*Preliminary and incomplete*
*Please do not cite without permission*

# Location and Intergenerational Educational Mobility

Jung Hyun Choi[1]
Urban Institute

Richard Green[2]
USC School of Public Policy & Marshall School of Business

**Abstract**

High school dropouts are more likely to have children in cities where college share is high, while those who received greater education are less likely to have children in these cities. This pattern is puzzling as cities that attract college graduates have higher cost of living, and can be more expensive to raise children, especially for the least educated households. We provide one compelling explanation for why the less educated households locate in high skilled cities – better education for their children. Using the Census and ACS data from 1980 to 2010, our study finds that children in ages 16 to 24 living with a high school dropout head are more likely be enrolled in school in cities with high share of college graduates. We do not find such relationship for children of parents with higher educational attainment. These results hold after addressing endogeneity and self-selection. Further, by examining PUMAs within MSAs, we find that peer effect provides a strong explanation of why the children of the least educated receive most educational benefit from living in a high skilled city. Our findings suggest that location can have greater impact for the children in households with less resource to support them.

**Keywords:** child school enrollment, parent education, intergenerational mobility, high skilled city, peer effect

**JEL:** *I24, R12, R23*

[1] jchoi@urban.org
[2] richarkg@usc.edu

## I. Introduction

Chetty and Hendren (2018a, 2018b) have shown that, for children, location really matters – children living in certain counties have better educational and employment outcomes than children living in others. This study takes the analysis forward in two dimensions: (1) we examine see whether children in better educated cities perform better than children in less educated cities, and whether this impact varies depending on the educational level of the parent, and (2) we investigate specific channels, particularly peer effects and educational resources, to determine why there might be a link between a city's skill level and the outcomes of its children/

The motivation for this study arises from a stylized fact that puzzled us – the share of unskilled adults with children in high skill cities exceeds that of unskilled adults in low skill cities, despite the fact that living costs are higher in high skill cities (see Berry and Glaeser, 2005). This contrasts with adults with higher levels of educational attainment, whose share of having children rates drop as the skill level of their city rises. Figure I plots share of households with children under the age of 25 against cities' adult population share of college graduates, with panels for four education groups—high school dropouts, high school graduates, some post-high school education, and BAs.[3] The data come from the Decennial Census in years 1980, 1990, 2000, and 5-year American Community Survey (ACS) in 2008-2012.

This suggests that less educated adults may find skilled cities better places to raise children, and one possible reason for this may be better educational opportunities. More specifically, children of low skill adults in high skills cities may perform better, relative to their baseline, than children of high skill adults who are likely to have sufficient internal resources to support their child's education. Figure II suggests this is highly plausible—while all children are more likely to stay in school in high skill cities, the slope of the relationship between school enrollment and city skill level is much steeper for children of parents without a high school diploma.[4]

If high skill cities are indeed better places for child education, it makes the findings of Moretti (2013) and others—that we see migration induced divergence in skill levels across cities—more alarming. If low skill people are being pushed out of high skill cities or have entrance barrier to these places because of rising cost, there are potentially dire implications for their children in the years to come.

The two patterns shown in Figures I and II survive after considering a broad set of controls and specifications. After controlling for both individual and city level variables, high school dropouts are more likely to have children in cities with higher college share. Furthermore, their children are more likely to be enrolled in school compared to the children of high school

[3] As children of low income households may delay moving out of their parent's households in expensive cities, we also restrict our sample to those with children below age 20 and find that our patterns remain unchanged (Figure A2).

[4] Similar patterns are shown when we further divide our sample into two groups: (1) children ages between 16-19 (Figure A3) and (2) children ages between 20-24 (Figure A4).

dropouts living in less educated cities. Our results show that a 10-percentage point increase in college share leads to a 1.7 percentage point increase in the likelihood of children with high school dropout parents to be enrolled in school. The locational influence decreases with parent's education level. In fact, we find that the school enrollment children of parents who received more than high school education are not affected by the share of college graduate in the city they live in. This suggests that location matters more for families with less within-family resources to support child's education.

Confirming a causal link between school enrollment and college share is challenging due to unobservables. The OLS regression does not control for any time varying city level unobserved variables that can be associated with both the college share and child's likelihood of being enrolled in school. For example, city's college share is likely to be correlated with industrial structure and labor market conditions that are associated with local productivity shocks. These shocks can lead to different employment opportunities across cities which affect child's decision to work or stay in school. Omitting the time varying local factors is likely to cause a downward bias in our OLS coefficients. The regression also does not address the issue of self-selection. Acknowledging the importance of location, the less educated parents may have greater motivation to live in highly educated cities as they lack internal means to support their child's education. High school dropout parents with greater aspiration for their child's education may stay or move to cities with higher college share. If so, our results will be biased upward.

We address the endogeneity issue via three strategies. First, we directly control for local productivity shock by using Bartik indices and find that our results remain unchanged. Second, we further control for city level time-varying unobservables by instrumenting the share of college graduate using two instrumental variables: the presence of land grant universities and the share of land unavailable for development. While the first IV has been commonly used in many research (e.g. Moretti, 2004; Choi et al., 2018), the second IV, to our knowledge, is first to be used to instrument college share. Gyuorko et al. (2013) finds that as the average income went up nationally over time, some cities with inelastic supply of land experienced significant increase in house prices and became "Superstars". The rise in the cost of living in these cities crowded out the low-income households, resulting in a higher share of high income households.

The patterns from the OLS regression remains stable in the IV regressions – college share has a greater impact on the likelihood of school enrollment for the children of low skilled parents. However, the results also question whether the two frequently used IVs meet the exclusion restriction. These IVs can also be correlated with the unobserved local demand shock and thereby inflate the size of the coefficients. We believe that the real impact of college graduate on child's school enrollment is slightly higher than our OLS coefficients but significantly lower than the IV coefficients.

Third, in order to address for the self-selection issue, we compare the relationship between college share and child's school enrollment for "recent-movers" and "stayers". If our results are driven by self-selection, then children of high school dropout parents who recently moved to high skilled cities will have similar likelihood of being enrolled in school compared those who did not move. Our findings show that length of the stay matters for the least educated group. The children of high school dropout “stayers” are more likely to be enrolled in school in high skilled cities. On the other hand, the children of high school dropout “movers” are less likely to be enrolled in school if they move to cities with higher college share. This suggests that children of least educated parents may be experiencing greater difficulty of adjusting to a new environment. These results are in line with Chetty and Hendren (2018b) who finds that the length of the stay matters for a place to have an impact on child’s outcome. We do not find any differences between the “movers” and stayers” for other three groups.

Our finding leads us to ask what leads to higher school enrollment rate for children of less educated parents living in high skilled cities. Peer effect provides one potential explanation. Since the seminal work of James Coleman and others (1966), numerous studies have documented that peers can have a positive influence on student academic outcomes. Child’s school enrollment and parent’s education attainment are strongly correlated (Figure III). Thus, cities with greater share of college graduates, on average, have greater share of students enrolled in school. Children of less educated parent living in a more educated city could be choosing to stay in school or pursue college education as more peers around them do so.

Another possible explanation for Figure II is related to the recent study of Rebecca Diamond (2016). Her study finds that cities with greater college share experienced a greater improvement in urban amenities, including government spending per student for K-12 education. Perhaps highly educated cities provide better educational services to students which encourage them to remain in high school and continue onto college.

In our final analysis, we test these two explanations using PUMA level school enrollment rate and PUMA level government spending per student data. We find strong evidence that children of less educated parents are more likely to be enrolled in school because they live in neighborhoods where greater share of their friends are going to school, supporting the peer effect theory. We do not find any evidence that higher government spending on public education is increasing the likelihood of children with high school dropout parent to be enrolled in school.

Overall, our findings indicate that location matters more for the children with less educated parents who have fewer family resources to support them. As the cost of living has become more expensive in (most of) the high skilled cities, in the long-run, low skilled households either potentially have to make adjustments (e.g. work extra hours, or change living arrangements) to stay in these cities, or move to places with less educational opportunities for their children.

## II. Data & Method

*Data* Our data comes from the Decennial Census and the American Community Survey (ACS) in years 1980, 1990, 2000 and 2008-2012. The dataset consists of both city and individual level variables. For each city, the share of college share is calculated by dividing population over 25 years old with a bachelor’s degree by the total population over age 25. To obtain consistent MSA boundaries over time, we download the variables at the county level and aggregate it to the MSA level using the 1990 Census county-MSA boundary. We merge this data to the individual level variable from IPUMs. We restrict our sample to households with head between ages 25 and 65.[5] Note that our study uses the term MSA and city interchangeably.

Table I provides summary statistics. We categorize households into four groups according to head's education attainment. The two key dependent variables in our study are whether child exists in the household and whether the child (between ages 16 and 24) are enrolled in school. According to the table, the likelihood of having children decreases but the likelihood of child's school enrollment increases with head's educational attainment. About 60 percent of households with high school dropout heads have children in the household, while 46 percent of households with college graduate heads have children. On the other hand, only 55 percent of children between ages 16 and 24 whose parent did not complete high school are enrolled in school, while 81 percent of children whose parent graduated college are in school. This reflects the lack of intergenerational education mobility. Additionally, standard deviation of school enrollment rate is higher for the least educated household suggesting that there is greater variation within this group. Homeownership rate, annual household income and annual housing costs also increase with head's educational attainment.

The average age of the head ranges from 42 to 47 across the four groups. Share of households headed by female ranges from 32 to 36 percent. Households with a college graduate head are more likely to be married and at the same time more likely to be never married. This is because only 15 percent of these households are divorced or separated while more than 20 percent of households in the three other groups are either divorced or separated. Greater proportion of heads who dropped out from high school are widowed and less of them have never been married compared to households with a more educated head.

Race and ethnic composition also show significant differences across the four groups. Less educated heads are more likely to be Black or Hispanic, while more educated heads are more likely to be White or Asian. In fact, about 86 percent of heads with a college degree are either White or Asian, while only 48 percent of heads without a high school diploma are either of the two races. On the other hand, Hispanics and Blacks account for 51 percent high school dropout heads but only account for 13 percent of college graduate heads. The proportion of immigrants is high in both the least and the most educated households, reflecting the high share of Hispanics and Asian in the two groups. We find a high correlation between head's education and spouse education.[6] Also, a spouse of the more educated is more likely to work. Finally, the least educated households have the lowest across city mobility rate. Households with college graduate heads are twice as likely to move across cities as those with high school dropout heads.

Table I also presents the mean and the standard deviation of the MSA level explanatory variables. These variables show whether there are some differences in the MSAs where the four groups live. The average share of college graduates in cities, where households headed

[5] The recent average marital age for male in the US is around 30. Therefore, average heads are likely to be around 45-55 when their first child is between 16 and 24. To account for earlier marriages and birth in the past periods, as well as household formation, we also run our regressions with households with heads below age 55 and also age 45. Our results from the subsample analyses remain largely similar and can be provided upon request.

[6] The omitted category is those who do not have a spouse.

by high school dropout, is 23 percent. The average is 28 percent in cities where college graduate headed households live. The average college share for cities where households with heads who graduated from high school or received some college education live is 25 and 26 percent, respectively. This shows that more educated households are more likely to live in high skilled city where the cost of living is relatively expensive. About 30 percent of the households live in cities where land grant universities exist. Households with the least and the most educated heads are more likely to live in cities with land grant university. Similarly, these two groups are more likely to live in large cities compared to households in between. No significant variation is observed across the four groups in the share of land available for development.

*Method* Using the variables in Table I, we run the following model to test whether college share affects household's likelihood of having children and child's likelihood of being enrolled in school.

$$Y_{ict} = \alpha X_{it} + \beta CS_{ct} + \gamma CS_{ct} \times EDUC_{it} + \delta Z_{ct} + \pi_t + \mu_c + \varepsilon_{ict}$$

$Y_{ict}$ represents two dependent dummy variables: (1) whether households have a child, or (2) whether a child between ages of 16 and 24 is enrolled in school. While our dependent variables are bivariate, we use the OLS method in our main analyses because the sample size is large and coefficients from the OLS are easy to interpret. Studies, including Angrist and Pischke (2009), suggest that the difference between marginal effects calculated from the linear probability model and logit or probit models is minor when the mean of the dependent variable ranged between 0.2 and 0.8. The mean values of our two dependent variables fall within these ranges. For robustness, we also ran probit model for all our regressions with bivariate dependent variables. These results show similar pattern to our OLS results and are available in the online appendix.

$X_{it}$ is a vector of individual characteristics, presented in Table I; $CS_{ct}$ represents the share of college educated individuals in city c at year t; $EDUC_{it}$ represents dummy variables for head's education attainment (without high school diploma, high school graduate, received less than four years of college education, college graduate); $Z_{ct}$ is a vector of city characteristics that may be correlated with $CS_{ct}$; $\pi_t$ and is the year fixed effects and $\varepsilon_{ict}$ is the error term. We also include $\mu_c$, the city fixed effect, in some of our regressions.

The key coefficients of interest are $\beta$ and $\gamma$: $\beta$ shows whether college share affects household's likelihood of having children and children's likelihood of being in school, and $\gamma$ shows whether the size of this effect differs across households with heads in different education categories. In addition to OLS regressions, we examine the causal relation between college share and child's school enrollment by using IV regressions and compare outcomes between "stayers" and "movers". We also modify the above regression model to examine the mechanisms behind our findings by including two PUMA level variables – school enrollment rates and government spending per student. Details of these analyses will be further explained in sections IV, V and VI.

## III. Results

*Child Existence* We first examine how college share is associated with households' likelihood of having children below age 25. In all our regressions, we include demographic and socioeconomic variables presented in Table I. We also include a dummy variable for owning a home, as homeownership can be related both decisions of having children and child's educational attainment. Studies, including Green and White (1997), find that homeownership is positively associated with children's educational attainment. Columns (1) and (2) present results for cross-sectional variations across MSAs and columns (3) and (4) present results for within MSA variations by including MSA fixed effects. All regressions include year fixed effects. Standard errors are clustered by year and city.

The first column in Table II shows that households are less likely to have children in more educated cities. The likelihood of having children also decreases by head's educational attainment. In column (2), we interact head's educational attainment with college share to identify whether the association between college share and likelihood of having children differs by head's education. When we include the control variables, we find that the likelihood of having children does not differ by the level of college share for households with high school dropout heads (first row). As for the other three groups, we find that college share is negatively associated with the likelihood of having children, in line with Figure I.[7]

The results including MSA fixed effects also shows similar patterns. While result in column (3) show no relationship between college share and having children, when we disaggregate this relationship by head's educational attainment, we find significant variations across households – the likelihood of having children increases in cities that experience a rise in the college share only for the least educated households. As for households headed by a high school dropout, we find that a 10-percentage point increase in the college share increases the likelihood of having children by 1.9 percentage point.

The objective of this paper is to understand what leads to these differences across households with different educational attainment. However, before proceeding to our main result that examines the relationship between child's school enrollment and college share, we investigate how college share is related to various income and housing outcomes to rule out other possible explanations.

*Income and Housing Outcomes* Table III demonstrates the relationship college share and homeownership, income and housing costs.[8] Except for the likelihood of owning a home in columns (1) and (2), four other dependent variables are in log values, showing the percent changes. The first column shows that the homeownership rate is lower in cities where college

---

[7] As for other control variables not included in the table, we find the following. The age of the head is positively associated with the likelihood of having a child, although the likelihood decreases marginally as the age increases. Households with female heads have higher likelihood of having children. As expected, the coefficient for owning and household income is positive and significant. Minorities, immigrants and those who are married are also more likely to have children. Households where spouse also works are less likely to have children.

[8] For renters, housing cost includes annual contract rent plus additional costs for utilities (water, electricity and gas) and fuels. For homeowners, we calculate cost of owning by adding mortgage payments, deeds of trust, contracts to purchase, adjusted estate taxes and cost of utilities and fuels. This measure is less accurate than housing cost for renters as it does not include cost of maintenance and homeowner's tax deduction. The measure also does not capture capital gains that occur when selling and buying new properties.

shares are greater, reflecting the high housing cost in these areas. In column (2), where we interact college share with head's educational attainment, we find households headed by high school dropout are significantly less likely to be owners in cities with higher college share. On the other hand, the likelihood of owning for college graduates does not differ significantly by city's college share.

Table III also shows that cities with high share of college graduates have higher income and high housing cost. However, while income increases more with head's educational attainment, the percent increase of housing cost is about the same all four education groups. Therefore, residual income increases most for the college graduated households, while the housing cost to income ratio goes up the most for the least educated household in relationship to the college share. While the residual income of households with high school dropout head is positive in cities with greater college share, the statistical significance is low. Furthermore, as the Census data is cross-sectional, we are unable to control for unobserved variable, such as individual's ability. Using panel data, Choi et al. (2018) find that the positive relationship between residual income and college share disappears for the least educated households, once individual fixed effects are included.

If the households with high school dropout heads gain the least economic benefit from living in highly educated cities, why are they relatively more likely to have children in these cities? The result is puzzling since many of these households could be economically better off by moving to less expensive-lower educated cities. Furthermore, households with children, on average, have extra items to spend in addition to housing compared to households without children. As the cost for other expenses are also likely to be more expensive in cities with high housing costs, raising children in these can places be financially challenging.

Despite the higher cost burden and lower likelihood of becoming a homeowner, the least educated households continue to stay in these cities and are more likely to have children in these cities. While there may be numerous reasons, including job opportunities and access to better urban amenities, we focus on one possible explanation behind this decision: a better education opportunity for their children. More specifically, we examine whether higher college share results in greater likelihood of children being enrolled in school, especially for children of parents with low educational attainment.

*Child School Enrollment* Table IV presents how college share is associated with children's likelihood of school enrollment. The sample includes all children between ages 16 and 24. The first column shows that the likelihood of child's school enrollment is higher in cities with greater proportion of college graduates. A 10-percentage point is associated with 0.5 percentage point increase the likelihood of child's school enrollment. Parent's educational attainment is also significantly associated with child's school enrollment – children of more educated heads are more likely to be enrolled in school. Column (2) demonstrates that the relationship between college share and child's school enrollment differs across education groups. Consistent with Figure II, we find that children of less educated parents, especially those living with high school dropout heads, are more likely to be in school in cities where the share of college graduate is high. For high school dropout households, a 10-percentage point increase in the city level college share is associated with 1.7 percentage point increase in child's likelihood of being enrolled in school.[9]

Patterns in columns (2) remain consistence when we control for MSA unobservables by including MSA fixed effects. While the relationship between college share and child's school enrollment becomes insignificant once the MSA fixed effects are included, we still observe substantial variations in the city's college share-child's school enrollment association across education groups. Children who lives with a high school dropout parent experience an increase in their likelihood of being enrolled in school as college share increases in the city they live in, relative to the children of least educated households living in cities that do not experience such increase in the college share. In fact, the size of the college share coefficient for the least educated households is similar to regression result without MSA fixed effects. The school enrollment of children from highly educated households is not positively affected by the within city increase of college share.

In appendix Table A1, we further divide our sample of children into two groups: (1) children between ages 16 and 19 and (2) children between ages 20 and 24. We do so as children's likelihood for being enrolled in high school may differ from their likelihood of being enrolled in college as receiving college education is more selective. Furthermore, children are more likely to move out of the households and also moved to a different location when they pursue college education. The result in the appendix shows that college share significantly enhances the propensity of enrolling in school for children of high school dropout heads for the younger age groups. We observe a weaker relationship for the older age group. Although we find weaker statistical relationship, we find similar patterns for both groups, especially in regressions examining cross-city comparison. Again, children of the less educated parents are more likely to be enrolled in school if they live in cities with high share of college graduates. For children of more educated parents, we find that college share does not increase their likelihood of being enrolled in school.

To check the robustness of our results in Table IV, we first include the educational attainment of the household spouse (Table V). Less educated heads living in a high skilled city may have a higher chance of marrying a spouse with a higher educational attainment. If so, a child of a high school dropout head living in a high skilled city may have a higher likelihood of enrolling in school due to the influence of their other parent who is more educated. Results in column (1) and (2) shows that this is not a major reason behind our findings. In fact, our OLS coefficients remain largely similar to those in Table IV after controlling for the educational attainment of the spouse.

---

[9] As for other control variables, we find that age is negatively associated with school enrollment as college enrollment rate is lower than high school enrollment rate. Female are more likely to be in school than male. Asians are significantly more likely to be in school than whites, while black and Hispanic dummies do not show a strong significance. As black and Hispanic parents, on average, have lower educational attainment, once parent's educational level is controlled, the relationship between race and school enrollment weakens. Children of immigrant households are more likely to be enrolled in school. Children living in married households are also more likely to be in school compared to children living in households where only one of the two parents are present. In agreement with Green and White (1997), we find that children of homeowners are more likely to be enrolled in school, although we are not claiming for causality. Finally, the size of the city is weakly associated with child's school enrollment.

Another factor that could affect our result is the shifts in labor market environment. For example, an increase in the national demand for skilled workers in a certain industry, will lead to a greater positive labor demand shock of skilled workers in cities that employs a greater share of workers in that industry. This shift in the labor demand could affect child's decision to go to school or leave school and find a job. Following Katz and Murphy (1992), we use Bartik indices to control for exogenous shifts in relative demand for high skilled (college educated or more) workers and low skilled workers (high school graduate or less). The indices are calculated by weighting the nationwide employment growth for each industry with the city-specific employment share in those industries to predict the employment changes for high skilled and low skilled workers in each city.[10] Again, including the Bartik shocks in the regression (Columns (3) and (4) in Table V) do not change our previous findings in Table IV.

Our findings suggest that location can have greater impact for the children of less educated households. As educated parents may already have sufficient resources to provide educational support their children, where they live may have less influence on the educational attainment of their children. We further investigate possible channels that explain our findings, after addressing the endogeneity problem in the following two sections.

**IV. Time Varying MSA Unobservables: Instrumental Variable**

While MSA fixed effects control for time-invariant unobserved variables at the MSA level, there could be time-varying unobservables that affect both college share and school enrollment. In addition to share of skilled population, cities differ widely in weather, industrial structure, technology and urban amenities. If there exist any time varying factors that correlated with changes in college share that are related to school enrollment, our OLS coefficients will be biased. For example, a transitory productivity shock can attract high skilled workers to the city and simultaneously affect child's decision to work or staying in school. Our coefficients will be biased downwards if more students choose to work in response to the positive productivity shock. While we have used Bartik shocks to control for local productivity shock, as there could be some measurement errors in our estimates, we also implement instrumental variable method to address this issue.

We use two instrumental variables – (1) presence of land grant university and (2) share of land unavailable for development. Existence of land grant university has been one of the most commonly used instruments for college share (Moretti, 2004; Winters, 2012; Choi et al., 2018) Since the passage of the Morrill Acts in 1862 and 1890, 73 land-grant universities have been established in the US. These institutions were created to strengthen higher education, with a focus on engineering, agriculture and military science. All 50 states in the US have at

---

[10] Using Decennial Census 1980, 1990, 2000 and ACS 2008-12, we create two following Bartik indices for both college graduates and those who received at most high school education:

$$\text{Bartik}_{\text{jc}}=\sum_{s=1}^{66} \theta_{sc}\, \Delta E_{js}$$

where $\theta_{sc}$ is the share of total hours worked in industry s (two digit sic-code) in years 1980, 1990, 2000 and 2010; $\Delta E_{js}$ is the change in the log of total hours of employers in education group j who worked in industry in s for each year.

least one land-grant universities. Previous studies have argued that geographical locations of land-grant universities were randomly selected, and therefore the presence of these universities serves as a valid instrument (Nervis, 1962; Williams, 1991, Morretti, 2004).

To our knowledge, land unavailability has not yet been used to instrument college share. Land unavailability, created by Saiz (2010), measures the availability of developable land in terms of topographic restriction. The measure has been a widely used as a proxy for housing supply inelasticity. Recently, this variable has become a widely used for instrumenting house price appreciation (Aditya Aladangady, 2017; Choi and Green 2017; Chakraborty et al., 2018).

According to Gyuoko et at. (2013) some inelastic cities have experienced significant increases in house prices when national income level rose, as greater share of high income households migrated to those cities. Low income households have been crowded out from these cities, leading to an increase in the share of high income (who are also likely to be highly educated) households. While rivers and mountains restricts land development and can reshape city's educational composition, it is unlikely to have a direct impact on child's educational attainment. Thus, we use the land unavailability measure to instrument city level college share.

Table VI presents regression results using the two instrumental variables.[11] The first stage regression results in column (1) shows that both instruments are a strong predictor of college share. F-statistics are also significantly greater than 10, which indicate that the instruments are strong. Next five columns examine whether college share have different impact on children's school enrollment across household head's educational attainment. Column (1) in both IV regressions shows that college share increases children's likelihood of being enrolled in school. The size of the two coefficients is significantly larger than the OLS coefficient in Table III. This suggests that the omission of unobserved MSA variables may have created a download bias in the OLS estimates.

Next four columns present the result of four separate 2SLS regressions for each education group. In line with the findings in the OLS regression, the size of the coefficient in columns (2), (3) and (4) becomes smaller with the level of head's educational attainment.[12] However, we find all coefficient s statistically significant in the results using the land grant university as instrument. In the regressions with land unavailability measures as an IV, only the coefficient for the households with high school dropout and high school graduate heads are significant. Furthermore, coefficients in all regression results are significantly larger than the OLS results. For example, we find that a 10-percentage point increase in share of college graduates leads to a 10.3 percentage point increase in the child's school enrollment rate in the land grant IV result and a 8.9 percentage point increase in the child's school enrollment rate in the land unavailability IV result. These numbers are unrealistically high and questions whether the

[11] Sample size in the IV regressions become smaller, as both IVs are not available for all 273 MSAs in the sample.

[12] In the appendix Tables A3 and A4, we provide separate results for both ages 16-19 and 20-24 as we did in Table A2.

two frequently used IVs meet the exclusion restriction.

Davidoff (2016) suggested that supply constraints are correlated with many local demand factors, including national employment growth in locally dominant industries which is associated with the unobserved local demand shock. As changes in the local labor demand affects child's decision to stay in school, supply constraints are not a valid instrument to deal with endogeneity. The use of Land Grant University location as an instrument creates a similar sort of issues. While the location of Land Grants is, in the modern context, exogenous, they may well produce amenities that are correlated with demand, and that have similar complications to supply constraints. Because an increase in local demand is likely to induce children to select work over school, we believe that the magnitude of the IV coefficients are substantially inflated although the patterns are in line with the findings from the OLS analyses.

**V. Individual Unobservables: Self-Selection**

Even when MSA unobservables are properly controlled for, we cannot claim causality from our results due to the possibility of self-selection. It is possible that parents' aspiration for children's education differ across cities, especially for the least educated households. If so, the higher likelihood of school enrollment for children of less educated parents living in high skilled cities may be reflecting the unobserved differences across households in different cities. In this case, our OLS coefficients are likely to be biased upward as parents with greater aspiration for their child's education are likely to move into or stay in high skilled cities.

To examine whether our results are driven by self-selection we compare our results between the "recent movers" and the "stayers". Recent movers are those who moved from another MSA during the previous year or previous 5 years.[13] Our assumption is that those who move into high skilled cities have similar or perhaps even greater aspiration for their child's education than those who have stayed in the same city. If our previous results are due to the differences in the parent's aspiration, we will find a similar relationship between college share and child's school enrollment for the "movers" and the "stayers". However, if location does have an impact of child's school enrollment for the least educated household, then the coefficient size will differ between the "movers" and the "stayers". Chetty and Hendren (2018b) study, which examines how places matter for children of low income families, shows that for each additional year the child stays in a better county, their income increases by 0.5%. If their study applies to ours, we will observe that children of the less educated "stayers" will benefit more from living in high skilled cities than the "recent movers".

To identify this hypothesis, we add an interaction term of recent mover dummy variable and city's share of college graduates to our regression. In column (1) of Table VII, the coefficient for the interaction term (college share effect on child's school enrollment for the "movers") is negative and significant. The absolute size of this coefficient is slightly larger than the coefficient for the "stayers". This suggests that child's school enrollment of recent movers is not affected by the college share. Only the stayers benefit from the high college share. The

[13] For years prior to 2005, the U.S. Census asked whether the household moved from a different MSA from 5 years ago. Since 2005, the question changed. Therefore, for the year 2010, the recent movers are those who moved from a different MSA from the prior year.

next four columns present the results for the four education groups separately. Again, we find that only children of the less educated parents benefit from higher college share.[14] Furthermore, we only find a significant difference in the college share coefficient between the recent movers and the stayers, for households with high school dropout heads. For this group, the coefficient of the "stayers" is significantly positive while the coefficient for the "movers" is significantly negative. Additionally, the absolute coefficient size of the college share variable for the "movers" is almost twice as large as that of the "stayers." For the other three groups, the coefficient for the interaction term is insignificant, indicating the college share-school enrollment relationship is similar between the "movers" and the "stayers."

The results in Table VII indicate that self-selection is not driving our previous findings. Only the school enrollment propensity of children of less educated "stayers" increases from living in high skilled cities, but the children of less educated "movers" do not show such pattern. In fact, our findings show that child's school enrollment of the least educated "movers" drop, suggesting that the children of these households may face initial difficulty of adjusting to the high skilled cities, especially as their parents are likely to lack sufficient capacity to support them compared to the "mover" parents with greater educational attainment.

## VI. Peer Effect vs. Government Spending

Our findings naturally raise the question of why. To examine the underlying mechanisms for our findings, we look at smaller geographical areas than MSAs, specifically PUMAs. PUMA boundaries are defined by the US census and contain about 100,000 people.[15]These boundaries change over time as specific geographical areas grow and shrink. We use boundaries defined in the 2012-2016 ACS, years when the PUMA boundaries stayed consistent, as the foundation of our smaller area analysis. We calculated PUMA level school enrollment rate using the ACS data, and obtained 2012 school district average government per student spending from the National Center for Education Statistics and mapped it to each PUMA using the weights provided by Missouri Census Data Center.

We test two hypotheses: (1) whether peer effects or the (2) government spending per student influence our enrollment outcomes. Peer effect theory suggests that children will be influenced by their peers. If children live in a local area where more of their peers are enrolled in school, they will also be more likely to go to school. The second hypothesis is related to Diamond (2016), who finds that government spending per student in K-12 schools increased more rapidly in cities with higher skilled populations. If public investment in education leads to greater resources for each child, such as higher teacher to student ratios, then this could reduce children's likelihood of dropping out of school.

Figure IV shows that households with children between the ages of 16 and 24 are more likely to live in PUMAs with higher school enrollment rates if they reside in cities that have higher shares of college graduates. This pattern is consistent across all four parental education

---

[14] Note that the size of the coefficient is slightly higher for high school graduates than high school dropouts. The results differ from the OLS results in Table III as the comparison group has changed. It also differs from the IV regression results as the MSA unobservables are not controlled for.

[15] While using census tract or school district data could generate more accurate results, these smaller geographic boundaries are not public available in the IPUMs data.

groups. In fact, the average PUMA level school enrollment rate for children of high school dropout heads living in cities with college shares greater than 35 percent is higher than the average PUMA level school enrollment rate for children of college graduates living in cities with college shares of less than 25 percent.

Government spending per student is also higher in cities with college share greater than 35 percent (Figure V). However, this is because households with higher educational attainment in high skilled cities reside in PUMAs with significantly higher average government spending per student. In fact, the least educated households are more likely to live in PUMAs with greater government spending per student in lower skilled cities. These differences may be due to differences in the political power across educational groups within cities. While high skilled cities, on average, do have greater government spending per student, the increase in spending is concentrated in PUMAs with higher shares of college graduate parents. The two figures suggest that peer effect is likely to explain the findings the previous section.

The regression result in Table VIII indeed confirms the peer effect theory. The three dependent variables in the regressions are, (1) college share, (2) share of children between 16 and 24 enrolled in school and (3) average government spending per student. All three variables are estimated at the PUMA level and are interacted with head's educational attainment. Since our dataset is cross-sectional, including MSA fixed effects controls for the level of college share across MSAs as well as MSA unobservables.

The first column shows that the share of college graduates at the PUMA level has a significant relationship with child's school enrollment for those living with less educated parents. While the size of the coefficient is slightly smaller for high school dropout households and larger for high school graduate households, the PUMA level college share results shows similar trends to MSA level college share results – children of less educated households benefit more from living in places with higher college share. The second column shows that PUMA-level school enrollment rate is also highly correlated with child's school enrollment, again, especially in the less educated households. The size of the coefficient on local enrollment (in the second column) is larger than the size of coefficient on local BA+ share (in the first column). For example, a 10-percentage point increase in the school enrollment rate at the PUMA increases the likelihood of child's school enrollment by 4.5 percentage point for those with high school dropout parent.

On the other hand, we find no evidence that the government spending per student increases child's school enrollment rate (Column (3)). For all four groups government spending per student is not statistically associated with child's school enrollment. Column (4) shows that when we include all three sets of explanatory variables, the effect of school enrollment dominates. Most of the college share variables become insignificant while school enrollment variables remain strong and significant. This supports the hypothesis that children are influenced by nearby peers. The coefficient size of school enrollment rate variable decreases with the increase of household head's educational attainment. This shows that the children of least educated households receive most impact from living in places with higher shares of school enrollment.

## VII. Conclusion

This study finds that children of high school dropout parents are more likely be enrolled in school, if they live in cities with high shares of college graduates. College share has, however, little or no impact on the likelihood of school enrollment for children of highly educated parents. These results provide some explanation why less educated households are more likely to have children in cities with high share of college graduates, despite the high cost of living. To provide better educational opportunities for their children, less educated parents may be willing to stay in or move to these cities by trading off their current financial betterment for their child's future achievement.

Our findings provide evidence that location matters more for less educated households. As educated parents may have sufficient household resources to support their children, location may have less influence on the educational attainment of their children. On the other hand, as less educated parents rely more on outside support to their children, living in a highly educated city can provide greater benefits to them. We find that households (with children) in high skilled cities are more likely to live in neighborhoods with higher proportions of children enrolled in school. We also find evidence that having more friends nearby who are in school encourages children of less educated households to stay in school, in line with the peer effect hypothesis. Further research is required to identify additional underlying causal mechanisms behind our findings.

While we find that the children of the least educated households receive greater impact from the city they live in, cities with higher shares of college graduates are relatively expensive, especially for households with lower educational attainment. Thus, many of these households will not be able to afford to live in a high-college-share city, despite the positive educational influence their children could receive from residing in these places. Since 1980, after a long period of convergence, regional income divergence across cities increased, in line with the increase in skill divergence during this period (Ganong and Shoag, 2017). This is because housing costs increased more in cities where college share increased, deterring less skilled households from migrating into these cities.

Gyourko et al. (2016) also find that cities that have higher locational preferences, but low housing supply elasticity have experienced a greater increase in housing costs, which lead to out migration of low income households. These studies indicate that living in high skilled cities has become more difficult for the least educated households over time, owing to increasing housing costs. Our results suggest that decreasing access to high skilled cities for the least educated households can further impede intergenerational mobility of education. Our study implies that supporting children of low skill parents migrate to and stay in high skill cities is an important mechanism for improving intergenerational mobility.

**References**


Angrist J.D., & Pischke, J. (2009). Mostly Harmless Econometrics: An Empiricist's Companion. *Princeton University Press.*

Berry, C. R., & Glaeser, E. L. (2005). The Divergence of Human Capital Levels across Cities. *Papers in Regional Science*, *84*(3), 407–444.

Chakraborty, I., Goldstein, I., & Mackinlay, A. (Forthcoming). Housing Price Booms and Crowding-Out Effects in Bank Lending. *Review of Financial Studies*.

Chetty, R., & Hendren, N. (2018a). *The Impacts of Neighborhoods on Intergenerational Mobility I: County-Level Estimates*. Quarterly Journal of Economics, 133 (3), 1107-1162.

Chetty, R., & Hendren, N. (2018b). *The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates*. Quarterly Journal of Economics, 133 (3), 1163-1228.

Choi, J. H., & Green, R. K. (2017). House Price Shock and Changes in Inequality across Cities. *Working Paper*.

Choi, J. H., Green, R. K., & Noh, E. (2018). Wage Trickle Down vs. Rent Trickle Down: How does increase in college graduates affect wages and rents? *Working Paper*.

Coleman, J. S., E. Q. Campbell, C. F. Hobson, J. McPartland, A. M. Mood, F. D. Weinfeld, and R. L. York. (1966). Equality of Educational Opportunity. Washington, D.C.: Office of Education, U.S. Department of Health, Education, and Welfare

Davidoff, T. (2016). Supply Constraints Are Not Valid Instrumental Variables for Home Prices Because They Are Correlated with Many Demand Factors. *Critical Finance Review 5 (2*), 177–206

Diamond, R. (2016). The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980–2000. *American Economic Review*, *106*(3), 479–524.

Ganong, P., & Shoag, D. W. (2017). *Why Has Regional Income Convergence in the U.S. Declined?* (Working Paper No. 23609). National Bureau of Economic Research.

Green, R., & White, M. J. (1997). Measuring the Benefits of Homeowning: Effects on Children. *Journal of Urban Economics*, *41*(3), 441–461.

Gyourko, J., Mayer, C., & Sinai, T. (2013). Superstar Cities. *American Economic Journal: Economic Policy*, *5*(4), 167–199.

Katz, L. F., & Murphy, K. M. (1992). Changes in Relative Wages, 1963–1987: Supply and Demand Factors. *The Quarterly Journal of Economics*, *107*(1), 35–78.

Moretti, E. (2004). Estimating the Social Return to Higher Education: Evidence from Longitudinal and Repeated Cross-Sectional Data. *Journal of Econometrics*, *121*(1–2), 175–212.

Moretti, E. (2013). Real Wage Inequality. *American Economic Journal: Applied Economics*, *5*(1), 65–103.

Nervis, A. (1962). The State Universities and Democracy. University of Illinois Press, Champaign, IL.

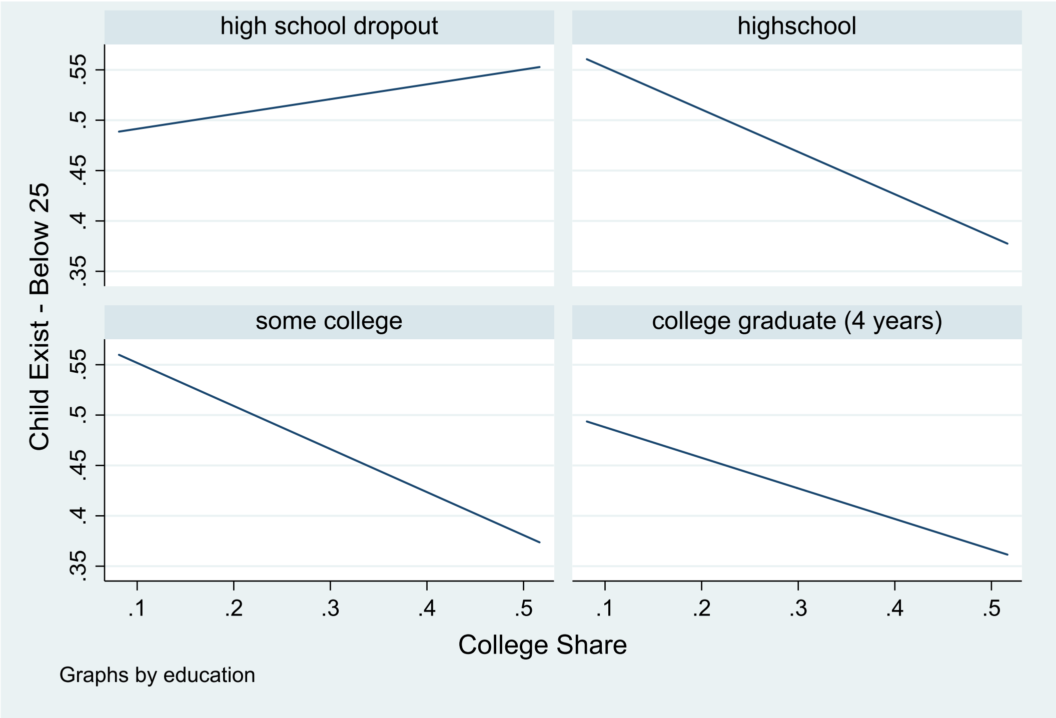
Saiz, A. (2010). The Geographic Determinants of Housing Supply. *The Quarterly Journal of Economics*, *125*(3), 1253–1296.

Williams, R. L. (1991). The Origins of Federal Support for Higher Education. The Pennsylvania State University Press, Pennsylvania.

Winters, J. V. (2013). Human Capital Externalities and Employment Differences across Metropolitan Areas of the USA. *Journal of Economic Geography*, *13*(5), 799–822.

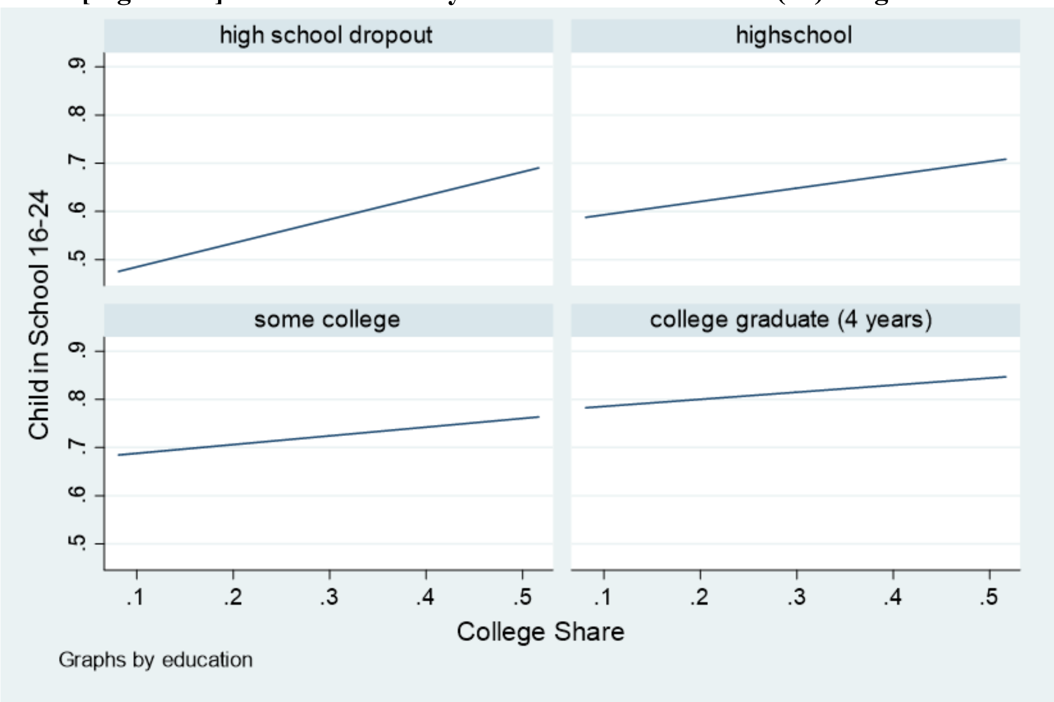
## Tables & Figures

**[Figure I] Household with Child Age Below 25 by Head's Education Level (%)**



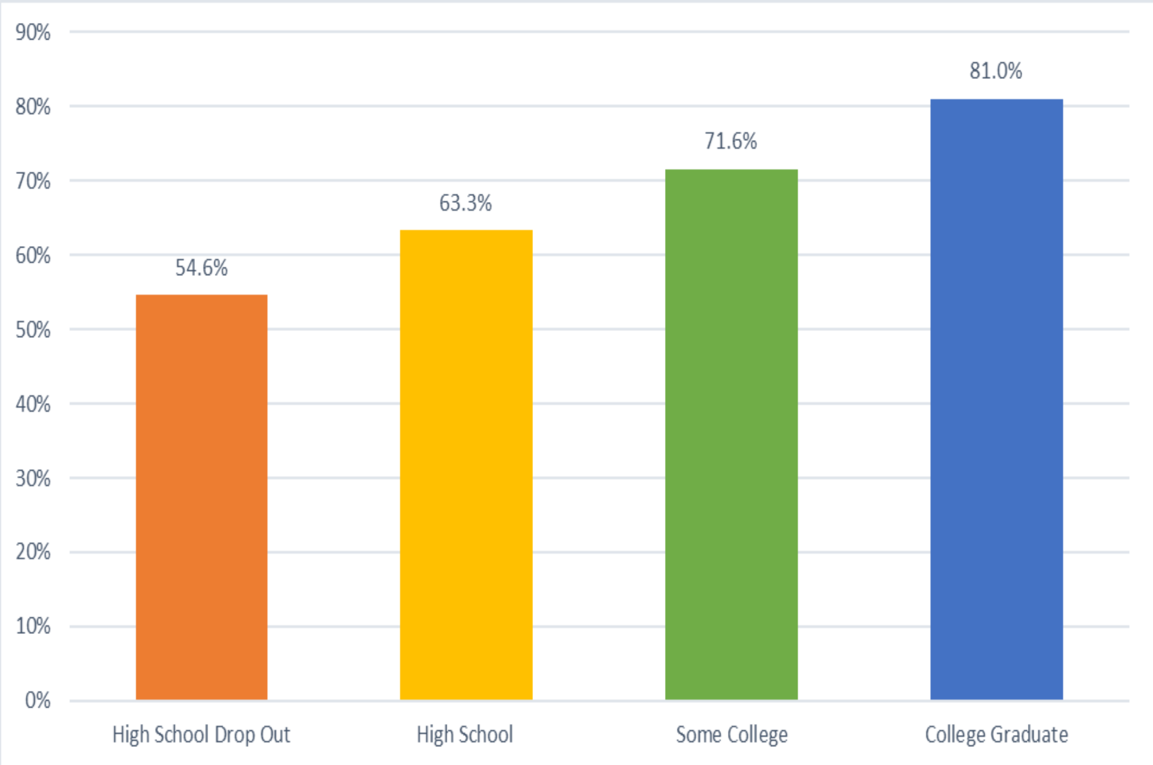

Source: Decennial Census 1980,1990, 2000 & American Community Survey 2008-12

**[Figure III] Child in School by Head's Education Level (%) – Age 16-24**



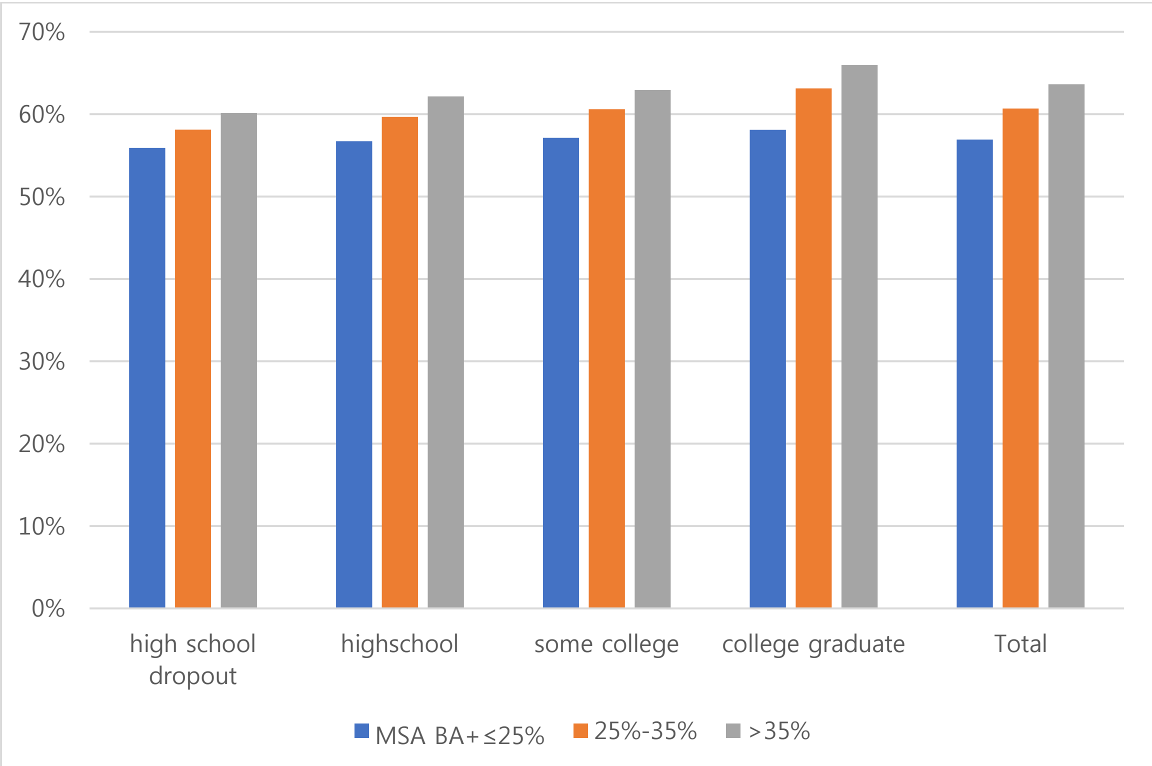

Source: Decennial Census 1980,1990, 2000 & American Community Survey 2008-12

**[Figure III] % Child Enrolled in School 16-24 by Head's Education Level**



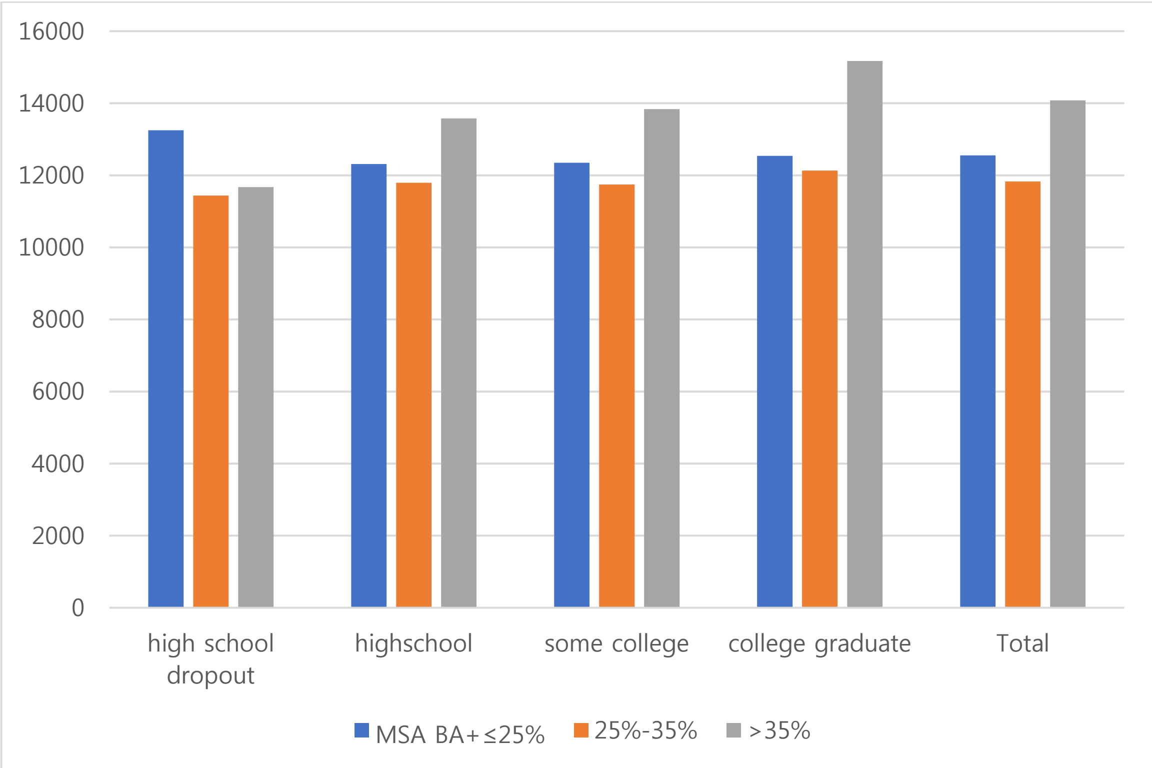

Source: Decennial Census 1980,1990, 2000 & American Community Survey 2008-12

**[Figure IV] % Enrolled in School in Puma – Heads with Children Age 16-24**




Source: American Community Survey 2012-16

**[Figure V] Expenditure per Student in Puma – Heads with Children Age 16-24**



Source: American Community Survey 2012-16

**[Table I] Summary Statistics by Education Group**

| Variable | High School Dropout | | High School Graduate | | Some College | | College Graduate | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| *Dependent Variables* | | | | | | | | |
| Child Exist | 0.59 | 0.49 | 0.55 | 0.50 | 0.53 | 0.50 | 0.46 | 0.50 |
| Child (Age 1624) in School | 0.55 | 0.50 | 0.63 | 0.48 | 0.72 | 0.45 | 0.81 | 0.39 |
| Home Ownership | 0.49 | 0.50 | 0.60 | 0.49 | 0.62 | 0.49 | 0.70 | 0.46 |
| Household Income | 44872 | 41145 | 60869 | 49621 | 72674 | 58093 | 113670 | 98145 |
| Annual Housing Cost | 9920 | 7641 | 12842 | 9057 | 15362 | 10467 | 20645 | 14724 |
| *Explanatory Variable: Individual Level* | | | | | | | | |
| Age | 46.74 | 11.76 | 44.28 | 11.43 | 42.54 | 11.05 | 42.83 | 11.02 |
| Female | 0.35 | 0.48 | 0.36 | 0.48 | 0.36 | 0.48 | 0.32 | 0.47 |
| Marital Status | | | | | | | | |
| Divorced/Separated | 0.21 | 0.41 | 0.23 | 0.42 | 0.23 | 0.42 | 0.15 | 0.35 |
| Widowed | 0.08 | 0.28 | 0.05 | 0.22 | 0.03 | 0.18 | 0.02 | 0.14 |
| Never Married | 0.14 | 0.34 | 0.16 | 0.37 | 0.18 | 0.39 | 0.22 | 0.42 |
| Race & Ethnicity | | | | | | | | |
| Black | 0.18 | 0.39 | 0.16 | 0.37 | 0.15 | 0.36 | 0.08 | 0.27 |
| Asian | 0.03 | 0.17 | 0.02 | 0.15 | 0.03 | 0.17 | 0.07 | 0.26 |
| Hispanic | 0.32 | 0.47 | 0.12 | 0.32 | 0.09 | 0.29 | 0.05 | 0.22 |
| Others | 0.01 | 0.11 | 0.01 | 0.12 | 0.02 | 0.13 | 0.01 | 0.11 |
| Immigrant | 0.30 | 0.46 | 0.12 | 0.33 | 0.11 | 0.31 | 0.14 | 0.35 |
| Spouse Education | | | | | | | | |
| High School Drop Out | 0.31 | 0.46 | 0.07 | 0.26 | 0.03 | 0.17 | 0.01 | 0.10 |
| High School Graduate | 0.18 | 0.38 | 0.32 | 0.47 | 0.20 | 0.40 | 0.10 | 0.30 |
| Some College | 0.05 | 0.21 | 0.10 | 0.30 | 0.20 | 0.40 | 0.14 | 0.35 |
| College Graduate | 0.01 | 0.12 | 0.05 | 0.21 | 0.10 | 0.30 | 0.35 | 0.48 |
| Spouse Working | 0.27 | 0.44 | 0.34 | 0.47 | 0.37 | 0.48 | 0.40 | 0.49 |
| Move | 0.02 | 0.06 | 0.02 | 0.07 | 0.03 | 0.08 | 0.04 | 0.10 |
| *Explanatory Variable:MSA Level* | | | | | | | | |
| % BA+ | 0.23 | 0.07 | 0.25 | 0.07 | 0.26 | 0.07 | 0.28 | 0.08 |
| MSA Population | 3150028 | 3107068 | 2746169 | 2770881 | 2785771 | 2741086 | 3103680 | 2865940 |
| No. of Obs | 1096594 | | 2467709 | | 1930297 | | 2523351 | |

**[Table II] Child Below Age 25 Exist & Share of College Graduate**

| Variables | OLS (1) Total | (2) by Education | (3) Total | (4) by Education |
|---|---|---|---|---|
| % BA+ | -0.073*** | 0.029 | 0.055 | 0.185*** |
| | (0.022) | (0.028) | (0.048) | (0.054) |
| % BA+ X High School | | -0.144*** | | -0.164*** |
| | | (0.018) | | (0.016) |
| % BA+ X Some College | | -0.110*** | | -0.126*** |
| | | (0.023) | | (0.021) |
| % BA+ X College+ | | -0.095*** | | -0.112*** |
| | | (0.034) | | (0.031) |
| High School | -0.027*** | 0.006 | -0.027*** | 0.011** |
| | (0.002) | (0.005) | (0.002) | (0.004) |
| Some College | -0.050*** | -0.025*** | -0.048*** | -0.020*** |
| | (0.002) | (0.006) | (0.002) | (0.006) |
| College | -0.091*** | -0.070*** | -0.088*** | -0.063*** |
| | (0.002) | (0.009) | (0.002) | (0.009) |
| Control | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| MSA FE | N | N | Y | Y |
| Observations | 7,969,682 | 7,969,682 | 7,969,682 | 7,969,682 |
| R-squared | 0.312 | 0.312 | 0.314 | 0.314 |

Note: Dependent variable equals to 1 for households with children and 0 otherwise. The control variables include age, age$^2$, female, marital status, race and ethnicity, immigrant status, whether spouse is working, owning a home, log value of household income, and log value of MSA population. All regressions are weighted by household weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1). Results for probit regressions are available in the online appendix.

[Table III] College Share & Housing/Income Outcomes by Head's Education (OLS)

| | Homeownership | | Household Income | | Housing Cost | | Residual Income | | Housing Cost/Income | |
|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| % BA+ | -0.233*** | -0.533*** | 1.081*** | 0.515*** | 1.611*** | 1.539*** | 0.956*** | 0.253* | 0.530*** | 0.987*** |
| | (0.068) | (0.0739) | (0.101) | (0.139) | (0.157) | (0.169) | (0.094) | (0.134) | (0.096) | (0.129) |
| % BA+ X High School | | 0.201*** | | 0.167** | | 0.072 | | 0.187*** | | -0.062 |
| | | (0.0355) | | (0.066) | | (0.069) | | (0.065) | | (0.070) |
| % BA+ X Some College | | 0.316*** | | 0.484*** | | -0.006 | | 0.596*** | | -0.448*** |
| | | (0.0431) | | (0.086) | | (0.076) | | (0.088) | | (0.100) |
| % BA+ X College | | 0.465*** | | 1.126*** | | 0.148 | | 1.388*** | | -0.924*** |
| | | (0.0517) | | (0.126) | | (0.099) | | (0.139) | | (0.129) |
| High School | 0.093*** | 0.0500*** | 0.288*** | 0.259*** | 0.171*** | 0.154*** | 0.295*** | 0.264*** | -0.122*** | -0.117*** |
| | (0.002) | (0.00845) | (0.005) | (0.015) | (0.004) | (0.017) | (0.005) | (0.016) | (0.006) | (0.017) |
| Some College | 0.130*** | 0.0582*** | 0.467*** | 0.360*** | 0.323*** | 0.327*** | 0.472*** | 0.340*** | -0.150*** | -0.048** |
| | (0.002) | (0.0105) | (0.006) | (0.020) | (0.005) | (0.019) | (0.006) | (0.022) | (0.008) | (0.023) |
| College | 0.186*** | 0.0725*** | 0.799*** | 0.517*** | 0.516*** | 0.478*** | 0.842*** | 0.492*** | -0.290*** | -0.056* |
| | (0.003) | (0.0129) | (0.011) | (0.030) | (0.007) | (0.025) | (0.012) | (0.033) | (0.012) | (0.030) |
| Control | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 8,060,682 | 8,060,682 | 7,969,682 | 7,969,682 | 7,746,275 | 7,746,275 | 7,463,464 | 7,463,464 | 7,661,678 | 7,661,678 |
| R-squared | 0.249 | 0.249 | 0.324 | 0.326 | 0.284 | 0.284 | 0.286 | 0.287 | 0.121 | 0.122 |

Note: Homeownership is a dummy variable which equals to 1 if the households own a home and 0 otherwise. The remaining four dependent variables are log values. The control variables include age, age$^2$, female, marital status, race and ethnicity, immigrant status, whether spouse is working, and log value of MSA population. All regressions are weighted by household weights. Robust standard errors, corrected for city X year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1). Results for probit regressions are available in the online appendix

**[Table IV] Child in School & Share of College Graduate (Age 16-24)**

| Variables | OLS | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Total | by Education | Total | by Education |
| % BA+ | 0.055** | 0.169*** | -0.010 | 0.167*** |
| | (0.024) | (0.040) | (0.049) | (0.056) |
| % BA+ X High School | | -0.053* | | -0.080*** |
| | | (0.028) | | (0.024) |
| % BA+ X Some College | | -0.124*** | | -0.147*** |
| | | (0.034) | | (0.028) |
| % BA+ X College+ | | -0.263*** | | -0.292*** |
| | | (0.038) | | (0.034) |
| High School | 0.076*** | 0.086*** | 0.0748*** | 0.091*** |
| | (0.002) | (0.006) | (0.002) | (0.006) |
| Some College | 0.142*** | 0.170*** | 0.140*** | 0.172*** |
| | (0.003) | (0.008) | (0.002) | (0.006) |
| College | 0.207*** | 0.272*** | 0.205*** | 0.276*** |
| | (0.003) | (0.009) | (0.003) | (0.008) |
| Control | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| MSA FE | N | N | Y | Y |
| Observations | 2,072,092 | 2,072,092 | 2,072,092 | 2,072,092 |
| R-squared | 0.308 | 0.308 | 0.310 | 0.311 |

Note: Dependent variable equals to 1 if children between ages 16 and 24 are in school and 0 otherwise. The control variables include child's age, child's age$^2$, child's sex, child's race and ethnicity, head's marital status, head's immigrant status, owning a home, log value of household income, and log value of MSA population. All regressions are weighted by individual weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1). Results for probit regressions are available in the online appendix.

**[Table V] Child in School & Share of College Graduate (Age 16-24)**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | Spouse Education | | Bartik Shock | |
| % BA+ | 0.161*** | 0.171*** | 0.158*** | 0.164*** |
| | (0.039) | (0.056) | (0.039) | (0.057) |
| % BA+ X High School | -0.066** | -0.092*** | -0.068** | -0.092*** |
| | (0.028) | (0.024) | (0.027) | (0.024) |
| % BA+ X Some College | -0.131*** | -0.155*** | -0.132*** | -0.155*** |
| | (0.032) | (0.027) | (0.032) | (0.027) |
| % BA+ X College+ | -0.264*** | -0.294*** | -0.264*** | -0.294*** |
| | (0.036) | (0.033) | (0.036) | (0.033) |
| High School | 0.075*** | 0.081*** | 0.076*** | 0.081*** |
| | (0.006) | (0.005) | (0.006) | (0.005) |
| Some College | 0.149*** | 0.152*** | 0.149*** | 0.152*** |
| | (0.007) | (0.006) | (0.007) | (0.006) |
| College | 0.236*** | 0.241*** | 0.235*** | 0.241*** |
| | (0.009) | (0.008) | (0.009) | (0.008) |
| Spouse: High School Dropout | 0.002 | 0.002 | | |
| | (0.004) | (0.004) | | |
| Spouse: High School | 0.050*** | 0.050*** | | |
| | (0.003) | (0.003) | | |
| Spouse: Some College | 0.091*** | 0.091*** | | |
| | (0.003) | (0.003) | | |
| Spouse: College+ | 0.107*** | 0.106*** | | |
| | (0.003) | (0.003) | | |
| Bartik_BA | | | 0.001 | -0.022 |
| | | | (0.020) | (0.026) |
| Bartik_HS | | | 0.095* | -0.003 |
| | | | (0.057) | (0.045) |
| Control | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| MSA FE | N | Y | Y | Y |
| Observations | 2,043,186 | 2,043,186 | 2,043,186 | 2,043,186 |
| R-squared | 0.311 | 0.314 | 0.311 | 0.314 |

Note: Dependent variable equals to 1 if children between ages 16 and 24 are in school and 0 otherwise. The control variables include child's age, child's age$^2$, child's sex, child's race and ethnicity, head's marital status, head's immigrant status, owning a home, log value of household income, and log value of MSA population. All regressions are weighted by individual weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

**[Table VI] IV– Child in School & Share of College Graduate (Age 16-24)**

| Variables | (1) % BA+ | (2) Total | (3) HS Drop Out | (4) High School | (5) Some College | (6) College |
|---|---|---|---|---|---|---|
| IV: Land Grant | | | | | | |
| % BA+ (Land Grant) | 0.026*** | 1.032*** | 1.869*** | 0.989*** | 0.860** | 0.485** |
| | (0.000) | (0.366) | (0.575) | (0.325) | (0.407) | (0.219) |
| Control | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Observations | 1,728,905 | 1,728,905 | 363,037 | 582,136 | 390,528 | 393,204 |
| R-squared | 0.489 | 0.296 | 0.284 | 0.304 | 0.252 | 0.241 |
| IV: Land Unavailability | | | | | | |
| % BA+ | 0.038*** | 0.888* | 1.452** | 1.003 | 0.475 | -0.0326 |
| (Land Unavailability) | (0.000) | (0.483) | (0.575) | (0.692) | (0.342) | (0.220) |
| Control | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Observations | 1,878,386 | 1,878,386 | 393,955 | 630,641 | 422,205 | 431,585 |
| R-squared | 0.537 | 0.299 | 0.297 | 0.303 | 0.259 | 0.248 |

Note: The first column presents first stage regression results, where the dependent variable is the share of college graduate. The first instrumental variable is a dummy variable that equals 1 if the MSA has a land grant university and 0 otherwise. The second instrumental variable is the share of land unavailable for development, created by Saiz (2010). For the remaining for columns the dependent variable equals to 1 if children between ages 16 and 24 are in school and 0 otherwise. The control variables include child's age, child's age$^2$, child's sex, child's race and ethnicity, head's marital status, head's immigrant status, owning a home, log value of household income, and log value of MSA population. All regressions are weighted by individual weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1). Results for probit regressions are available in the online appendix.

**[Table VII] Movers vs. Non-Movers: Child in School & Share of College Graduate (Age 16-24)**

| Variables | OLS | | | | |
|---|---|---|---|---|---|
| | (1) Total | (2) High School Drop Out | (3) High School | (4) Some College | (5) College |
| % BA+ | 0.060** | 0.087** | 0.099** | 0.039 | -0.007 |
| | (0.024) | (0.040) | (0.041) | (0.028) | (0.018) |
| % BA+ X Recent Mover | -0.078** | -0.171** | -0.068 | 0.002 | -0.051 |
| | (0.031) | (0.070) | (0.052) | (0.044) | (0.034) |
| Recent Mover | -0.006 | -0.017 | -0.004 | -0.024** | 0.002 |
| | (0.008) | (0.016) | (0.012) | (0.011) | (0.009) |
| Control | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Observations | 2,072,092 | 424,331 | 694,091 | 467,546 | 486,124 |
| R-squared | 0.308 | 0.316 | 0.312 | 0.262 | 0.250 |

Note: Dependent variable equals to 1 if children between ages 16 and 24 are in school and 0 otherwise. The control variables include child's age, child's age$^2$, child's sex, child's race and ethnicity, head's marital status, head's immigrant status, owning a home, log value of household income, and log value of MSA population. All regressions are weighted by individual weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1). Results for probit regressions are available in the online appendix.

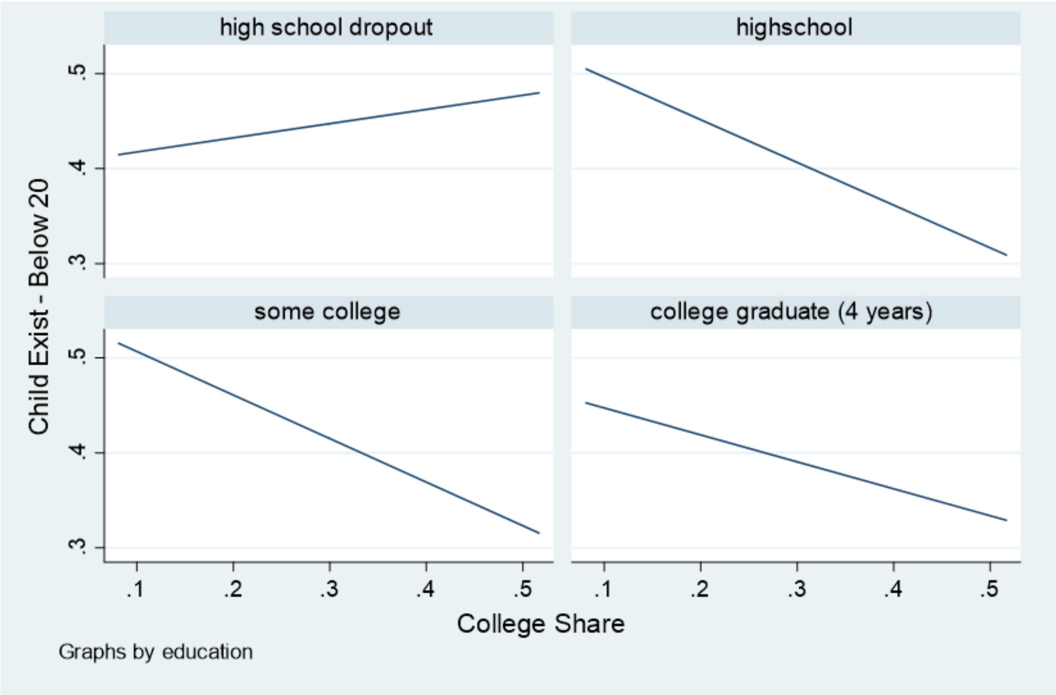
**[Table VIII] Peer Effect vs. Government Spending on Education – PUMA Analysis (Age 16-24)**

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| % PUMA BA+ | 0.106*** | | | -0.021 |
| | (0.022) | | | (0.025) |
| % PUMA BA+ X High School | 0.058** | | | 0.062** |
| | (0.026) | | | (0.031) |
| % PUMA BA+ X Some College | 0.013 | | | 0.027 |
| | (0.028) | | | (0.030) |
| % PUMA BA+ X College+ | -0.065** | | | 0.024 |
| | (0.027) | | | (0.029) |
| % In School | | 0.450*** | | 0.466*** |
| | | (0.039) | | (0.043) |
| % In School X High School | | -0.047 | | -0.102** |
| | | (0.043) | | (0.050) |
| % In School X Some College | | -0.111*** | | -0.133*** |
| | | (0.043) | | (0.045) |
| % In School X College+ | | -0.312*** | | -0.331*** |
| | | (0.044) | | (0.046) |
| Per Student Expenditure | | | 0.0002 | 0.0001 |
| | | | (0.000) | (0.000) |
| Per Student Expenditure X High School | | | -0.0002 | -0.0003 |
| | | | (0.000) | (0.000) |
| Per Student Expenditure+ X Some College | | | -0.0002 | -0.0002 |
| | | | (0.000) | (0.000) |
| Per Student Expenditure X College+ | | | -0.0002 | -0.0002 |
| | | | (0.000) | (0.000) |
| Control | Y | Y | Y | Y |
| MSA FE | Y | Y | Y | Y |
| Observations | 743,612 | 743,612 | 743,612 | 743,612 |
| R-squared | 0.309 | 0.311 | 0.309 | 0.311 |

Note: Dependent variable equals to 1 if children between ages 16 and 24 are in school and 0 otherwise. The control variables include child's age, child's age$^2$, child's sex, child's race and ethnicity, head's education, head's marital status, head's immigrant status, owning a home, log value of household income, and log value of MSA population. All regressions are weighted by individual weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1). Results for probit regressions are available in the online appendix.

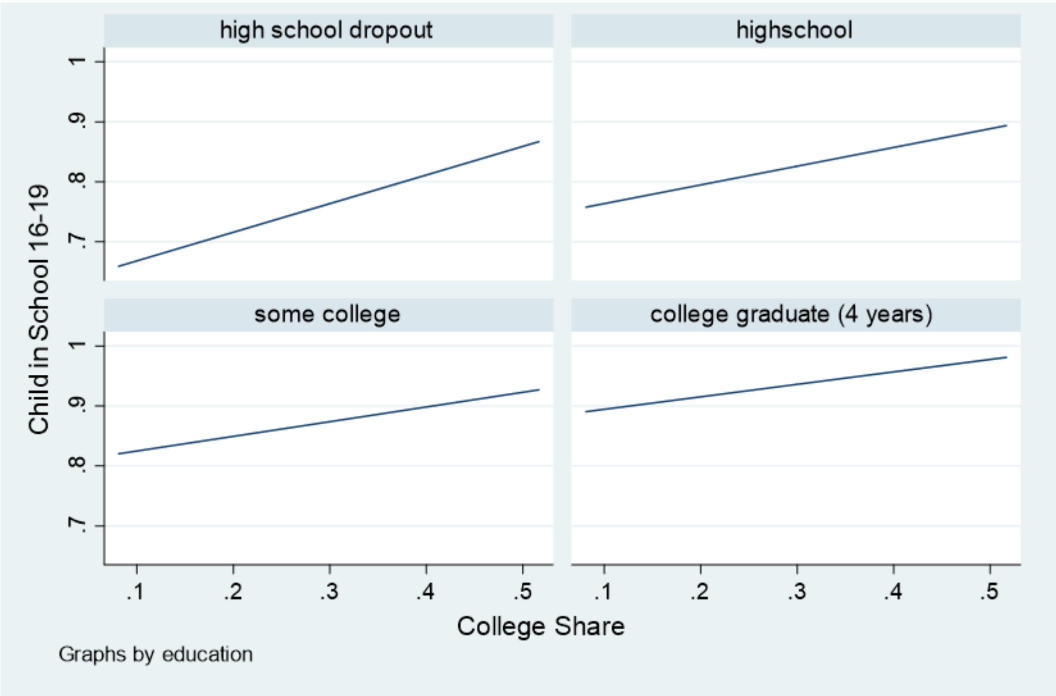
**Appendix**

**[Figure A1] Child Exist & Share of College Graduate – Age Below 20**



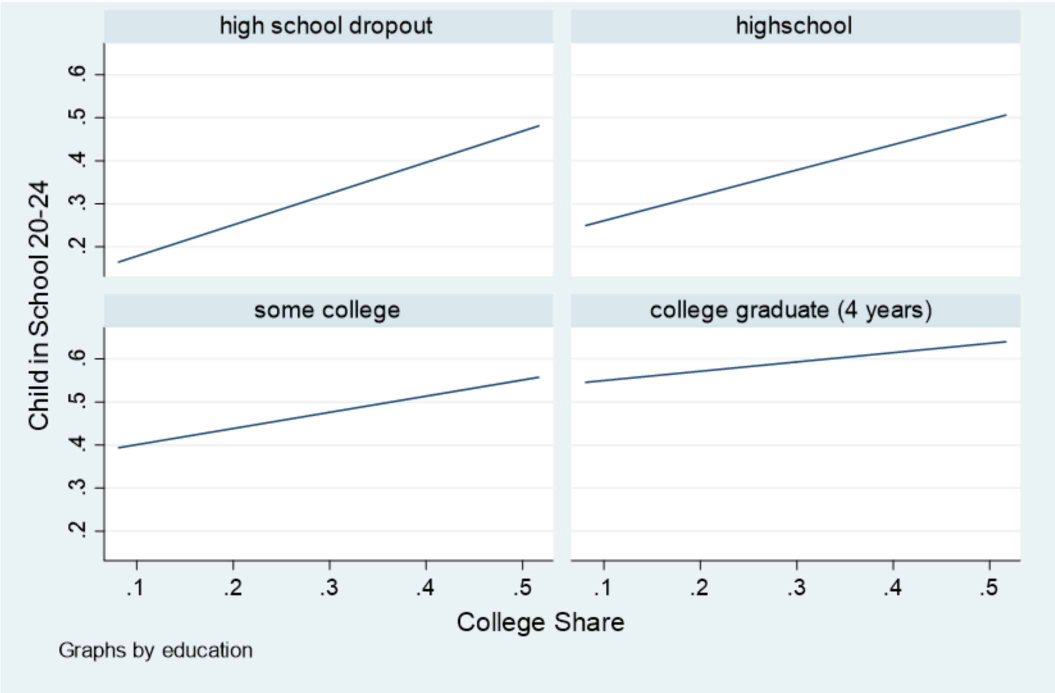

Source: Decennial Census 1980,1990, 2000 & American Community Survey 2008-12

**[Figure A2] Child in School by Head's Education Level (%) – Age 16-19**




Source: Decennial Census 1980,1990, 2000 & American Community Survey 2008-12

**[Figure A3] Child in School by Head's Education Level (%) – Age 20-24**




Source: Decennial Census 1980,1990, 2000 & American Community Survey 2008-12

**[Table A1] Child in School & Share of College Graduate (Age 16-19 & Age 20-24)**

| Variables | OLS: Age 16-19 | | | | OLS: Age 20-24 | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| | total | by education | total | by education | total | by education | total | by education |
| % BA+ | 0.0377** | 0.183*** | 0.0207 | 0.238*** | 0.0766** | 0.147*** | -0.162** | -0.0401 |
| | (0.0179) | (0.0358) | (0.0442) | (0.0518) | (0.0378) | (0.0561) | (0.0756) | (0.0860) |
| % BA+ X High School | | -0.104*** | | -0.132*** | | 0.0563 | | 0.0347 |
| | | (0.0282) | | (0.0246) | | (0.0378) | | (0.0347) |
| % BA+ X Some College | | -0.162*** | | -0.193*** | | -0.0785 | | -0.0875** |
| | | (0.0319) | | (0.0275) | | (0.0491) | | (0.0430) |
| % BA+ X College | | -0.273*** | | -0.312*** | | -0.302*** | | -0.315*** |
| | | (0.0362) | | (0.0329) | | (0.0593) | | (0.0564) |
| High School | 0.0707*** | 0.0923*** | 0.0702*** | 0.0980*** | 0.0783*** | 0.0622*** | 0.0768*** | 0.0658*** |
| | (0.00231) | (0.00654) | (0.00229) | (0.00576) | (0.00237) | (0.00860) | (0.00235) | (0.00797) |
| Some College | 0.114*** | 0.150*** | 0.113*** | 0.156*** | 0.180*** | 0.198*** | 0.176*** | 0.195*** |
| | (0.00284) | (0.00755) | (0.00273) | (0.00652) | (0.00340) | (0.0114) | (0.00315) | (0.00996) |
| College | 0.155*** | 0.220*** | 0.153*** | 0.228*** | 0.289*** | 0.367*** | 0.284*** | 0.365*** |
| | (0.00326) | (0.00868) | (0.00321) | (0.00804) | (0.00494) | (0.0143) | (0.00483) | (0.0138) |
| Control | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| MSA FE | N | N | Y | Y | N | N | Y | Y |
| Observations | 1,292,889 | 1,292,889 | 1,292,889 | 1,292,889 | 779,203 | 779,203 | 779,203 | 779,203 |
| R-squared | 0.190 | 0.191 | 0.193 | 0.193 | 0.124 | 0.124 | 0.129 | 0.129 |

Note: Dependent variable equals to 1 if children between ages 16 and 24 are in school and 0 otherwise. The control variables include child's age, child's age$^2$, child's sex, child's race and ethnicity, head's marital status, head's immigrant status, owning a home, log value of household income, and log value of MSA population. All regressions are weighted by individual weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

**[Table A2] IV: Land Grant – Child in School & Share of College Graduate (Age 16-19 & Age 20-24)**

| Variables | (1) Total | (2) High School Drop Out | (3) High School | (4) Some College | (5) College |
|---|---|---|---|---|---|
| IV - Land Grant: Age 16-19 | | | | | |
| % BA+ | 0.601*** | 1.402*** | 0.563*** | 0.392** | 0.210** |
| | (0.215) | (0.473) | (0.194) | (0.182) | (0.085) |
| Control | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Observations | 1,086,766 | 218,353 | 361,770 | 248,926 | 257,717 |
| R-squared | 0.186 | 0.175 | 0.198 | 0.145 | 0.093 |
| IV - Land Grant: Age 20-24 | | | | | |
| % BA+ | 1.801*** | 2.521*** | 1.720*** | 1.852* | 1.054* |
| | (0.679) | (0.745) | (0.588) | (1.012) | (0.568) |
| Control | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Observations | 642,139 | 144,684 | 220,366 | 141,602 | 135,487 |
| R-squared | 0.088 | 0.012 | 0.040 | 0.030 | 0.083 |

Note: The first column presents first stage regression results, where the dependent variable is the share of college graduate. The instrumental variable is a dummy variable that equals 1 if the MSA has a land grant university and 0 otherwise. For the remaining four columns the dependent variable equals to 1 if children between ages 16 and 24 are in school and 0 otherwise. The control variables include child's age, child's age2, child's sex, child's race and ethnicity, head's marital status, head's immigrant status, owning a home, and log value of household income. All regressions are weighted by individual weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1). Results for probit regressions are available in the online appendix.

**[Table A3] IV: Land Unavailability – Child in School & Share of College Graduate**

**(Age 16-19 & Age 20-24)**

| Variables | (1) Total | (2) HS Drop Out | (3) High School | (4) Some College | (5) College |
|---|---|---|---|---|---|
| IV - Land Unavailability: Age 16-19 | | | | | |
| % BA+ | 0.277 | 0.969** | 0.068 | -0.029 | -0.435 |
| | (0.242) | (0.446) | (0.358) | (0.239) | (0.335) |
| Control | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Observations | 1,176,870 | 236,587 | 390,087 | 268,095 | 282,101 |
| R-squared | 0.191 | 0.188 | 0.201 | 0.148 | 0.084 |
| IV - Land Unavailability: Age 20-24 | | | | | |
| % BA+ | 1.770** | 2.090*** | 2.312 | 1.260* | 0.675 |
| | (0.900) | (0.773) | (1.411) | (0.705) | (0.672) |
| Control | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Observations | 701,516 | 157,368 | 240,554 | 154,110 | 149,484 |
| R-squared | 0.089 | 0.037 | 0.016 | 0.052 | 0.093 |

Note: The first column presents first stage regression results, where the dependent variable is the share of college graduate. The instrumental variable is the share of land unavailable for development, created by Saiz (2010). For the remaining for columns the dependent variable equals to 1 if children between ages 16 and 24 are in school and 0 otherwise. The control variables include child's age, child's age$^2$, child's sex, child's race and ethnicity, head's marital status, head's immigrant status, owning a home, log value of household income, and log value of MSA population. All regressions are weighted by individual weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1). Results for probit regressions are available in the online appendix.

**Online Appendix**

**Table O1. College Share and Homeownership by Head's Education (Probit)**

| | Homeownership | |
|---|---|---|
| VARIABLES | (1) | (2) |
| % BA+ | -0.759*** | -1.545*** |
| | (0.223) | (0.232) |
| % BA+ X High School | | 0.489*** |
| | | (0.114) |
| % BA+ X Some College | | 0.844*** |
| | | (0.139) |
| % BA+ X College | | 1.296*** |
| | | (0.180) |
| High School | 0.290*** | 0.187*** |
| | (0.006) | (0.0270) |
| Some College | 0.411*** | 0.218*** |
| | (0.007) | (0.0331) |
| College | 0.608*** | 0.289*** |
| | (0.011) | (0.0454) |
| Control | Y | Y |
| Year FE | Y | Y |
| Observations | 8,029,804 | 8,029,804 |

Note: Homeownership is a dummy variable which equals to 1 if the households own a home and 0 otherwise. The control variables include age, age$^2$, female, marital status, race and ethnicity, immigrant status, whether spouse is working, and log value of MSA population. All regressions are weighted by household weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

**Table O2. Probit: Child Below Age 25 Exist & Share of College Graduate**

| Variables | Probit | | | |
|---|---|---|---|---|
| | (1) Total | (2) by Education | (3) Total | (4) by Education |
| % BA+ | -0.273*** | 0.041 | 0.094 | 0.496*** |
| | (0.077) | (0.100) | (0.155) | (0.178) |
| % BA+ X High School | | -0.427*** | | -0.491*** |
| | | (0.064) | | (0.057) |
| % BA+ X Some College | | -0.311*** | | -0.361*** |
| | | (0.081) | | (0.074) |
| % BA+ X College+ | | -0.317*** | | -0.368*** |
| | | (0.122) | | (0.111) |
| High School | -0.108*** | -0.009 | -0.108*** | 0.006 |
| | (0.005) | (0.016) | (0.005) | (0.015) |
| Some College | -0.187*** | -0.117*** | -0.182*** | -0.101*** |
| | (0.007) | (0.022) | (0.007) | (0.020) |
| College | -0.335*** | -0.264*** | -0.329*** | -0.246*** |
| | (0.008) | (0.032) | (0.008) | (0.030) |
| Control | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| MSA FE | N | N | Y | Y |
| Observations | 7,969,682 | 7,969,682 | 7,969,682 | 7,969,682 |

Note: Dependent variable equals to 1 for households with children and 0 otherwise. The control variables include age, $age^2$, female, marital status, race and ethnicity, immigrant status, whether spouse is working, owning a home, log value of household income, and log value of MSA population. All regressions are weighted by household weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

**Table O3. Probit: Child in School & Share of College Graduate (Age 16-24)**

| Variables | Probit | | | |
|---|---|---|---|---|
| | (1) Total | (2) by Education | (3) Total | (4) by Education |
| % BA+ | 0.220** | 0.449*** | -0.133 | 0.269 |
| | (0.0955) | (0.147) | (0.197) | (0.220) |
| % BA+ X High School | | -0.0999 | | -0.196** |
| | | (0.102) | | (0.0875) |
| % BA+ X Some College | | -0.272** | | -0.362*** |
| | | (0.122) | | (0.101) |
| % BA+ X College+ | | -0.624*** | | -0.738*** |
| | | (0.149) | | (0.136) |
| High School | 0.258*** | 0.277*** | 0.255*** | 0.296*** |
| | (0.00734) | (0.0230) | (0.00738) | (0.0202) |
| Some College | 0.500*** | 0.560*** | 0.493*** | 0.575*** |
| | (0.00973) | (0.0283) | (0.00915) | (0.0234) |
| College | 0.800*** | 0.955*** | 0.794*** | 0.975*** |
| | (0.0123) | (0.0346) | (0.0123) | (0.0324) |
| Control | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| MSA FE | N | N | Y | Y |
| Observations | 2,072,092 | 2,072,092 | 2,072,092 | 2,072,092 |

Note: Dependent variable equals to 1 if children between ages 16 and 24 are in school and 0 otherwise. The control variables include child's age, child's age$^2$, child's sex, child's race and ethnicity, head's marital status, head's immigrant status, owning a home, log value of household income, and log value of MSA population. All regressions are weighted by individual weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

**Table O4. IV Probit: Land Grant – Child in School & Share of College Graduate**

| Variables | (1) Total | (2) HS Drop Out | (3) High School | (4) Some College | (5) College |
|---|---|---|---|---|---|
| IV Probit - Land Grant: Age 16-24 | | | | | |
| % BA+ | 3.945*** | 6.221*** | 3.651*** | 3.306** | 2.291** |
| | (1.338) | (1.749) | (1.165) | (1.516) | (1.005) |
| Control | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Observations | 1,728,905 | 363,037 | 582,136 | 390,528 | 393,204 |
| IV Probit - Land Grant: Age 16-19 | | | | | |
| % BA+ | 2.939*** | 5.051*** | 2.548*** | 2.009** | 1.561** |
| | (1.025) | (1.630) | (0.872) | (0.948) | (0.642) |
| Control | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Observations | 1,086,766 | 218,353 | 361,770 | 248,926 | 257,717 |
| IV Probit - Land Grant: Age 20-24 | | | | | |
| % BA+ | 5.036*** | 7.555*** | 4.828*** | 4.788** | 2.922* |
| | (1.770) | (1.934) | (1.550) | (2.438) | (1.529) |
| Control | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Observations | 642,139 | 144,684 | 220,366 | 141,602 | 135,487 |

Note: The first column presents first stage regression results, where the dependent variable is the share of college graduate. The instrumental variable is a dummy variable that equals 1 if the MSA has a land grant university and 0 otherwise. For the remaining four columns the dependent variable equals to 1 if children between ages 16 and 24 are in school and 0 otherwise. The control variables include child's age, child's age2, child's sex, child's race and ethnicity, head's marital status, head's immigrant status, owning a home, and log value of household income. All regressions are weighted by individual weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

**Table O5. IV Probit: Land Unavailability – Child in School & Share of College Graduate**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|

| Variables | Total | High School Drop Out | High School | Some College | College |
|---|---|---|---|---|---|
| IV Probit - Land Unavailability: Age 16-24 | | | | | |
| % BA+ | 3.171* | 4.885*** | 3.522 | 1.758 | -0.502 |
| | (1.704) | (1.839) | (2.389) | (1.290) | (1.128) |
| Control | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Observations | 1,878,386 | 393,955 | 630,641 | 422,205 | 431,585 |
| IV Probit - Land Unavailability: Age 16-19 | | | | | |
| % BA+ | 1.103 | 3.559** | 0.263 | -0.274 | -3.534 |
| | (1.149) | (1.606) | (1.644) | (1.309) | (2.641) |
| Control | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Observations | 1,176,870 | 236,587 | 390,087 | 268,095 | 282,101 |
| IV Probit - Land Unavailability: : Age 20-24 | | | | | |
| % BA+ | 4.943** | 6.395*** | 6.379* | 3.349* | 1.808 |
| | (2.350) | (2.152) | (3.494) | (1.806) | (1.814) |
| Control | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Observations | 701,516 | 157,368 | 240,554 | 154,110 | 149,484 |

Note: The first column presents first stage regression results, where the dependent variable is the share of college graduate. The instrumental variable is the share of land unavailable for development, created by Saiz (2010). For the remaining four columns the dependent variable equals to 1 if children between ages 16 and 24 are in school and 0 otherwise. The control variables include child's age, child's age$^2$, child's sex, child's race and ethnicity, head's marital status, head's immigrant status, owning a home, log value of household income, and log value of MSA population. All regressions are weighted by individual weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

**Table O6. Probit: Movers vs. Non-Movers: Child in School & Share of College Graduate**

| Variables | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|

| | Total | High School Drop Out | High School | Some College | College |
|---|---|---|---|---|---|
| % BA+ | 0.234** | 0.277** | 0.334** | 0.145 | -0.015 |
| | (0.0947) | (0.141) | (0.153) | (0.112) | (0.089) |
| % BA+ X Recent Mover | -0.238** | -0.601** | -0.147 | 0.0567 | -0.21 |
| | (0.119) | (0.240) | (0.194) | (0.179) | (0.167) |
| Recent Mover | -0.052* | -0.061 | -0.0464 | -0.118*** | -0.019 |
| | (0.029) | (0.053) | (0.0432) | (0.0426) | (0.044) |
| Control | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Observations | 2,072,092 | 424,331 | 694,091 | 467,546 | 486,124 |

Note: Dependent variable equals to 1 if children between ages 16 and 24 are in school and 0 otherwise. The control variables include child's age, child's age$^2$, child's sex, child's race and ethnicity, head's marital status, head's immigrant status, owning a home, log value of household income, and log value of MSA population. All regressions are weighted by individual weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

**Table O7. Probit: Movers vs. Non-Movers: Child in School & Share of College Graduate**

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| % PUMA BA+ | 0.370*** | | | -0.077 |
| | (0.080) | | | (0.095) |
| % PUMA BA+ X High School | 0.243** | | | 0.262** |
| | (0.099) | | | (0.117) |
| % PUMA BA+ X Some College | 0.129 | | | 0.144 |
| | (0.102) | | | (0.114) |
| % PUMA BA+ X College+ | 0.019 | | | 0.257** |
| | (0.106) | | | (0.111) |
| % In School | | 1.609*** | | 1.657*** |
| | | (0.140) | | (0.159) |
| % In School X High School | | -0.154 | | -0.384** |
| | | (0.159) | | (0.188) |
| % In School X Some College | | -0.263* | | -0.382** |
| | | (0.155) | | (0.168) |
| % In School X College+ | | -0.707*** | | -0.957*** |
| | | (0.170) | | (0.177) |
| Per Student Expenditure | | | 0.0004 | 0.0003 |
| | | | (0.001) | (0.001) |
| Per Student Expenditure X High School | | | -0.0006 | -0.0008 |
| | | | (0.001) | (0.001) |
| Per Student Expenditure+ X Some College | | | -0.0005 | -0.0007 |
| | | | (0.001) | (0.001) |
| Per Student Expenditure X College+ | | | -0.0006 | -0.0006 |
| | | | (0.001) | (0.001) |
| Control | Y | Y | Y | Y |
| MSA FE | Y | Y | Y | Y |
| Observations | 743,612 | 743,612 | 743,612 | 743,612 |

Note: Dependent variable equals to 1 if children between ages 16 and 24 are in school and 0 otherwise. The control variables include child's age, child's age$^2$, child's sex, child's race and ethnicity, head's education, head's marital status, head's immigrant status, owning a home, log value of household income, and log value of MSA population. All regressions are weighted by individual weights. Robust standard errors, corrected for MSA by year clustering, are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).