	−.206 (.462)
Origin Fixed Effects	No	No	Yes
F-stat			
$\beta_{\text{API}-\ln(\text{no.:}6-12)} = 0, \beta_{\text{API}-\ln(\text{no.:}12-18)} = 0$		19.5***	14.6***
$\beta_{\text{API}-\ln(\text{no.:}6-12)} = \beta_{\text{API}-\ln(\text{no.:}12-18)}$		2.45	1.03
No. of Obs.	3,650	3,650	3,650
Log-likelihood/1000	−15.0	−14.9	−14.5
Marginal Effect			
×ln(no.ofchildren)	−.068 [4.12]	−.319 [16.9 %]	.231 [16.4 %]
×ln(no.ofchildren:6–12)		.186 [9.86 %]	.156 [11.1 %]
×ln(no.ofchildren:12–18)		.290 [15.4 %]	.209 [14.9 %]

PANEL B: Income Quintiles

	Q1	Q2	Q3	Q4	Q5
API/1000					
×ln(no.ofchildren)	−3.14 *** (.662)	−.960 (.980)	−4.76*** (1.83)	.511 (2.86)	1.87 (3.33)
×ln(no.ofchildren:6–12)	1.19 (.932)	2.09** (.968)	4.24*** (1.28)	2.28 (1.91)	−.1.05 (2.81)
×ln(no.ofchildren:12–18)	2.41 *** (.734)	1.50* (.781)	2.89** (1.29)	1.13 (2.22)	−.632 (3.22)
Origin Fixed Effects	Yes	Yes	Yes	Yes	Yes
F-stat					
$\beta_{\text{API-ln(no.:}6-12)} = 0, \beta_{\text{API-ln(no.:}12-18)} = 0$	15.6***	5.67*	11.5***	1.61	0.14
$\beta_{\text{API-ln(no.:}6-12)} = \beta_{\text{API-ln(no.:}12-18)}$	4.64**	0.43	.269	0.48	0.01
No. of Obs.	1,652	842	542	342	201
Log-likelihood/1000	−6.69	−3.40	−2.16	−1.27	−.772

*significant at 10 %; ** significant at 5 %; *** significant at 1 %

Regressions are estimated by the conditional logit model on the sample of immigrant parents. The dependent variable is an indicator for residential location choice among 84 PUMAs. Robust standard errors are reported in parentheses. The reported marginal effect is the average increase in the odds of choosing a PUMA with top 10 % API if the total number of children or the number of children in certain age range increases from the mean to 1 S.D. higher. The percentage changes are reported in brackets

API score and the log number of children under 18 in the household. That is, I assume that the value on school quality embodied in residential location choices is linearly related to the log number of children. The estimates are shown in column 1 Panel A in Table 9. Presumably due to contradictory effects of number of children, the interaction term is not significantly different from zero. In column 2, I add two additional interactions: one between the API and the log number of children between 6 and 12; and one between the API and the log number of children between 12 and 18. When the these two interactions are added, the total number of children is negatively and significantly related to the weight on the API; and both measures for school-aged children are positively and significantly related to the weight on the API. As the value placed on school quality may vary in a systematic manner across origins, I further control for country fixed effects in column 3 so that the numbers of children is unlikely to capture the country effects through differential ethnic social norms on fertility. Similar estimates are produced.

These results may suggest that immigrant households with more school-aged children value school quality more when deciding where to live since they can benefit more from better schools. When origin fixed effects are controlled for, increasing the number of children aged 6–12 from mean to one standard deviation higher leads to an increase of 0.2 percentage points (11 %) in choosing a PUMA with top 10 % APIs; and increasing the number of children aged 12–18 from mean to one standard deviation higher leads to an increase of 0.2 percentage points (15 %) in choosing a PUMA with top 10 % APIs. On the other hand, given a fixed number of direct consumers of public schooling services, the total number of children is negatively related to the weight placed on school, presumably because of tighter budget or lower general value on children's education.

I also examine the relationship between weight on school and number of children by income quintile. The results are displayed in Panel B Table 9. The pattern of the estimates among the lower three quintiles resemble those estimated from the whole sample. But among the upper two quintiles, the total number of children, or number of children of a certain age range does not show much explanatory power for the weights assigned to school quality. It is possible that when less financially restricted, immigrant parents choose to locate in good school districts in spite of the number of children benefited. Nonetheless, the much smaller group size leads to larger standard errors.

6.2 Selective migration

One potential explanation for immigrants to place the more weight on school quality than their native counterparts is that migrants have higher aspirations for labor market success (Chiswick 1978; Borjas 1987; Chiswick 2000). Since the motivation of native-born population is difficult to quantify, I examine the varying motivation and quality among immigrants through selective migration. The effects of the selection on weight assigned to school quality are estimated using Eq. 9. That is, I interact the six selection measures listed in Table 4 and years since migration with the API. Only households with children are included in this analysis.

Table 10 Value on school quality and selective migration

	Immigrant Parents				
	(1)	(2)	(3)	(4)	(5)
API/1000	1.06 (..774)	.952 (.808)	−1.54 (1.41)	−3.56* (.221)	−3.95* (.229)
×Distance	.242*** (.080)	.318*** (.115)	.487*** (.128)	.637*** (.206)	.642*** (.208)
×1(Eng. Official)	−2.22 (1.58)	−2.87* (1.76)	−3.29** (1.52)	−3.37** (1.56)	−3.39** (1.58)
×%Refugees	−.034 (.022)	−.069 (.054)	−.072 (.052)	−.071 (.051)	
×Income Inequality			.294 (.497)	.502 (.521)	.495 (.525)
×GDP Per Capita			.339*** (.106)	.363*** (.105)	.366*** (.105)
×Share of National Origin (%)				.048 (.034)	.048 (.035)
×Years Migrated					.058 (.038)
×Household Income	.685 (.569)	.675 (.561)	1.15*** (.428)	1.20*** (.430)	1.16*** (.432)
×Householder's Education	.086 (.420)	−.017 (.416)	.046 (.543)	.120 (.519)	.113 (.517)
F-stat	9.24***	8.55**	21.2***	23.6***	23.7***
No. of Obs.	3,554	3,554	2,250	2,250	2,250
No. of Origins	59	59	41	41	41
Log-likelihood/1000	−14.5	−14.5	−9.15	−9.15	−9.15
Marginal Effect					
Distance	.232 [15.9 %]	.306 [21.2 %]	.472 [33.5 %]	.659 [43.3 %]	.668 [43.3 %]
1(Eng. Official)	.488 [44.2 %]	.614 [61.3 %]	.675 [73.4 %]	.727 [73.1 %]	.736 [73.4 %]
%Refugees		−.181 [12.5%]	−.345 [24.4 %]	−.378 [24.8 %]	−.375 [24.4 %]
Income Inequality			.132 [9.38 %]	.241 [15.8 %]	.238 [15.5 %]
GDP Per Capita			.541 [38.4 %]	.608 [39.9 %]	.617 [40.1 %]

*significant at 10 %; ** significant at 5 %; *** significant at 1 %

Regressions are estimated by the conditional logit model on the sample of immigrant parents. The dependent variable is an indicator for residential location choice among 84 PUMAs. Robust standard errors are reported in parentheses and clustered at the origin level. The F-stat is to test the joint significance of the selection measures. The reported marginal effect for distance to the U.S., percent refugees, income inequality, or GDP per capita is the average increase in the odds of choosing a PUMA with top 10 % API if the variable of interest increases from the mean to 1 S.D. higher; that for English being an official language is the average difference in the odds of choosing a PUMA with top 10 % API between immigrants from non-English-speaking countries and English-speaking countries. The percentage changes are reported in brackets

Table 10 displays the regression results. All the location attributes are controlled for. The weights placed on these attributes are allowed to vary by household income and householder's education so that the measures for selective migration are unlikely to pick up the effects of income or education.[27] The first column only investigates the effects of distance to the U.S. and whether English is an official language in the origin country. Fraction of refugees, income inequality measure and per capita GDP, share of national origin, and years since migration to the U.S. are introduced to the model one by one.

The distance between the source country and the U.S. is positively associated with the propensity that households choose to live in areas with good public schools, while English being an official language is negatively related to the odds of living in better school districts. This finding supports the argument by Chiswick and DebBurman (2004) that immigrants from non-English speaking countries manifest a higher demand for investment in education so as to increase the transferability of origin country skills. The coefficient on the interaction between the API and GDP per capita is positive and significant, which may suggest that households originated from wealthier countries are likely to locate in neighborhoods of high school quality.

Table 11 presents the coefficients estimated using the specification in column 3 Table 10 by income quintile. For all income quintiles, distance to the U.S. and English as an official language show some effects on the value assigned to school quality, and they all have the same sign as those estimated from the whole sample of immigrant parents. The interaction effect of API and origin GDP per capita is positive and significant in most cases. Both the national origin share and the years migrated are significant and positive in the lowest income quintile. This may suggest that, among the low-income households, those who have a bigger ethnic network and those who have a better knowledge of the U.S. tend to locate in better school district. Nevertheless, as number of households in the upper three quintiles declines, most of the estimates become less statistically significant due to larger standard errors.[28]

In addition, I estimate the effect of selective migration among immigrant households with and without children under 18 using a two-step model (Card and Krueger 1992). The first step is to estimate the origin-specific value on school quality by interacting the API-child interaction with a set of origin dummies from all immigrant households involved in earlier analysis.[29] In the second step, I regress the estimated origin-specific API-child interaction effect on the seven measures by weighted least squares, employing the inverse of the sample variance of the origin-specific parent-non-parent difference, estimated in the first step, as the weight. Although the two-step regression model does not compare to the one-step regression perfectly for a non-linear model like the conditional logit model, it helps illustrate the diversity in the

[27] As predicted by the literature, the origin-specific income inequality measure is negatively correlated with both household income and householders' educational attainment. However, both correlations are low and around 0.1.

[28] To rule out the probability that the regression results are driven by the high share of Mexican immigrants in the Los Angeles Metropolitan Area, I re-estimate all the specification in Tables 10 and 11 excluding immigrant households from Mexico in my sample. The results are very similar.

[29] I use the full model specification in Table 6 to estimate the origin-specific weight placed on school quality, excluding origins with less than five households in the sample.

Table 11 Value on school quality and selective migration by income quintile

	Income				
	Q1	Q2	Q3	Q4	Q5
API/1000	−7.83** (3.44)	1.22 (7.46)	−4.15 (3.53)	−4.41 (6.06)	.392 (7.36)
×Distance	.813*** (.255)	.534** (.255)	.247 (.276)	.508 (.381)	.348 (.371)
×1(Eng. Official)	−4.69*** (1.41)	−4.93*** (1.60)	−2.48 (1.88)	−1.37 (2.35)	−6.74** (2.91)
× %Refugees	−.093* (.055)	−.116** (.051)	−.061 (.084)	−.069 (.107)	−.079 (.088)
×Income Inequality	.600 (.470)	−.378 (.613)	1.29 (1.00)	1.04 (.975)	.144 (.688)
×GDP Per Capita	.360** (.156)	.424*** (.145)	.351** (.144)	.382** (.181)	.325 (.273)
×Share of National Origin (%)	.063* (.033)	− .014 (.051)	− .050 (.057)	.044 (.060)	.031 (.105)
×Years Migrated	.105** (.046)	− .010 (.086)	−.052 (.069)	.166 (.165)	−.605 (.219)
F-stat	−20.0***	−31.4***	21.2***	−6.42	9.02*
No. of Obs.	−1,185	−515	272	187	91
No. of Origins	−35	−37	34	31	24
Log-likelihood/1000	−4.80	−2.06	−1.09	−.687	−.327

* significant at 10 %; ** significant at 5 %; *** significant at 1 %

Regressions are estimated by the conditional logit model on the sample of immigrant parents. The dependent variable is an indicator for residential location choice among 84 PUMAs. Standard errors are reported in parentheses and clustered at the origin level. The F-stat is to test the joint significance of the selection measures

value placed on school quality by origins and enables verification of the approximate extent to which selective migration captures an important component of the country effects. The coefficients estimated by a two-step model have analogous magnitude to those derived from a conditional logit model. The R-square suggests that the seven variables together explain approximately 20 % of the variation in the value put on school quality among immigrants across origins. This may imply that selective migration may partly explain the emphasis immigrants place on school quality in the U.S.

6.3 Returns to education

The effect of ”local” returns to education on the value placed on school quality in location choices by immigrant parents is also estimated by Equation 9. Table 12 displays the regression results for the link between the returns to education and the value placed on school. The first three columns only include the interaction between the API and returns to education, and the latter three control for additional origin characteristics as the returns to education among immigrants are in part determined by their self-selection.

Table 12 Value on school quality and returns to education

	w/o Other Origin Char.			w/ Other Origin Char.		
	API/1000	×Returns to Edu.	Marg. Effect	API/1000	×Returns to Edu.	Marg. Effect
All	−.100 (1.12)	72.6*** (17.3)	.306 [22.2 %]	−8.51*** (2.39)	153 *** (54.6)	.647 [50.6 %]
Income						
Q1	−.512 (1.23)	116*** (32.4)	.936 [29.0 %]	−11.4*** (4.45)	131* (73.0)	1.14 [19.7 %]
Q2	.319 (.871)	109*** (35.3)	.537 [22.6 %]	−3.03 (7.90)	113* (64.3)	..400 [25.2 %]
Q3	.648 (1.77)	57.1** (25.3)	.232 [16.0 %]	−11.0*** (3.80)	189* (112)	.681 [62.9 %]
Q4	2.37 (2.06)	112 *** (33.5)	.312 [34.5 %]	−6.36 (7.03)	99.2 (101)	.003 [27.3 %]
Q5	5.43** (2.50)	91.8 (66.8)	.569 [19.4 %]	−10.9 (6.93)	186 ** (76.8)	1.00 [55.0 %]

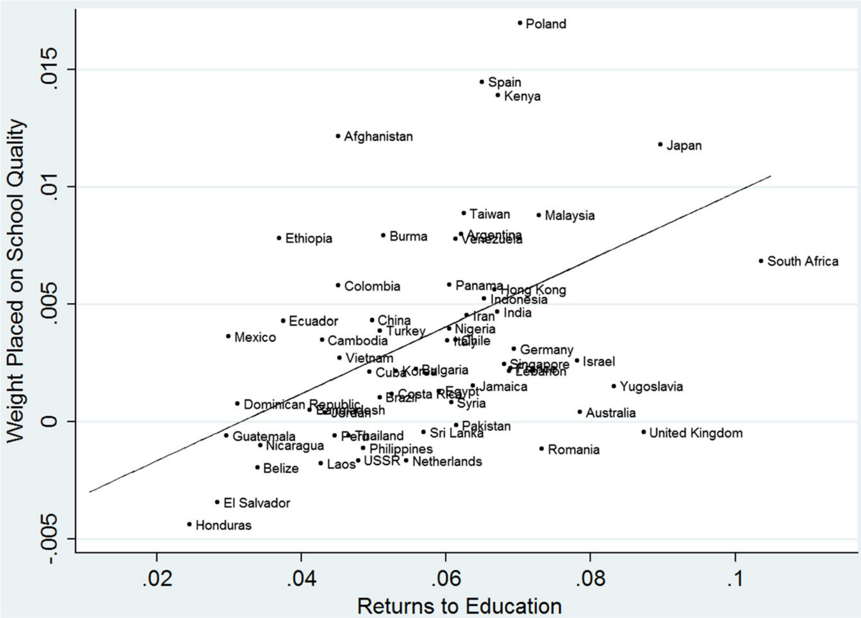
*significant at 10 %; ** significant at 5 %; *** significant at 1 %

Regressions are estimated by the conditional logit model on the sample of immigrant parents. The dependent variable is an indicator for residential location choice among 84 PUMAs. Robust standard errors are reported in parentheses and clustered at the origin level. The reported marginal effect of returns to education is the average change in the propensity to choose a PUMA with top 10 % API if the returns to education increase from the mean to 1 S.D. higher. The percentage changes are reported in brackets

For the whole sample of immigrant households with children, the estimated coefficient on the interaction between the API and returns to education is positive and significant no matter the measures for selective migration are controlled or not. Based on the estimates in column 5, if the returns to education increase by one standard deviation from the mean, the average propensity for immigrant parents to choose a PUMA with top 10 % API score in the Los Angeles Metropolitan Area would increase by about 0.6 percentage points, accounting for a 50 % change. Given potential heterogeneity in the location choice set across households with different income levels, I estimate the relation between returns to education and value on school by income quintile. There is no clear pattern of the effect of returns to education across income quintiles. In general, returns to education are positively associated with how households value school quality regardless of household income. Its effect is the significant in most subgroups.[30]

I also utilize a two-step regression model to test the effect of returns to education on values placed on school quality. Different from the previous section, in the second step, I regress the estimated origin-specific API-child interaction effect on the returns to education. Figure 3 depicts the estimated origin-specific weights on school quality against the immigrants' returns to education as well as the regression line obtained in the second step. The slope of the regression line is 143. The R-square suggests about 28 % of the heterogeneity in the weights placed on school quality across origins is

[30] Similar as the previous section, I run the regressions without Mexican immigrants. The results are not affected.



NOTE: The WLS regression line has a slope of 143 and standard error of 32.3, with R^2 being .276.

Fig. 3 Weight placed on school quality v.s. returns to education

explained by returns to education. If other origin characteristics are also included in the second step, the eight variables together explain more than 48 % of the variation in weight on school. Hence it may be concluded that returns to education partly influence how households value school quality, and parents are more willing to invest on education if the potential payoff for their children is higher in the future.

Last, provided that cities are not isolated economies and immigrants flow between cities, I test replacing the "local" returns to education with the U.S. "universal" returns to education estimated by Bratsberg and Terrell (2002).[31] The regression results resemble those in Table 12.

7 Conclusion and discussion

This paper studies whether and why immigrants value school for their children in host countries. The values placed on school quality are assessed through households' residential location choices.

[31]The correlation between "local" returns to education in the Los Angeles Metropolitan Area and the "universal" returns to education estimated by Bratsberg and Terrell (2002) is about 0.7.

The empirical analysis suggests that immigrant parents exercise school choice through the choice of residential locations in the United States. When allowing for income heterogeneity in the weights assigned to school quality, the importance of schools increases as household income or householder's education increases.

I explore the potential reasons why immigrants are willing to invest on school for their offspring. First, households with school-aged children incline to value school quality more than households with children below school age. The number of school-aged children is positively associated with the weight assigned to schools in residential location choice. Second, selective migration explains a part of the heterogeneity in value placed on school among immigrant parents. Immigrants who migrated to the U.S. from a far away or a non-English speaking country are more likely to reside areas with better schools. These results may indicate that immigrants who are more motivated for labor market success tend to emphasize their children's education more. Last, higher expected returns to education lead immigrant parents to invest more in children's education. When allowing the value placed on school quality in location choices to vary by country of origin, the origin-specific returns to education show a positive relationship with the probability of immigrant households with children selecting areas where school quality is high. The measures for selective migration and that for returns to education explain approximately 20 % and 28 % of the cross-origin variation in weights put on education respectively.

The paper has a number of policy implications for immigration and public education. First, the Immigration and Nationality Act of 1965 which proposed a preference system on immigrants' skills and family relationships has resulted in a remarkable increase in the number of immigrants from Asia and Latin America to the U.S. Despite the overall declining entry earnings of the immigrants subject to the 1965 Amendments (Borjas 1987; 1995a; Jasso et al. 2000), the paper verifies a close link between favorable self-selection and aspirations for human capital investment in their offspring among the new immigrants.[32] On the one hand, the higher incentive to invest in human capital may lead migrants with low initial skills, such as those coming under family-tie categories, to catch up faster to the native-born population (Duleep and Regets 1999). On the other hand, since the 1965 act also favors skills, a sizable proportion of current immigrants have matched or even surpassed the majority of natives in socioeconomic status soon after arrival (Yu 2003), and are thereby not financially restricted in exercising their children's school choice through residential selection. Hence, the change in the immigration policy may lead to an increasing demand for educational quality in the U.S. Relevant questions that arise may include whether the inflow of immigrants who place a high value on school increases the

[32] Only 3 % of the immigrant households in the sample analyzed in this paper migrated to the U.S. prior to 1965. The majority of the immigrant sample entered the U.S. subject to the Immigration and Nationality Act of 1965.

provision level (quality) of public schooling services or causes it to deteriorate by lowering public expenditure per student.

Second, the paper provides additional evidence on immigrant human capital investment and assimilation (Chiswick 1978; Duleep and Regets 1999). The relationship between motivation for migration and value placed on school quality by immigrant parents may help explain the dynamics in the labor market of immigrant receiving societies, more specifically, the higher achievements in education and the labor market of second-generation immigrants (Chiswick 1988; Boyd and Grieco 1998; Chiswick and DebBurman 2004). Due to the increasing importance of immigrants and their descendants in the U.S. workforce and the critical role of education in labor market success, it is necessary to understand the educational and earning advantages of the second generation and relate them to the immigration regulations.

Third, the findings in this paper shed light on the effects of school quality on the residential sorting of immigrants. Relative to earlier studies on location choices of immigrants that are mostly conducted at a broader level (Jaeger 2004; Chiswick and Miller 2004), such as choices of regions or metropolitans, this paper provides insights into immigrants' choices of communities within a metropolitan area. Estimates of a wider range of underlying preference parameters help understand how immigrant households sort in the local housing market, which in turn determines the pattern of residential segregation and the matching of households to schools. Residential sorting not only affects the spatial assimilation of immigrants themselves, but also influences the dynamics in ethnic enclaves, the local labor market, and public good provision in destination economies. The change in the sociodemographics of neighborhoods and the body of students in local schools as well as the matching of immigrant households to local public schools are closely related to the impact of immigration on public education.

Finally, in addition to the predominant understanding of the ethnic clustering of immigrants, the paper finds that similar to the natives, immigrant parents care about public school quality in residential location choices. From a policy perspective, the result may imply that the provision of public goods, specifically, public schooling services, could be used as a tool by the government to regulate the residential sorting of immigrants and influence their spatial assimilation. Since immigrants are in general less likely to choose private schools than natives, they are more likely to benefit from public education reforms. In particular, providing more educational options that relax the strict link between residential location and school choice, such as enacting school choice programs and intradistrict open enrollment, may reduce both residential and school segregation and improve the overall welfare of immigrant households as well as other groups. Moreover, as both immigrant and native parents value school quality, an improvement of the general level of school quality may also help both groups.

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Appendix A.1: Parents v.s. non-parents

The empirical analysis on the weight immigrant parents assign to school quality in residential location choice relies on the assumption that unobserved location attributes affect households with and without children similarly. I employ propensity score trimming to balance the characteristics of the two types of households so that their preferences toward non-school location attributes would align better.

To justify the effectiveness of this approach, I explore how results vary as I change the cutoffs of propensity score trimming based on the model specification in column 5 Table 5. Table 13 reports the estimates on the interaction terms between neighborhood characteristics and the child indicator. Besides the school quality, parents and non-parents display differential weights on a few attributes, including neighborhood age structure, unemployment rate, education level, homeownership, crime rate, metro stations, and number of colleges. Nevertheless, the majority of the differences result from residential sorting and different demographic characteristics of households with and without children. The preferences toward non-school amenities, namely, house features and public goods provision, do not differ much. In general, when trimming the sample to a tighter range of propensity score, the weights assigned to non-school neighborhood attributes by the two types of households converge more. Yet the parent-non-parent difference in the value on school quality is insensitive to the changes in trimming.

These evidences help bolster that trimming is a useful way to balance the sample on preferences and reassure the assumption that households with and without children value unobserved neighborhood characteristics is plausible. I use the trimming from 0.1–0.9 in the main text to have my sample more representative for the immigrant population in the Los Angeles Metropolitan Area.

Appendix A.2: Local returns to education

The origin-specific "local" returns to education among immigrants in the Los Angeles Metropolitan Area are estimated in the same manner as Card and Krueger (1992) and Bratsberg and Terrell (2002). The estimation proceeds as follows:

$$\ln w_{ij} = \theta X_i + \sum_j \eta_j D_{ij} \cdot edu_i + \varepsilon_{ij} \tag{A1}$$

where w_{ij} denotes the weekly wage of immigrant i born in country j; X_i is a vector of socioeconomic characteristics, including age and its square, English fluency, marital

Table 13 Residential location choice: parents v.s. non-parents

	Pr(child<18)				
	0–1	.1–.9	.2 –.8	.3–.7	.4–.6
1(child<18)					
× API/1000	1.87*** (.432)	1.57*** (.487)	1.04** (.537)	1.24** (.616)	1.55* (.834)
× % Under 18	.050*** (.010)	.030*** (.011)	.027** (.012)	.014 (.015)	.023 (.020)
× % Over 62	.033** (.014)	.024 (.016)	.020 (.018)	.006 (.020)	−.059** (.027)
× % Unemployed	.015 (.021)	.059** (.024)	.070*** (.026)	.074** (.031)	.086** (.044)
× Median Household Income/1000	−.014** (.006)	.004 (.007)	.007 (.008)	.009 (.009)	.006 (.013)
× Median Educational Attainment	.077** (.039)	.088* (.045)	.123** (.050)	.117** (.060)	.089 (.044)
× % Homeownership	−.016*** (.005)	−.013** (.006)	−.009 (.007)	−.010 (.008)	−.017 (.012)
× Avg. House Age (Years)	−.003 (.006)	.000 (.007)	.002 (.008)	.005 (.009)	.016 (.012)
× Avg. No. of Bedrooms	−.077 (.190)	−.132 (.219)	−.033 (.244)	−.071 (.286)	−.129 (.403)
× Avg. Commute Time	.006 (.007)	.009 (.008)	.007 (.009)	.007 (.011)	.000 (.015)
× Crime Rate (%)	−.018 (.025)	−.048* (.028)	−.050* (.031)	−.067* (.037)	−.070 (.051)
× No. of Metro Stations	−.007 (.016)	−.035* (.019)	.037* (.021)	−.028 (.024)	−.051 (.034)
× No. of Parks	.003 (.002)	.002 (.002)	.002 (.003)	.003 (.003)	.003 (.004)
× No. of Colleges	−.065** (.029)	−.023 (.033)	−.010 (.037)	−.023 (.044)	.004 (.060)
× No. of Hospitals	.008 (.016)	.014 (.018)	.011 (.020)	.005 (.024)	.011 (.033)
F-stat					
All 1(child<18) interactions=0	274***	110***	56.9***	50.6***	21.7*
Local amenities× 1(child<18)=0	10.7	7.75	5.65	5.13	5.57
No. of Obs.	11,821	8,371	6,622	4,773	2,491
Log-likelihood/1000	−48.4	−34.4	−27.1	−19.4	−10.1

* significant at 10 %; ** significant at 5 %; *** significant at 1 %

Regressions are estimated by the conditional logit model using the specification in column 5 Table 5 on the sample of immigrant households untrimmed or trimmed by propensity score for having children under 18 at different ranges. The dependent variable is an indicator for residential location choice among 84 PUMAs. The estimated coefficients on the interactions between child indicator and location characteristics are reported with robust standard errors in parentheses

status, health status, year of immigration, and county of residence; D_{ij} is a binary indicator which is equal to one if the immigrant was born in country j and zero otherwise; edu_i is the years of schooling of immigrant i; and ε_{ij} is the stochastic error term. The parameter η_j measures the value of the Los Angeles labor market placed on a year of schooling of immigrants who originate from country j. I examine male immigrants aged 35–54 and currently employed in Los Angeles Metropolitan Area. Only countries of origin with at least 10 individuals that satisfy the criteria are included. There are 31,326 immigrants from 95 countries in the sample accordingly. The equation is estimated through weighted linear squares, using the Census person weight as weight.

Appendix A.3: Robustness checks

A.3.1 Choice of private schools

In considering the above results, one concern is whether the value placed on school quality is affected by the omission of private school choices. Private schools serve as a substitute for public schools to households with children, and partly break the strict link between school choice and residential location (Hanushek et al. 2011). It is possible that parents who have sent or plan to send their children to private schools would value public school quality less when deciding where to live.

Therefore, I re-estimate the conditional logit regressions in the previous sections by including the fraction of private school enrollment among households with children in each PUMA and an interaction between this fraction and the child indicator. Since limited information on private schools in the Los Angeles Metropolitan Area, such as their quality and locations, is publicly available, it is hard to incorporate private school choices directly into the analysis. I use the percentage of households who send children to private schools as a proxy for the propensity that households living in a certain area choose private schools over public schools. The correlation between the API and the fraction of households who choose private school is 0.6, so that private schools tend to be located in areas with good public schools.

Table 14 reports the regression result when private school choices are taken into account. Compared to the estimates in Table 5, the coefficient on the API-child interaction term increases slightly, suggesting the availability of private school options may mitigate the importance of public school quality in residential choices.

A.3.2 Mischaracterized choice sets

A.3.2.1 Naturalized citizens

One concern is whether the choice sets of immigrant households have been mischaracterized. Because the Census surveys all the foreign-born individuals in the United States, illegal immigrants and temporary migrants are also included. Due to their immigration status, illegal immigrants have limited access to certain public goods. Temporary migrants, such as those on a student visa, are very likely to relocate back to their home countries after a certain period. Borjas and Bratsberg (1996) find that about one-quarter of the foreign-born population in the U.S. emigrated after 10 years, and argue that return migration may have been planned as part of an optimal life-cycle residential location sequence. A foreseeable tendency to move would alter the calculus in residential location decisions.

Therefore, as a robustness check, I focus solely on naturalized immigrant households in this section. These people may be more comparable to natives and are less likely to leave the country (Hook and Zhang 2011). They may also be better informed in their selection of residential locations. There are 1,511 households with householders being naturalized citizens, making up about 18 % of the trimmed sample of immigrants. On average, these households are wealthier and better educated than other immigrant households, whereas the fraction of households with children is slightly higher. As reported in Table 14, the interaction effect of school quality on naturalized citizens with children is of similar scope.

Table 14 School quality and residential location choices: robustness checks

PANEL A				
	Private School	*Natural. Citizen*	*Notin School*	*Prime Aged*
API/1000	.555* (.303)	.969 (.753)	.367 (.317)	.337 (.396)
API/1000×1(child<18)	1.71*** (.282)	1.41** (.557)	1.33*** (.256)	1.91*** (.319)
%Private	.020*** (.004)			
%Private×1(child<18)	−.013*** (.004)			
No. of Obs.	8,371	1,511	7,428	4,671
Log-likelihood/1000	-34.4	-6.20	-30.5	-19.1
Marginal Effect	.235 [19.9 %]	.200 [16.9 %]	.176 [14.8 %]	.260 [21.9 %]
PANEL B				
	Parents −to−be	*Renter*	*Out−State Mover*	*Alter. Measure*
API/1000	.373 (.316)	.562* (.332)	.808** (.323)	
API/1000×1(child< 18)	1.49*** (.266)	.973*** (.279)	1.16*** (.269)	
API/1000 × 1(parents-to-be)	.743** (.346)			
SAT/1000				−.120 (.297)
SAT/1000×1(child< 18)				1.09*** (.221)
No. of Obs.	8,371	6,392	6,927	8,371
Log-likelihood/1000	−34.4	−26.0	−28.3	−34.4
Marginal Effect	.200 [16.9 %]	.129 [10.9 %]	.159 [13.4 %]	.151 [12.8 %]

*significant at 10 %; ** significant at 5 %; *** significant at 1 %

Regressions are estimated by the conditional logit model using the specification in column 4 Table 5 with modifications. Robust standard errors are reported in parentheses. The reported marginal effects are the average percentage point change and the average percentage change in parent-non-parent difference in choosing a PUMA given a 1 S.D. increase in API or SAT of that PUMA

A.3.2.2 Householders not in school

In the trimmed sample of immigrant households, about 11 % of household heads are still in school. Compared to the sample, these householders are significantly younger, better educated but less wealthy. Among them, 23 % have children under 18 years of age. It is likely that this group is mainly composed by immigrants who migrate to the United States for higher education. For ”student” families, the residential location choice is more restricted by the location of school/college, especially for the households with lower income. It is difficult to disentangle values of education for children or for the parents themselves. As discussed above, the ”student” families may also have a higher propensity to migrate back to their source countries.

Hence, I estimate the parent-non-parent difference in weight assigned to school quality only among households whose heads are no longer in school. The regression produces very similar results.

A.3.3 Differential unobserved preferences

A.3.3.1 Prime-aged householders

The preferences toward location attributes, especially local amenities may be associated with the age of householders. For instance, seniors may have a greater demand for medical care. Yet trimming by the propensity to have children under 18 may not perfectly balance the sample so that households with and without children would have similar views about non-school location characteristics. Accordingly, I restrict the sample to households with household heads aged 30 to 54. This age group is likely to have children, and their preferences toward location attributes other than public schooling are more likely to be homogenous.

Table 14 presents the estimates for households with prime-aged householders only. The estimated interaction effect of school quality on households with children is noticeably larger than the one estimated using households of the whole age range, and stays statistically significant.

A.3.3.2 Potential parents-to-be

The identification of the key parameters in the paper relies on comparison between households with and without children. Yet it is possible that certain immigrant households without children may consider school quality the same way as those with children if they are similarly motivated. One group of potential candidates with similar motivations are households planning on fertility. Even if these households do not have a current demand for schooling services, they may take their future needs into account when deciding where to live. Treating these households the same as other household without children underestimates the value placed on school quality by households with children.

Therefore, I define a group of ”potential” parents-to-be by the householder’s marital status and age. Specifically, married couples in the childbearing age, i.e. 20–40, are considered as the most likely to have children in the near future. I generate a dummy variable for this group, and interact it with the API. Table 14 presents the results when this additional interaction term is included. As expected, parents-to-be place significantly higher value on schools than other households without children. If I allow the weight assigned to school quality by parents to vary by the age of their children, parents-to-be resembles households with children between 6 and 12 in regard to the weight placed on school quality. When the case of parents-to-be is considered, the interaction effect of the API appears to be higher on households with children.

A.3.3.3 Homeowners v.s. renters

When households purchase a house, they are likely to choose locations with good neighborhood schools even if they do not have children for two reasons. First, housing price is closely linked to school quality (Black 1999; Kane et al. 2006). So the value of the properties in good school districts is less likely to depreciate. Second, compared to renters, the cost to move for homeowners would be higher. When choosing residential locations, homebuyers may take their long-term plans into consideration.

The difference between homeowners and renters complicates the interpretation of the previous results. This section thereby examines the renters only. In general, renters have lower income than homeowners. Given lower mobility cost, the residential locations of renters may better reflect their current demands for as well as the trade-offs among local amenities. The regression results are presented in Table 14. The parent-non-parent difference is positive and significant among renters, but smaller compared to the whole sample, which might be a result from the lower income.

A.3.4 Differential mobility

A.3.4.1 Out-of-state movers

The lock-in effect of Proposition 13 in California results in differential incentives to relocate among households who moved within California and those who moved across states.[33] At the same time, out-of-state movers are more likely to undergo a move-inducing shock (Thomas 2011). Thus, this section examines out-of-state movers who are less likely to have been subject to Proposition 13 lock-in. Looking at out-of-state movers would also address the problem linked with households that move right across the border line of the Los Angeles Metropolitan Area because of some endogenous changes in the preferences over local public goods provision.

[33] California's Proposition 13, passed in 1978, mandates a property tax rate of one percent and limits its growth rate. At the same time, housing prices have increased dramatically in California. Accordingly, households who have owned a house in California for many years have a disincentive to move because of the higher property tax on the new home's assessed market value they have to pay.

This group composes about 83 % of the trimmed sample, and about 80 % of them were abroad one year ago. Estimates from the out-of-state movers are reported in Table 14 and are very similar to those obtained from the sample including within-state movers.

A.3.4.2 Movers within Los Angeles metropolitan area

Since I restrict the sample to households who moved to the Los Angeles Metropolitan Area from outside the area with the past five years, the sample includes a sizable fraction of new immigrants, i.e. immigrants who migrated to the United States in the past five years. One concern is that when the immigrants first arrived in the U.S., their residential choice might be highly restricted by their job locations, family and/or friend ties. Therefore, it may provide more insights to examine immigrant households who migrated within the Los Angeles Metropolitan Area in the past five years because these people have spent some time in the area and gained more information about neighborhoods and school districts.

However, the main problem to study the local movers is that, if the Tiebout sorting is effective in the first place and the local amenities stay the same, people move again only because their preferences over public goods change. For example, households may move to neighborhoods with good school when their children reach school age, whereas the empty-nest movers do the opposite to reduce the exposure to local school spending. It is hard to believe that these two types of movers would value the unobserved location attributes the same.

Accordingly, I focus on immigrant households with children aged 12–18 and use immigrant households with no children under age of 23 as the baseline. Supposedly, neither group moves within Los Angeles because of changes in the demand for schooling services. Therefore, for whatever reason they moved, they are more likely to share a similar view over the unobserved neighborhood characteristics. I trim the sample by the propensity score approach to better balance their preferences.[34]

The results are presented in Table 15. In general, when financially capable, immigrant households with secondary-school-aged children tend to locate in areas with better public schools when moving within the metropolitan area.

A.3.5 Alternative school quality measure

Another school quality measure that is commonly available to the public is the SAT score. Very often, real estate agencies make the information regarding a school district's average SAT score available to potential homebuyers. I use the school

[34]The propensity score is estimated among immigrant households with children aged 12–18 and immigrant households with no children under 23 using the same set of household characteristics presented in Table 2. I drop the observations is the propensity score lower than 0.1 or higher than 0.9.

Table 15 School quality and residential location choices: local movers

	$API/1000$	API/1000 ×1(child:12–18)	No. of Obs.	Marginal Effect % Pts.Δ	%Δ
All	.232 (.187)	.167 (.161)	21,012	.021 (.010)	1.74 %
Income					
Q1	.524 (.651)	−.093 (.298)	5,935	−.012 (.007)	.989 %
Q2	3.29** (1.65)	1.10*** (.300)	6,014	.191 (.136)	16.2 %
Q3	−.457 (.436)	1.23*** (.362)	4,114	.150 (.077)	12.7 %
Q4	1.09 (1.21)	1.18** (.497)	2,770	.167 (.095)	14.1 %
Q5	−1.68** (.815)	.993* (.590)	2,179	.106 (.064)	8.91 %

*significant at 10 %; ** significant at 5 %; *** significant at 1 %

Regressions are estimated using the full model specification in column 4 Table 5 on immigrant households who moved within the Los Angeles Metropolitan Area in the past five years. Robust standard errors are reported in parentheses. The reported marginal effects are the average percentage point change and average percentage change in parent-non-parent difference in choosing a PUMA given a 1 S.D. increase in API of that PUMA

average SAT score during the 1998–1999 academic year provided by the California Department of Education Policy and Evaluation Division and aggregate the school averages to the PUMA level in the same manner as I aggregate the API. The summery statistics of the SAT score[35] are presented in Table 3. The correlation between the API and SAT score is .88.I employ the SAT score instead of the API in the regression and the results are shown in Table 14. The interaction between the SAT score and the child indicator is positive and significant. The marginal effect calculated according has similar magnitude as the marginal effect reported in Table 5.

Appendix A.4: Immigrants v.s. natives

In order to make the choice sets of immigrant and native households more comparable, I employ the propensity score method, and estimate the propensity score for being an immigrant household from observable household and householder characteristics using a probit model:

$$\Pr\left(img_h = 1\right) = \Phi\left(\lambda X_h + u_h\right). \tag{A2}$$

[35] Possible scores on the SAT range from 400 to 1600 in the 1998–1999 academic year.

X_h represents observable household characteristics, including household type, household income, family size, number of families in a household, homeownership, linguistic isolation, whether there are children under 18 householder's gender, marital status, educational attainment, school attendance, and race. u_h is the unobserved

Table 16 Summary statistics for natives vs. immigrants

Variables	Native			Immig.
	All	Mover	Trim.	Trim.
Household Income ($1000)	72.9 (76.2)	57.3 (65.7)	73.3 (70.6)	57.7 (65.6)
Adjusted Household Income ($1000)	131 (146)	126 (148)	108 (103)	74.0 (91.2)
Householder's Age	41.4 (13.2)	33.6 (10.9)	37.5 (11.8)	34.8 (10.6)
Female Householder (=1)	.480 (.495)	.420 (.494)	.395 (.489)	.355 (.479)
Householder's Education	14.0 (2.67)	14.5 (2.59)	14.2 (2.72)	13.0 (4.56)
Number of Children	.650 (1.03)	.383 (.851)	.802 (1.09)	.806 (1.12)
School Attendance (=1)	.114 (.318)	.174 (.379)	.099 (.298)	.121 (.327)
Linguistic Isolation (=1)	.011 (.104)	.010 (.101)	.007 (.084)	.072 (.258)
Family Size	2.40 (1.57)	1.88 (1.38)	2.83 (1.47)	3.46 (1.86)
No. of Families	1.32 (.675)	1.57 (.861)	1.21 (.577)	1.31 (.703)
Children under 18 (=1)	.311 (.463)	.228 (.419)	.440 (.496)	.448 (.497)
No. of Children under 18	.586 (1.00)	.485 (1.13)	.945 (1.42)	.950 (1.44)
Private School (=1)	.089 (.285)	.086 (.280)	.095 (.309)	.075 (.273)
Home Ownership (=1)	.448 (.497)	.286 (.452)	.366 (.481)	.303 (.459)
White (=1)	.647 (.478)	.728 (.445)	.577 (.494)	.232 (.422)
Black (=1)	.116 (.320)	.081 (.273)	.132 (.339)	.044 (.205)
Asian (=1)	.036 (.186)	.042 (.200)	.045 (.208)	.259 (.438)
Hispanic (=1)	.184 (.387)	.116 (.321)	.188 (.391)	.436 (.496)
Move Within State (=1)	.054 (.226)	.394 (.489)	.269 (.443)	.232 (.422)
No. of Obs.	109,794	14,980	5,349	3,937

Reported are the means of variables with standard deviations in parentheses among different groups. The first column is for all native households in the Los Angeles Metropolitan Area; second column is for native households that moved to the area within the past 5 years; and the third and fourth columns are for the native and immigrant movers adjusted for both the propensity scores for having children under 18 and being immigrant. Adjusted household income is total household income divided by family equivalent scale

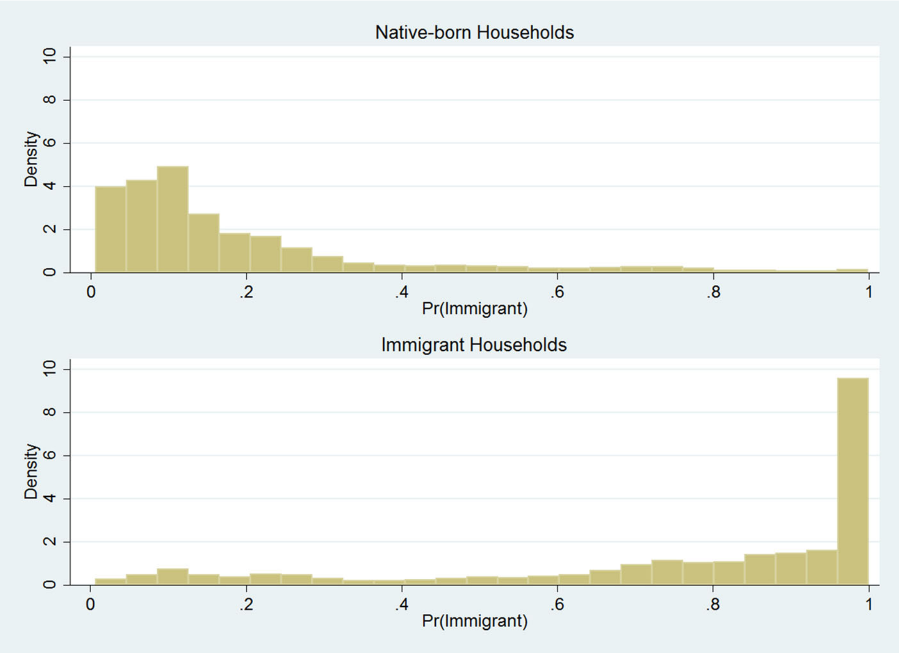

Fig. 4 Propensity score for being an immigrant household

characteristics related to being an immigrant. I drop observations with estimated propensities below 0.1 and above 0.9 as before.

Table 16 presents the summary statistics for the natives. Compared to immigrants, native households have higher income, higher education, less children, and smaller families. The two groups have distinct racial compositions: the majority of natives are White, whereas Blacks and Hispanics comprise sizable proportions; yet the majority of immigrants are Hispanics and Asians.

Figure 4 depicts the distribution of propensity score for being immigrant among both the native and immigrant households. The strongest predictors here are language isolation and race, which may be the culprits for the spike at the right tail of the propensity score distribution of immigrants. Figure 5 compares the distributions of household characteristics that may distinguish immigrants from natives and also affect location decisions by the propensity score to be an immigrant. Three characteristics are examined: adjusted household income, linguistic isolation, and whether there are children under 18 in the household. The propensity score appears to match the three characteristics pretty well.

I trim the combined sample of movers by the propensity score for having children under 18 and the propensity score for being immigrant in the household sequentially. The last two columns in Table 16 report the summary statistics for the trimmed

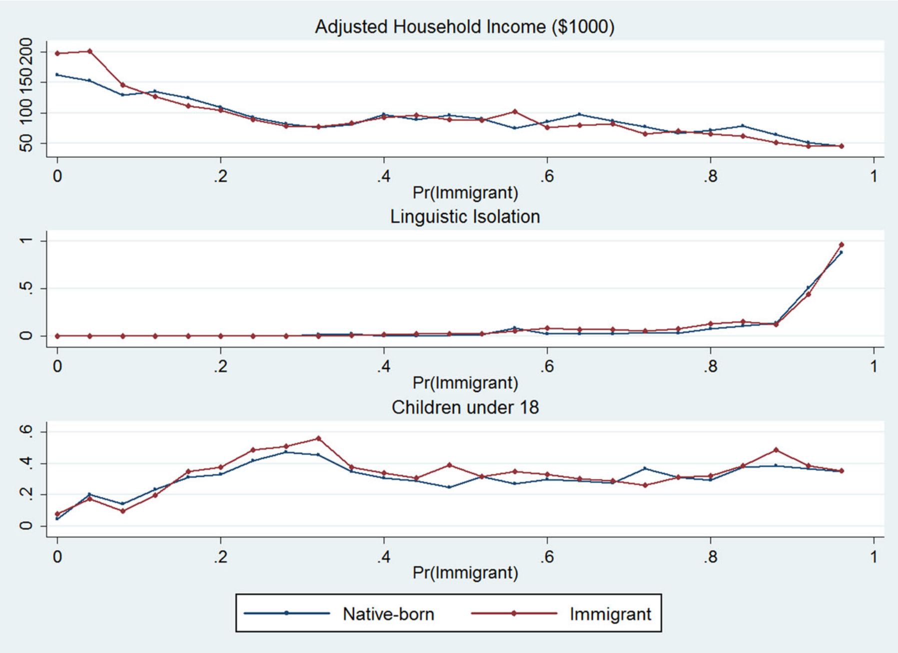

Fig. 5 Family characteristics by propensity score

sample of natives and immigrants respectively. After trimming, the characteristics of immigrant and native-born households converge to a more or less extent.

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