Assessing Intergenerational Mobility, Transmission of Education for Immigrants in the United States

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Abstract
up in the intergenerational race to the top? And how does it differ across regions in the United States? Using the New Immigration Survey (NIS) data, this paper analyzes how educational outcomes of individuals compare to their immigrant parents. The underlying presumption is that if a person achieves higher education than his/her parents, then s/he "moved up". Furthermore, this may not be the case for immigrants. The contribution of this paper lies in using legal immigrants as the focus population. Additionally, it characterizes intergenerational mobility through three generations, and compares such mobility across 14 regions of the United States. Results show that an additional year of education of the parent is associated with an increase between 0.3 to 0.4 years of education of the individual. This is compelling evidence to say that children of immigrants have higher education than their parents, hence "moving up".
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1. Introduction

Whether an individual's economic outcomes, such as income or education, depend on their parents, is an important topic in regional economics. If some regions allow for more opportunities, regardless of family background, individuals have incentives to move to such regions, especially those with a less fortunate upbringing. However, other circumstances, for example not knowing the destination's language, may prevent the individual from taking full advantage of the destination's opportunities. In this paper, I evaluate the intergenerational mobility of legal immigrants in the United States based on educational outcomes, and compare it across the country.

Using the New Immigration Survey (NIS) data, I am able to compare educational outcomes of individuals to their parents. The idea is that, if a person achieves higher education than his/her parents, then s/he "moved up". Furthermore, this may not be the case for immigrants, since other variables such as language or different returns to education across locations may cause the person to "move down". In this sense, the contribution of this paper lies in using legal immigrants as the focus population. Additionally, I compare the intergenerational mobility through three generations, and across 14 regions of the United States. I seek to answer the following questions: are immigrants achieving higher education levels than their parents? Are their children moving up in the intergenerational race to the top? And how does it differ across regions in the United States? Results show that one additional year of education is associated with an increase between 0.3 to 0.4 years of education of the child. This is compelling evidence to say that children of immigrants have higher education than their parents, hence "moving up". Analysis of immigrants and their parents show similar coefficients, but it does not correct for endogeneity into being an immigrant. Future work will compare these numbers with statistics of intergenerational transmission of education of native born.

There is empirical evidence showing how an individual's outcomes such as education and income are correlated to their parents'. However, whether it is just a correlation or a causation story is a subject of debate. In other words, even though a parent's education is a good predictor for a person's educational attainment, it is not clear whether higher education of parents indeed helps an individual attain higher education. Consider, is this correlation masking higher innate ability of both parents and children? If such is the case, then other outcomes, such as income or earnings could mask this innate ability as well, attributing a child's "progress" to these variables and not the underlying innate ability.

The differentiation of correlation vs causation of intergenerational outcomes can have significant policy implications; because, identifying the mechanisms that allow intergenerational mobility guides where public resources are targeted. Such identification goes beyond the scope of this paper. However, even if this paper does not identify causality, characterizing intergenerational mobility across locations can give insights. Consider income as an outcome. In this case, characterizing the intergenerational income elasticity across regions can help identify which regions are better for the future generations. Focus study of those regions can reveal the mechanisms that help earn higher incomes.

Even though there has been many studies on intergenerational mobility, this paper fills the gap of contemplating a population that is not native to the location. In this paper I focus on intergenerational mobility of immigrants in the United States. Their status as immigrants comes with observable and unobservable characteristics that systematically separate them from the general population. A clear example is language. If a person does not know the language as well as the native, then the individual may not perform as well in school or at work as a native. This directly affects the expected lifetime income or educational attainment. Other more nuanced examples include self-selection to migration, lower outcomes due to cultural differences, or lower social capital, again when compared to natives. That is why this paper does not attempt to compare immigrants with natives, rather it compares immigrants to themselves.

The contribution of the paper lies not only on the fact that it is immigrants, but it also does such comparison across 3 generations, and across different regions of the United States. Going back to the language example. Given the same family background, two rational expected utility maximizer individuals, whose utility is a function solely on income, will choose to relocate to a region that gives the highest probability of income. If one individual is a native and another one is an immigrant, there are many reasons why one location will lead to higher income to one and not the other. One of such characteristics, as previously mentioned is language. Another characteristic is peer-groups and social networks. Even though this paper will not go into detail as of the reasons why intergenerational mobility differs across regions, it is a first step. This paper describes how the regions differ, so that future research can evaluate why they differ.

The following pages are structured as follows. Section two presents literature on intergenerational mobility and migration determinants. Section three sets up the canonical model for intergenerational mobility focusing on intergenerational elasticity. Section four describes the empirical strategy including the estimation approach, data description, and limitations. Section five shows the results, motivating the analysis by showing intergenerational mobility between immigrants and their children, as well as immigrants and their parents. This analysis sets up the econometric specification to which regional variables are added. Finally, section six concludes.

2. Literature Review

Before considering intergenerational mobility of migrants, it is important to mention some of the previous literature on intergenerational mobility, determinants of migration, and how they interject. This leads to possible reasons why intergenerational mobility differs by location, in particular for migrants. Some of these reasons include peer effects.

It is important to mention one of the reasons why migrants may be particularly different, and that is, self-selection. Migrants are different than natives, not only because they are coming from a different country, but because of unobserved factors that incite them to migrate. To understand this, migration research attempts to answer questions about why and how people migrate (determinants) and what are the effects of migration on origin and destination (effects). It is not always easy to differentiate between the two, because of the endogeneity. More on this in the following paragraphs. Furthermore, there is empirical and theoretical evidence that suggests the importance of economic related aspects such as private monetary costs of migration and returns to that investment, labor redistribution, employment, and expected income (Sjaastad 1962; Greenwood 1997; Massey et al. 1993; Faggian and McCann 2009; Chen and Rosenthal 2008). The literature on migration looks at either the effects on location from migration flows, or at the determinants of migration for an agent. Even if we focus only on an individual's incentives for migration, general equilibrium effects may lead to lower wages at the destination due to changes in the supply of labor because of migration flows. The Economics of Labor Migration by Charles Mueller (Mueller 2013) presents a review of some of the models used to understand individual incentives. This review focuses on the empirical literature and estimation methods. It gives insights on the main characteristics that determine an individual's propensity to migrate (demographics, human capital, employment history, household characteristics, etc.). Another well-cited, but slightly dated review is Borjas' Economic Theory and International Migration (Borjas 1989). Like

Mueller, it presents models for empirical estimation but gives a heavier emphasis on the effects on locations and how they are either 1. caused by the migration flows, or 2. characterize a location, further affecting the incentives of migrants. This clear endogeneity of people and space makes the study of a migration a wide and broad subject that goes beyond economics.

On another note, the characteristics of migrants can vary greatly, hence the difficulty to utilize one single general theory to model their incentives. As mentioned earlier, wage differentials and opportunity costs are an important determinant of migration, but they may interact with other aspects as well. In this paper, I consider two that can affect the framing of the maximization problem of the individual: returns to education and timespan. Returns to education refers to the correlation of higher income with higher levels of education. Consequently, an individual may decide to migrate expecting higher income due to either higher returns to education, or the possibility to acquire further education. In terms of timespan, when deciding to migrate, the individual may be maximizing not over its own lifetime, but including the possible returns for his descendants.

Intergenerational mobility may be one incentive for migration, but its importance goes beyond an individual's maximization problem. The persistence of intergenerational outcomes is an important topic for individual and social welfare. For example, if there is intergenerational persistence of poverty, it is important to understand if there are policies that can help future generations escape the poverty traps. Two important reviews on intergenerational mobility include Solon and Black and Devereux (Solon 1992; Black and Devereux 2010). The question has evolved from whether there is such a thing as intergenerational mobility (or persistence), to how to calculate it, and to what is the optimal level of mobility.

Even though intergenerational mobility could be assessed with different outcome variables, education is an important outcome. Not only there is evidence of the positive correlation between education and income (seminal review papers are Card 1994; Griliches and Mason 1972) but it can also improve individual and public welfare (Vallet 2017; Black and Devereux 2010). This paper focuses on intergenerational mobility using education as outcome, that is, how the education of individuals compares to their parents.

Even though several papers show a positive correlation between children's education and their parents, this one may vary on cohorts, gender of the parent or child, or the nature of the filial relationship -biological, step, adopted. (Chevalier 2004; Black and Devereux 2010; Black, Devereux, and Salvanes 2005; Dustmann 2004; Altonji and Dunn 1996; Chetty, Hendren, Kline, and Saez 2014). Additionally, other family background characteristic such as family size, birth order, and gender of siblings, matter (Kessler 1991; Ejrnæs and Pörtner 2004; Altonji and Dunn 1996). I will not elaborate on these characteristics. However, I do offer comparisons between intergenerational mobility when the youngest generation is the eldest in the family, vs. the most educated one.

Finally, empirical evidence also shows that depending on the location, the intergenerational mobility varies (Abbott and Gallipoli 2017; Andrews et al. 2017). Studies from Greece, Switzerland, England, and the United States, among others, show different estimates and different determinants of mobility (Bauer and Riphahn 2007; Solon 1992; Björklund, Jäntti, and Lindquist 2009; Daouli, Demoussis, and Giannakopoulos 2010; Chevalier 2004; Black, Devereux, and Salvanes 2005). These papers make significant efforts into identifying exogenous variation for identifying the mechanisms of mobility. Moreover, location differences can still give insights into what is it about those places that aids or hurts the future generation. For example, is it because of public investment in areas such as education (Poterba 1998) or is it because of peer effects (Chetty and Hendren 2014; Chetty, Hendren, Kline, Saez, et al. 2014). Given the extensive literature on intergenerational mobility, the next section delimits the theoretical model that will guide the analysis of this paper.

3. Theoretical Model

Models of inter-generational investment are based implicitly or explicitly on the lifetime utility maximizer agent. The agent invests in the future generation either because of an intangible objective (referred as altruism) or because of a tangential objective of returns on investment during the later ages in life (for a seminal paper see Becker and Tomes 1979). This paper is not concerned with identifying the parents' incentives for investment; rather, it focuses on intergenerational mobility for immigrants. The motivation behind intergenerational mobility lies on setting the first step to identify whether parents' migration decisions take into account future generations outcomes.

For measuring intergenerational mobility, let's start with Solon's model (Solon 1992) of the correlation between children's outcome to their parents. Let y_{1i} be an individual's long-run outcome and y_{0i} the parent's outcome. Then equation (1) denote the relationship between generations, where β is the parameter of interest.

Eq. (1)

$$y_i = \beta x_i + \varepsilon_i$$

If we take logs of both outcome variables, then β becomes the intergenerational elasticity, IGE. Following Chetty et al.'s (Chetty, Hendren, Kline, and Saez 2014) study, where the outcome variable is income, then IGE is the intergenerational elasticity of income. This relationship is denoted in equation (2). where $\rho_{xy} = Corr(\log x_i , \log y_i)$ is the correlation between the log of the individual's income and the log of his/her parent's income, and SD is standard deviation. In this case, $IGE = \beta$.

Eq (2).

$$IGE = \rho_{xy} \frac{SD(\log y_i)}{SD(\log x_i)}$$

This paper will follow this model, in order to find β for different immigrants in different regions of the US, with education as the outcome variables.

4. Empirical Strategy

It is important to note that in this paper there is no exogenous variation that can help identify the causality relationship between parent's characteristics and individual's outcomes. The contribution is based on a sample of immigrants for 3 generations, and it entertains estimates across regions. I first describe the empirical approach, followed by the description of the data and ending with the limitations due to the data availability. The next section will show the analysis and results.

Empirical Approach

I will follow a modified version of Bauer and Riphahn's (Bauer and Riphahn 2007) regression equation, eq. (3) and (4) below, that builds from equation (1) on section (3).

Eq. (3)

$$y_i = \alpha + \beta_1 x_i + \gamma_1 C_i + \gamma_2 R + \varepsilon_i$$

Eq. (4)

$$y_i = \alpha + \beta_1 x_i + \beta_2 (x_i * R) + \gamma_1 C_i + \gamma_2 R + \varepsilon_i$$

α is a constant, β_1 is the correlation between education attainment and parent's education, C stands for control variables, R stands for regional dummies, γ are the coefficcients on the control and regional variables, and β_2 is the coefficient on the interaction between parent's education and geographical location.

From equation (3), a positive value for β_1 means that there is positive correlation between education and the parent's education. This means that if the parent has more education, the child will likely have more education. In this equation, γ_2 identifies whether a region gives higher expected education levels for individuals, but does not relate to the intergenerational effects. Because of this, we have the modified equation (4), which includes the dummies for parents' education and regional variables. β_2 then indicates whether some regions will help or hurt the parents' motivation for better education attainment for their children.

Data

One important point of this paper is the use of immigrant data and the characterization over 3 generations. I will use the public use dataset of the New Immigrant Survey (NIS)[1] administered by the Office of Population Research at Princeton University. The NIS is a longitudinal survey of legal immigrants in the United States. NIS is a national representative sample and it contains socio-economic information of the households. This allows to identify education levels of parents of the respondent as well as children. The NIS had a pilot and 2 rounds administered in 2003. For this analysis, I used the first round of 2003.

The NIS had a sample frame of 12,500 household, of which 8,573 interviews where completed. Each household provided information on the head of the household, the children, and their parents. After filtering the data to those households that had children, the education information for children and respondent is available, and it is likely the children has attained its maximum level of education, the number of households reduces. The sample size for this study falls within the range of 500-1200 observations depending on the specification.

There are two relevant additional clarifications related to the sample used for analysis. One is in regards to complete observations, and the other one to age of education of the youngest generation. If an observation does not contain information on one of the variables of interest or control, the sample used for such analysis is deleted. Deleted observations includes answers of "refusal" or "do not know". In terms of the youngest generation, children under the age of 25 are taken away from the sample. Because lifetime education is the outcome variable, in order to avoid Life Cycle bias (for additional information see Black and Devereux 2010), I filtered the dataset

[1] For more information on the dataset go to http://nis.princeton.edu/data.html

such that the education of the person of interest (respondent or child) is likely finished. This age is also selected considering that college education is likely finished by this age. I used different specifications ranging from 18-30 and results are robust to ages above 25. Additional robustness checks could be made for those people that decide to go to school later in life, but the dataset does not contain a full education history.

Limitations

One of the main limitations of this analysis is that the data only contains income for the interviewed generation; consequently, I am not able to rank the other generations to identify whether there is moving up or down across generations. However, I can identify whether there is a correlation with parent's education, and if it varies across regions. Additionally, because the control variables are only for the respondent, in order to do comparisons across generations, I do not include additional controls on the regression, other than gender. Even if some demographic questions are asked for children or parents of the respondent, filtering the sample to those complete observations reduces the sample significantly.

Another limitation is the size of the regions. The regional areas are constrained by the availability of the data. I can only identify 14 regions and they are big in size, so there could be issues when aggregating regional control variables. I decide to not control for geographical characteristics, and leave it for future analysis.

Finally, the subsample selected for this analysis presents two important restrictions. First, even though NIS is a nationally representative sample for the United States, my subsample may not be a representative sample of each region. Second, after selecting the relevant and complete observations, the sample size is very small, especially per region. Sample size is a big concern when we think about power, that is why during the analysis I run different specifications.

5. Analysis and Results

Recall from section 2 and 3, that the coefficient of interest is β, or the correlation between education level across generations and across regions. I will start the section with summary statistics of the outcome variable of interest, education level. Next, I will show the relationship between education with parents from the three generations. Finally, I will show the estimates across regions. For each subsection, I will describe how I arrived to the selected sample, and interpret the results, given the limitations described in the previous section.

Summary Statistics

Let's start our analyzes by showing some descriptive statistics of our variables of interest, that is, education level of the respondent, his/her children, and his/her parents. Table 1 shoes the mean, standard deviation and number of observations.

Table 1

Variables	Mean	Standard Deviation	Observations
Years of education respondent (all)	12.68	5.074	8,535
Years of education respondent (females)	11.97	5.206	4,419
Years of education respondent (male)	13.44	4.816	4,116
Years of education child (all)	7.969	5.600	12,403
Years of education child age >24 (all)	12.05	4.411	4,447
Years of education child age >24 (most educated)	14.38	3.859	1,506
Years of education child age>24 (eldest)	12.96	4.248	1,034
Years of education mother	7.735	5.758	6,779
Years of education father	9.326	6.158	6,184

Based on these means, we see an increase in education across generations, with the eldest generation showing the lowest levels of education. From this table, we can also observe that average education of males is higher than females, across all three generations. Another important point to mention is the selection of the youngest generation. The mean education of all the children of every household is 12.05; however, when we select only one child per household, mean education increases. Studies about selective investment on children per household is beyond the scope of this paper, but this estimate is included for comparison. I used two criteria to select which child will be used as the final generation. One criteria is using the eldest son/daughter, and another criteria is using the son or daughter with the highest level of education. There could be bias in either of these specifications, and that is why I include both in my results. Furthermore, both criteria indicate that the youngest generation achieved higher levels of education. Future research could include selection of a different criteria or controlling family dynamic characteristics (such as number of siblings, order of birth, etc.).

Intergenerational Mobility of Education

The first analysis is regressing education of the children on the respondent's education level. This will show the relationship between an individual (the child) and its parents. Results are summarized on table 2. The coefficient on the Years of education of the respondent indicates how the education of the respondent is related to its children. A negative coefficient will hurt the child and a positive coefficient indicates higher education of parents imply higher education of children. Column (1) includes all children in the sample whose education is available. The negative coefficient is explained by the fact that some children have not finished lifetime school attainment, also explained by lifetime cycle bias. In order to avoid this bias, I limit the sample to those children whose age is above 25. Column (2) shows this result. On another point, including all the children in the sample gives a biased estimator, since households with more children will be weighted heavier. Because of this, I decide to use only one observation per household. This means that I have to select a criteria for the selection of the representative child. I decided this criteria to be to select one child per household and I include two different specifications in reference on how this representative child is selected. One is selecting the eldest, results on column (3); and the other one is selecting the most educated one, results on column (4). After correcting for lifecycle bias, the coefficient is positive. The estimate indicate that an additional year of school of the parent, is associated with around 0.4 more years of school for the child.

An advantage of this dataset is that it includes the immigrant's education level, his/her children's education, and his/her parent's education. Table 3 shows the results of regressing the immigrant's education attainment with his/her parents. Using only one parent shows that an additional year of school of a parent indicates half a year of school of the offspring, in this case the respondent. Furthermore, this coefficient reduces when we include both parents in the regression, having the father's education a higher impact on the child's education attainment. This indicates that it would be useful to include the education level of both parents in the regressions of table 2. Even though NIS does include spouse's education, it is incomplete and does not always include the education of the parent of the child of the respondent. Even if we cannot include both parents in the regression, table 3 gives evidence that our coefficients on the youngest generation are may be biased upward. Another point to mention is that, given that the gender of the parent affects how much education is important, it might be the same for the gender of the child. Column

(4) controls for gender. As predicted from the summary statistics, females have lower education levels.

Table 2

Variables	**(1) All children**	**(2) All children age>24**	**(3) Eldest child**	**(4) Most Educated child**
Years of education respondent	-0.0528***	0.450***	0.419***	0.338***
	(0.00901)	(0.00981)	(0.0197)	(0.0159)
Constant	8.531***	8.294***	9.145***	11.15***
	(0.109)	(0.0981)	(0.214)	(0.177)
Observations	12,358	4,170	940	1,381
R-squared	0.003	0.336	0.325	0.247

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3

Variables	**(1) Only Mother**	**(2) Only Father**	**(3) Both**	**(4) Controls**
Years of education mother	0.495***		0.197***	0.201***
	(0.00877)		(0.0146)	(0.0144)
Years of education father		0.499***	0.353***	0.346***
		(0.00819)	(0.0135)	(0.0134)
Gender Respondent				-1.069***
				(0.101)
Constant	9.159***	8.557***	8.387***	8.955***
	(0.0846)	(0.0916)	(0.0935)	(0.107)
Observations	6,779	6,184	5,876	5,876
R-squared	0.320	0.375	0.396	0.407

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Comparing results from table 3 and 4 indicate that there is a higher jump from immigrants with respect to their parents, than from immigrant children with respect to their parents. Some reasons that may explain this include:

- There is self-selection on immigrants. The sample of immigrants may be composed for those very ambitious individuals, and this ambition also helps them attain higher education than their parents.

- The opportunity cost of investment of education is higher for the children of immigrants. That is, there are higher returns from higher education levels for the immigrants, than for the children of immigrants.

This analysis does not show enough evidence to explain either theory, but it is a first step to realize that there are systematic differences between the groups.

Even though generations can be systematically different, it may be that education levels can be affected for more than one generation. That is, an individuals' education is affected not only by the parent but also by the grandparent's education. We return to the education of the youngest generation as the dependent variable and include gender and education of grandparents. Results are on table 4 and 5. Table 4 uses the most educated child and table 5 the eldest child as the representative child. I included an additional column on table 5, which is the same column (3) of table 4, for ease of viewing.

As expected, there are lower returns to parents' education to the most educated child, than the eldest child, but this is by construction. Since the most educated child has higher education on average, the marginal increase on education from an additional year of schooling of the parent will be lower for the most educated child. The most important result is the positive and significant coefficient on parents and grandparents coefficients, as well as its stability across specifications. Even though this estimate may be biased upwards, it means that an additional year of education is associated with an increase between 0.3-0.4 years of education of the child. This is compelling evidence to say that children of immigrants have higher education than their parents, hence they are "moving up".

From columns (4) and (5) of table 5 we can see other interesting results. First, contrary to our initial guess, men do not have higher education than women. The differences in means from the summary statistics section between genders, goes away after controlling for family's education. The estimates are not significant. However, the gender of the grandparent does matter. As we saw in table 3, father's education has a higher impact than mother's education. We are not able to include the education of both parents in the regression, but we are able to include both grandparents. Female intergenerational effect is still lower in comparison to male, but in our specification it becomes negative. Even though the coefficients are significant, they are small. Additionally, these coefficients may be capturing some of the effects of which parent has a higher impact, the mother or the father. Data on both parent's education can give further robustness to the study.

As explained earlier, data limitations on education of both parents lead to the inclusion of only one parent on the regression. An alternative solution to this issue is to include an interaction term between education of the parent and the gender of the parent. Including such term gives statistically and economically insignificant estimates but do not change the estimates of the parameter of interest, so I do not include them in the results. They are available upon request. Results are stable across specifications. Further interactions with gender of the child and education levels of the parent could give additional insights. Including such interactions do not change the basic results, but they are available upon request as well.

Table 4

Most Educated Child Variables	**(1) Simple**	**(2) Gender**	**(3) Intergenerational**
Years of education Parent	0.338***	0.343***	0.337***
	(0.0159)	(0.0162)	(0.0252)
Gender Parent		0.339*	0.296
		(0.193)	(0.239)
Gender child		-0.0604	-0.0898
		(0.178)	(0.228)
Years of education grand mother			-0.123***
			(0.0364)
Years of education Grandfather			0.123***
			(0.0322)
Constant	11.15***	10.91***	10.76***
	(0.177)	(0.251)	(0.313)
Observations	1,381	1,381	845
R-squared	0.247	0.249	0.290

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5

Eldest Child Variables	(1) Simple	(2) Gender	(3) Intergenerational	(4) Intergenerational Comparison
Years of education Parent/respondent	0.419***	0.426***	0.399***	0.337***
	(0.0197)	(0.0200)	(0.0314)	(0.0252)
Gender Parent/respondent		0.451*	0.233	0.296
		(0.245)	(0.307)	(0.239)
Gender Child		0.186	0.251	-0.0898
		(0.220)	(0.285)	(0.228)
Years of education Grand mother			-0.0778*	-0.123***
			(0.0451)	(0.0364)
Years of education Grand father			0.146***	0.123***
			(0.0399)	(0.0322)
Constant	9.145***	8.686***	8.521***	10.76***
	(0.214)	(0.307)	(0.384)	(0.313)
Observations	940	940	547	845
R-squared	0.325	0.328	0.402	0.290

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Regional Differences

The final section of this analysis includes the regional component. The NIS public access data identifies the location of the respondent at the time of interview in one of 16 regions, or outside of the United States. Table 6 shows the regions, its codification, and the states included in each region.

Following the previous analysis, I regress child's education on parents education, and include gender of child, gender of parent, and education of both grandparents. Results are on table 8. Before discussing the results, it is important to mention the distribution of the population across regions. Table 7 shows the count of observations per region, as well as what percentage of the population it represents. It does this for the sample with the eldest son/daughter, and the most educated son/daughter. It also includes it for the samples once the grandparents education. Recall that including grandparents' education reduces the sample because incomplete observations are dropped.

It is evident that the population is not equally distributed among regions. However, this is not unique to the samples used on this paper. Tabulating the population per region with the entire dataset also shows an unequal distribution. This may be either because of the use of weighting by the NIS, or because it is equally distributed in a more granular level. Including either weights or more granular data is not possible due to limitations by data and statistical skills of the analyst. Furthermore, even with an unbalance sample, we can draw conclusions about regional differences as long as sample size is big enough. It is noticeable the small number of observations to some of the regions, and this problem is only exacerbated by the specification that includes grandparents. Because of this, I provide results with and without the grandparents' education for reference, but only evaluate the specification without the grandparents.

Table 6

Code	Region	States Included
1	California	(CA)
2	Florida	(FL)
3	Illinois	(IL)
4	New Jersey	(NJ)
5	New York	(NY)
6	Texas	(TX)
7	New England	(CT,MA,ME,NH,RI,VT)
8	Middle Atlantic	(DE,DC,MD,PA)
9	South Atlantic	(GA,NC,SC,VA,WV)
10	East South Central	(AL,KY,TN,MS)
11	East North Central	(IN,MI,OH,WI)
12	West North Central	(IA,MN,MO,ND,SD,NE,KS)
13	West South Central	(LA,OK,AR)
14	Mountain	(AZ,CO,ID,NM,NV,UT,WY,MT)
15	Pacific	(AK,HI,OR,WA,FM,AP)
16	Non Continental U.S. Territories	(PR,VI,GU)
95	Not United States	
-1	Refused	
-2	Don't Know	

Table 8 shows the differences in education among regions. After controlling for parents' education, there are still differences in the education levels attained by the individuals across regions. A more robust analysis of intergenerational mobility could include interactions between the regional dummies and the parent's education, but sample size limits the capability of performing such analysis. Using the respondent and his/her parents gives a sample size big enough to perform such analysis. Most regional coefficients are not significant. The ones that are significant show the same direction as the non-interaction coefficients. This analysis however, does not entertain the immigrant aspect, so its interpretation is limited. I am not including the table of results but they are available upon request.

Table 7

	Eldest		**Intergeneration**		**Most Educated**		**Intergeneration**	
Region Code	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
1	301	32.33	173	31.92	425	31.34	263	31.65
2	63	6.77	33	6.09	106	7.82	65	7.82
3	50	5.37	36	6.64	74	5.46	52	6.26
4	64	6.87	39	7.2	75	5.53	47	5.66
5	140	15.04	75	13.84	200	14.75	105	12.64
6	59	6.34	31	5.72	89	6.56	54	6.5
7	39	4.19	24	4.43	65	4.79	44	5.29
8	46	4.94	27	4.98	65	4.79	40	4.81
9	53	5.69	31	5.72	76	5.6	41	4.93
10	3	0.32	2	0.37	6	0.44	4	0.48
11	26	2.79	17	3.14	37	2.73	23	2.77
12	12	1.29	6	1.11	20	1.47	11	1.32
13	2	0.21	2	0.37	3	0.22	3	0.36
14	37	3.97	23	4.24	56	4.13	37	4.45
15	36	3.87	23	4.24	58	4.28	41	4.93
Total	931		542		1,356		831	

Table 8

	(1)	(2)	(3)	(4)
Variables	**Eldest**		**Most Educated**	
Years of education Parent/respondent	0.413***	0.366***	0.341***	0.329***
	(0.0206)	(0.0334)	(0.0168)	(0.0260)
Gender Parent/respondent	0.473*	0.173	0.365*	0.301
	(0.247)	(0.320)	(0.197)	(0.245)
Gender child	0.181	-0.363		
	(0.222)	(0.299)		
years of education Grand mother		-0.143***		-0.113***
		(0.0480)		(0.0375)
Years of education Grand father		0.151***		0.118***
		(0.0420)		(0.0330)
2	-0.177	-0.0501	-0.139	0.143
	(0.483)	(0.651)	(0.371)	(0.463)
2	-0.574	0.175	-0.456	0.147
	(0.538)	(0.632)	(0.429)	(0.506)
4	1.051**	1.045*	1.070**	1.006*
	(0.482)	(0.611)	(0.425)	(0.526)
5	0.185	0.574	0.342	0.406
	(0.357)	(0.477)	(0.292)	(0.385)
6	0.891*	1.200*	0.323	0.598
	(0.497)	(0.665)	(0.396)	(0.494)
7	0.754	0.791	0.527	0.468
	(0.594)	(0.745)	(0.452)	(0.539)
8	1.218**	1.499**	0.484	0.695
	(0.558)	(0.714)	(0.455)	(0.566)
9	1.334**	1.167*	1.137***	1.102**
	(0.522)	(0.675)	(0.425)	(0.561)
10	1.366	1.308	-0.154	-0.0487
	(2.019)	(2.425)	(1.395)	(1.665)
11	1.213*	0.753	1.113*	0.694
	(0.720)	(0.886)	(0.588)	(0.727)
12	0.802	0.984	-0.567	-0.237
	(1.025)	(1.421)	(0.777)	(1.019)
13	0.352	1.276	0.506	0.937
	(2.471)	(2.448)	(1.972)	(1.932)
14	0.389	-0.555	0.138	-0.415

Variables	(1) Eldest	(2)	(3) Most Educated	(4)
	(0.606)	(0.763)	(0.483)	(0.585)
15	-0.00626	0.951	0.173	0.641
	(0.614)	(0.761)	(0.476)	(0.558)
16			-2.103	-1.812
			(3.396)	(3.318)
Gender Child			-0.0207	-0.0259
			(0.181)	(0.233)
Constant	8.470***	10.32***	10.66***	10.49***
	(0.340)	(0.439)	(0.281)	(0.351)
Observations	924	540	1,353	828
R-squared	0.346	0.364	0.264	0.301

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Focusing on the children of the immigrants shows that differences in educational attainment of children of immigrants differs across the country, but only in some particular areas. The region of reference is California. This means that the coefficients of each regional dummy shows the difference in years of education between California and such region. The only regions that have significant coefficients are New Jersey, Texas, Middle Atlantic, South Atlantic, and East North Central, and they are all positive. This means that these regions have higher average years of education than California. These differences range from 0.3 of a year to over more than year difference. Even though we cannot characterize regional differences on intergenerational elasticity of mobility, results are insightful for they show limited inter-regional differences in the majority of the country.

This section shows that there is an increase in education across generations from the children of immigrants. It also adds to the evidence of positive correlation between years of education and parent's education, this time with an emphasis on immigrants in the United States. Finally, it shows that, even though there are some areas that show higher education of children of immigrants, there is relative homogeneity on educational outcomes of immigrants across the country.

6. Conclusion

Do the children of immigrants “move up” with respect to their parents? Does it matter where in the US the immigrant lives? Data from the New Immigration Survey shows that there is intergenerational mobility among immigrants. Children of immigrants do better than their parents, but immigrants do even better than their parents in comparison to their children. Is it because immigrants have innate characteristics that their children may not have, or is it that the location of the children has an effect? The analysis of this paper does not establish the mechanisms of intergenerational mobility, but it is a first description to show that immigrants also experience intergenerational mobility in regards to education. Below is a list of possible extensions of this paper:

- Controlling for family and household characteristics. First, including data on education level of both parents can help with the upward bias of the estimations and give further robustness to the study. However, including other family background information can help identify whether it is the parent’s education that help the child’s higher attainment, or another family structure characteristic. Some characteristics are number of siblings, gender and age of siblings, order of birth, and age at which the parent/child migrated.
- Include more information describing the characteristics of each region. Controlling for geographical characteristics such as population density, average income, average education level per cohort at a location, unemployment level, or characteristics of the population as language or religion. These variables can help identify which mechanism is important for intergenerational mobility disparities.
- Similarly to above, include geographical characteristics, but not of the destination but of the origin. This can help identify the characteristics of immigrants in a particular area.
- Following other intergenerational mobility studies, additional extensions could include using other outcome variables such as income, health outcomes, or occupational/career outcomes.

These extensions can help disentangle the mechanisms of intergenerational mobility, or persistence.

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