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Intergenerational Transfer of Human Capital among Immigrant Families

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Intergenerational Transfer of Human Capital among Immigrant Families

Abstract

While immigrants in the United States tend to earn less than comparable natives, their children close the earnings gap. The purpose of this study is to determine how differences in intergenerational transfer of human capital between immigrant families and native families affect different earning outcomes for respondents of each group. Specifically, this study uses a human capital framework to analyze both the direct effect of parental education on respondent earnings and the indirect effect on earnings by first affecting respondent education, which in turn affects respondent earnings. Data from the 1979 National Longitudinal Survey of Youth allows background variables within a family from 1979 to be related to respondent earnings in 2006. Thus, human capital investments made by parents can be linked to respondent outcomes several years later. The analysis shows that while parental education is a strong predictor of respondent education and earnings in the native population, it is weaker for second generation immigrants. Perhaps second generation immigrants overcome deficiencies in their parents' human capital through higher levels of motivation.

Keywords

Immigrant, Human Capital, Intergenerational, Transfer

Cover Page Footnote

This was the author's senior honors thesis at Illinois Wesleyan University, advised by Dr. Michael Seeborg. The author is very thankful to Dr. Seeborg for his advice and guidance throughout the year.

In 1970 the foreign-born population in the United States was 4.7%; in 2003 it had increased to 11.7% (U.S. Census, 2009). The population demographics of immigrants in America have also changed dramatically since the 1950's. Early populations consisted mainly of Europeans and Canadians followed by Latinos, while later groups consisted primarily of Latinos followed by Asians. In the United States immigration is an important issue and has been a leading political topic for many years. Since revisions to the Immigration and Nationality Act began in 1965, relaxing the 1920's quota system, the number of immigrants has climbed to new heights.

An important implication of the increasing number and diversity of immigrants is the increasing number of immigrant descendants, especially those who have not fully assimilated to American culture. As this number grows, it becomes increasingly important to study the differences in human capital that immigrants offer compared to natives, and how that human capital benefits their children. Once this is understood, policy can be enacted both to increase the efficiency of these benefits for second generation immigrants and to try to translate these benefits to native children. This study will compare the intergenerational transfer of parental human capital from parents to children for native and immigrant families. A major focus is on how the human capital of immigrant parents affects the earnings of their children.

I. Review of the Literature

The statistical phenomenon of "regression towards the mean" accounts for some of the improvement in earnings second-generation immigrants experience over their parents. Theoretically, second-generation immigrants should naturally do better than their parents who perform below the native mean, but they should not, by simple law of regression towards the mean, perform above the native average (Borjas, 2006). Previous research can be divided into two separate schools of thought on this issue. Some work, especially early research, supports the theory that second-generation immigrants outperform natives, while other studies conclude that the apparent improvement is solely regression to the mean and that second-generation immigrants do not perform above the mean.

In early work on the subject, there is assumed to be something unaccounted for that gives second generation immigrants the extra boost to outperform comparable natives (Borjas, 2006). There are several theories explaining why second-generationers outperform their native counterparts and parents. Djajic (2003) proposes that while immigrants are at the mercy of discrimination and are likely to settle for a low-wage job, their children feel that they deserve what they earn, and will not accept discrimination, thus earning higher wages than their parents. Complementing this line of reasoning is the theory that immigrants have very high levels of motivation and pass them on to their children. This, along with assimilation into the U.S. labor force, accounts for second-generation immigrants earning more than their native counterparts and, thus, surpassing the mean.

Borjas (2006), searching for the unaccounted boost above the mean, summarized the evolution that research on this subject has undergone over the years. Early work considered members of three different generations (immigrants, second-generationers, and third-generationers) within the same census year. The problem here is that studying a single census year cross section does not allow researchers to follow specific immigrants and their descendents over time. Since different cohorts, or groups of immigrants who arrive in different years, often have different characteristics, the results from this single-census methodology may offer misleading conclusions.

Subsequent research improved upon this flaw by gathering data from different census years. For instance, immigrant data was collected from the 1940 census while second-generation information was obtained from the 1970 census. Thus, it can be assumed that many of the second-generation immigrants are direct descendents of the 1940 immigrants (Borjas, 2006). Hum and Simpson (2007) concluded that early research, with the single-census design, found second-generation immigrants to outperform their parents and their children, while later research, conducted over time, found the second- and third-generation immigrants inherit the disadvantage faced by their ancestral immigrants, which begins to support the theory of regression toward the mean, but not beyond. The later experimental design is a clear improvement upon earlier research, offering different results, but there is still no direct link between a specific set of immigrant parents and a specific second-generation immigrant. Social implications can also have an effect. For example, research has found a large increase in labor force participation among second-generation women over time, but this does not account for the general increase across the society. Thus, the increase cannot be solely attributed to the fact that these second-generation immigrant women work much more than second-generationers from previous cohorts. To this end, the factual difference between the two cohorts is probably overstated (Borjas, 2006). Because inter-cohort differences are likely not as extreme as they are presented to be, the argument for regression toward the mean can be sufficient despite supposed improvements by second-generation immigrants past the average of natives.

Galarneau and Morissette (2009) found that immigrants who are established in Canada tend to face the same disadvantages as new Canadian immigrants. Furthermore, they found that even with higher levels of education, established immigrants are still placed in low-skilled jobs. Though it also supports regression toward the mean, or at least argues against regression over the mean, these results are in contrast to most research in this area, which concludes that the longer an immigrant lives in a country, the more he or she learns about the culture, including language, training, and job information (see for example, Algan, Dustmann, Glitz & Manning, 2010).

Contrary to Galarneau and Morissette, Chiswick and Miller (2009) found that immigrants are more likely to be over-educated or under-educated for their jobs than are natives. Over-education among immigrants is due to the imperfect transferability of human capital across nations and diminishes over time as the workers can prove their qualifications. Under-education occurs when immigrants specialize in a specific skill or substitute immense motivation to accommodate for their lack of education (Chiswick & Miller, 2009). For example, if an immigrant and a native have the same job and level of education, the immigrant may supplement his or her education with other skills relevant to the job or work harder and longer so that the immigrant will be the employee to get a raise. This work does not allow for all second-generation immigrants to improve beyond natives, but does allow for some under-educated workers to specialize and, appear to rise above the mean for natives with similar educational attainment.

In support of the over- and under- education theory, Roy's Model argues that immigrants tend not to be average representatives of their origin countries. Because the move to America is not geographically difficult or expensive, and American social institutions may be beneficial to them, immigrants from nearby and poor nations likely possess a lesser amount of education, experience, and general human capital than the average citizen of their countries (Borjas, 2008). In the case of Mexico, for instance, a poor person who does not receive a lot of government assistance can move to America and receive higher income through work and transfers. Thus, a Mexican with low human capital may benefit from living in the United States, even when they do not expect to obtain a high-skill job. This is an example of negative selection in immigrant flows.

People from faraway nations, demonstrating positive selection, tend to represent above-average levels of human capital, relative to their national averages. This is partially due to the fact that it is simply much more expensive to move across an ocean. With regard to social institutions, citizens of more socialist countries, for instance Scandinavians, will be further benefited if they can expect to be among high wage earners in America because taxes tend to be lower (Borjas, 2008). Thus, Roy argues that the phenomenon of watching second-generation immigrants from some countries perform above the native mean earnings can be attributed to selection and that they may be regressing toward the mean of their parents which, in the case of positive selection, is higher than natives.

II. Theoretical Model

To analyze the earnings of second-generation immigrants, the most appropriate theoretical framework to use is human capital theory. The basic theory is that, as with a firm, individual people invest in themselves, through education for example, in the hopes of reaping higher returns, often in the form of income. These investments in human capital produce all the income generating skills and productive knowledge the person has.

This concept of "the productive capacities of human beings as income producing agents in the economy" was made an important topic of study in Adam Smith's *The Wealth of Nations* wherein he argued that improvements in workers' skills, and thus productivity, would lead to an increase in both economic progress and welfare (Rosen, 2008). Of special importance to the analysis of second-generation earnings is Alfred Marshall's work, which stated that human capital investments are long-term and emphasized the function of the family as a unit in acquiring these skills and knowledge (Rosen, 2008). This results from the motivation of parents to invest in their children in the hopes of securing them higher earnings in the future. The present project will use human capital theory in predicting the success (measured in earnings) of second-generation children based on the human capital of their parents.

One implication of human capital theory is that as the second-generation acquires more U.S.-specific human capital than their parents, they should experience upward income mobility and some sort of regression toward the mean earnings of natives. Barry Chiswick studied intergenerational mobility of human capital among immigrants and their native-born children and found that while immigrants earn much less than comparable natives, their second-generation children earn more than comparable natives. He also found that by the third-generation, immigrant grandchildren earn an amount equal to natives (Rosen, 2008). This supports the statistical theory of moving toward the mean: that earnings of immigrant families will increase steadily and quickly towards native levels.

The work of Chiswick acts as a foundation for the current analysis of second-generation earnings. Using his findings along with previous work in the field, the intergenerational mobility of immigrant and native human capital can be further analyzed. Based on previous literature and an understanding of the theory of human capital, it is hypothesized that second-generation immigrants will attain higher levels of education and thus record higher earnings than immigrants, and possibly natives, due to their high level of human capital contributed by their immigrant parents.

III. Data

The data used in this study is from the National Longitudinal Survey of Youth beginning in 1979 (National Longitudinal Survey, 2009). The data set follows 12,686 men and women who were between the ages of 14 and 22 years old in 1979, and contains information about family history, education, and specific labor force participation. It is assumed that most of these participants lived at home at the time of the 1979 interview and thus reflect the direct influence of their parents. Children born in the U.S. to immigrant parents (second-generation immigrants) and children born to non-immigrants (natives) will be included to compare across these groups.

This data source is rich and will enable the analysis of specific variables. Especially important for this study are variables measuring the educational attainment of parents. Also, the data includes a variable for which ethnic or racial origin the respondent identifies with the most. The thirty possible responses to this question were divided into two distinct categories: close to the U.S. and not close to the U.S. (detailed in Appendix 1). This strategy reduces the immediate problems with the variable in that the original coding allowed for the identification of either a place of origin or ethnic/racial identity. In the context of Roy's Model, the Close category represents immigrants who tend to underperform natives and the averages of their heritage nations, though geography is not the only variable in Roy's theory (Borjas, 2008). This is because of negative selection of immigrants from places near the U.S. that was discussed earlier.

The National Longitudinal Survey data is frequently used in economic research and is considered reliable. Possibly the most important aspect of it, however, is that it is longitudinal. This gives access to good data about family history and the environment of respondents at a young age, when they are presumably inheriting human capital from their parents, as well as accurate data about earnings when they are settled into the labor market. While most of the independent variables related to family are obtained from the 1979 survey, educational attainment and earnings are obtained from the 2006 survey. A full review of the variables obtained from the data set is located in Appendix 1.

IV. Analysis

The research in this paper will use longitudinal data so that the second-generation immigrants can be linked directly to their immigrant parents. The data base allows exact matching of immigrant parents with their second generation children. This will reduce cohort bias found in cross-sectional census studies that were critiqued by Borjas (2006).

Three types of analysis will be done. The first analysis will be a presentation of descriptive statistics comparing second generation immigrants to natives. The second is a Oaxaca Decomposition, which will begin to explain the observed differences in earnings between second generation immigrants and natives. The final method is a path analysis, which will explain the difference in transmission of human capital in immigrant and native families.

Descriptive Statistics

Simple descriptive statistics shown in Table 1 compare second generation immigrants to natives. Within the data set, second-generation immigrants do earn significantly more than natives and obtain significantly higher education levels. The low significance of the earnings difference (probability equals .017) may be due to high variation of earnings in the second generation immigrant population, possibly

Table 1: Descriptives of Second-Generation Immigrants and Natives (Standard Deviation)

	Second-Generation Immigrants		Natives		Mean Difference t-test
Dependent Variable:					
Wages and Salaries	$51,465.07	(48588)	$45,689.44	(46428)	-2.378*
Independent					
Parent Education	10.29	(4.580)	11.96	(3.048)	11.18***
Respondent Education	13.52	(2.617)	13.29	(2.436)	-2.08*
Library Card	75%	(0.435)	71%	(0.455)	-1.92
Family Size	3.96	(2.734)	3.83	(2.623)	-1.09
Close	58%	(0.494)	8.9%	(0.285)	-34.88***
Female	50%	(0.500)	51%	(0.500)	0.63
Approx. Sample Size	379		4872		

*** denotes significance at the .001 level
** denotes significance at the .01 level
* denotes significance at the .05 level

reflecting different characteristics based on country of origin. This supports the observations of much of the previous research, notably Djajic (2003) that second-generation immigrants surpass the native average level of education, thereby regressing beyond the mean on this measure. Table 1 also shows that the parents of second generation immigrants have significantly lower levels of education than natives. This undermines the assumption offered that parental education is a strong predictor of respondent education (Perreira, Harris, & Lee, 2006). Thus, second-generation immigrants appear to be propelled into above-average earnings by something other than parental education.

A possible explanation of second-generation immigrant performance that cannot be tested here is the role of language in child development. Speaking a second language may improve verbal skills at an early age and have a positive effect on educational attainment and earnings. In this data set, bilingualism cannot be addressed because it is too highly correlated with Immigrant Parents.

One implication of Roy's theory of negative and positive self-selection is that immigrants from nations close to the United States will underperform natives while immigrants from faraway nations will outperform natives (Borjas, 2008). Though Roy also considers several other factors of self-selection, including income equality in both the origin and target countries, social institutions among others, this analysis will only consider geographic relation of the origin country to the U.S. Comparing education levels of the parents of second generation immigrants who are from places close to the U.S. to those who are from places that are not close will identify whether positive and negative selection occur in this limited form of Roy's theory. Furthermore, a comparison of Close and Far second generation immigrants will determine whether negative and positive selection (from the limited definition of Roy's theory used) of immigrants is stable into the next generation. These three comparisons are presented in Table 2, and each one of them supports Roy. The largest difference is, as expected, found in the Parent Education variable. The Close and Far groups begin to converge in the second generation, showing smaller differences, and may converge completely after many generations in the United States. This supports the above-mentioned precaution that the second generation immigrant sample may have more variation than natives. These conclusions, however, require precaution because the identification of place of origin was subjective—both in the selection by the respondent and the assignment to groups by the author (described in Appendix 1). In addition, this is not a complete test of Roy's theory because many social factors that increase motivation to immigrate were not considered. The conclusions, however, do make it apparent that this distinction (Close or Far) should be used as a control variable throughout the rest of analysis.

Table 2: Descriptives of Close and Far second generation immigrants (Standard Deviation)

	Close		**Far**		**Mean Difference t-test**
Parent Education	8.36 years	(4.33)	12.90 years	(3.50)	12.389***
Respondent Education	13.15 years	(2.56)	14.03 years	(2.62)	3.794
Earnings	$46,330.94	(41541.18)	$58,990.88	(56680.75)	2.567**

*** denotes significance at the .001 level
** denotes significance at the .01 level
* denotes significance at the .05 level

Oaxaca Decomposition

Having identified a difference in earnings between second generation immigrants and natives, a Oaxaca Decomposition is performed to explain the cause of this gap. According to the Oaxaca Decomposition, this difference in earnings is the result of two causes: different means and different returns (Oaxaca, 1973). First, there can be different characteristics between natives and second generation immigrants that cause part of the difference in earnings. For example, the average educational attainment of natives could be different from second generation immigrants. Second, a portion of the earnings gap could be due to differences in returns from these characteristics. For example, an additional year of education could produce a larger increase in earnings for one group than the other.

The variables used throughout this research are defined in Table 3. The Immigrant Parents variable measures the effect of having immigrant human capital available on future earnings, and thus, is the primary variable of interest in this study. It is a dummy variable that has the value of one if at least one of the respondent's parents was an immigrant, and zero otherwise. Parent Education (the higher of either the mother's or father's education) is predicted to be the most powerful variable in predicting respondent earnings due to extensive literature showing a strong correlation between it and child earnings (Perreira, Harris, & Lee, 2006). The presence or absence of a Library Card serves as a proxy for parental

Table 3: Operational Definitions of Variables

Dependent Variable:	
Earnings (2006) in dollars	During 2005, dollar amount received from wages, salary, commissions, or tips from all (other) jobs, before deductions for taxes or anything else.
Respondent Education (2006) range: 1-20	Highest grade completed as of May 2006.
Independent Variables:	
Parent Education (1979) range: 1-20	Highest grade completed by the parent who completed the most schooling (1979).

Immigrant Parents (1979) range: 0,1	A dummy variable defined as 1 if one or both of the parents was born outside of the US, and 0 otherwise.
Library Card (1979) range: 0,1	From the question: At age 14, did any household member have a library card? A dummy variable defined as 1 if a library card was present and 0 otherwise.
Family Size (1979) actual number	From the question: How many siblings does the
Female (1979) range: 0,1	Sex of Respondent
Close (1979) range: 0,1	Defined from the question: What is your origin or descent / 1st racial ethnic origin? Grouped by geography (explained in Appendix 1). A dummy variable equal to 1 if the respondent reported a nation close to the United States, and 0 otherwise.

motivation. Having a library card signifies motivation by an adult either to increase his or her knowledge, or possibly to increase that of the entire family. Family Size is determined by the number of siblings a respondent has and is important in that it represents competition for resources within the family. This variable is included to control for competition for resources. Parents can offer all their spare time to a single child while they must divide their time if they have several children. Thus respondents with more siblings may have less interaction with their parents and may receive less of their parents' human capital (Lynn, 1996). A dummy variable for sex is included as an important control because males and females tend to earn different amounts. The final variable, Close, is included as a control in view of Roy's Theory (Borjas, 2008).

The first step of the Oaxaca Decomposition is to run Ordinary Least Squares (OLS) regressions for both natives and second generation immigrants that predict earnings as a function of family background characteristics and Respondent's own Education.

Native Earnings = $\alpha + \beta_1$ (Parental Education) + β_2 (Library Card) + β_3 (Female) + β_4 (Family Size) + β_5 (Respondent's Education) + u

Second Generation Immigrant Earnings = $\alpha + \beta_1$ (Parental Education) + β_2 (Library Card) + β_3 (Female) + β_4 (Family Size) + β_5 (Respondent's Education) + u

The Oaxaca decomposition requires that only one of the two equations presented above be chosen for estimation purposes. It is also sensitive to changes in coefficients; therefore, an insignificant coefficient is a strong threat to the accuracy of the technique. The demographic variable identifying how geographically close the respondents' ancestors were from the United States was initially included in this regression, as in Model 1 from the OLS Regression, but was dropped because it was not statistically significant. The native regression was chosen for estimation because all of its coefficients were statistically significant once Close was removed.

The Oaxaca Decomposition proceeds in five steps.

1. Compute the earnings difference between natives and second generation immigrants.
2. Estimate the native earnings equation (listed above) using OLS regression.
3. Use this equation (from step two) to estimate the earnings that second generation immigrants would earn if they had the same reward structure as natives. This is done by substituting the average characteristic values of second generation immigrants into the native equation.
4. Subtract the average earnings calculated in step three from native average earnings (used in step one). This difference is entirely due to differences in average characteristics between the two groups because the same equation is used (i.e., native equation), so that the returns (i.e., coefficients) must be the same.
5. Subtract the value computed in step four from the total difference in earnings calculated in step one to determine the difference due to different returns. Because the total difference in earnings is caused by only two things (different means and different returns), the difference not caused by different means must be caused by different returns.

The Oaxaca Decomposition is used to explain the difference in mean earnings between natives and second generation immigrants. While it only requires the equation for native respondents, a table is offered including the results of both the native regression and the second generation regression for comparison. The native regression has highly significant results so that the decomposition will not be compromised, but the second generation regression has fewer significant variables. This is a preliminary indication that these variables are not equally important for both groups.

1. (Second Generation Immigrant Earnings - Native Average Earnings);

   Earnings Gap = \$51,465.07 - \$45,689.44 = **\$5,775.63**

2. The earnings equations for natives and second generation immigrants are presented in Table 4.

Table 4: Earnings regressions for Natives and Second Generation Immigrants

	Native Coefficients	t-statistic	Second Generation Immigrant Coefficients	t-statistic
Constant	-41682.118***	-10.176	-48308.017***	-3.578
Parental Education	1167.876***	4.939	1079.931*	1.982
Library Card	4570.328***	3.262	-1650.725	-0.308
Female	-24373.302***	-20.303	-31704.399***	-7.330
Family Size	-696.834**	-2.784	245.365	0.282
Respondent Edu	6265.159***	22.488	7612.725***	8.255
Sample Size	4872		379	
Adjusted R^2	.207		.272	
Durbin-Watson	1.87		2.06	
White's Test	384.89		67.08	

*** significant at the .001 level
** significant at the .005 level
* significant at the .05 level

The White's Test for the Second Generation Immigrant regression found heteroscedasticity.

3. The estimated earnings for second generation immigrants assuming the native reward structure is calculated: -41,682.118 +1,167.876*(10.29 Parental Education) + 4,570.328*(0.75 Library Card) – 24,373.302*(0.5 Female) – 696.834*(3.96 Family Size) + 6,265.159*(13.52 Respondent Education) = **\$4,3521.91**. This is the difference due to returns.

4. To find the difference in earnings between the children of immigrants and the children of natives that is due to different average characteristics, the earnings number calculated from the Oaxaca regression (in step three) is subtracted from the average earnings for native children.

   \$45,689.44 - \$43,521.91 = **\$2,167.53**

5. Differing returns, as measured by coefficients, on these characteristics must cause the rest of the difference in earnings between second generation immigrants and natives. Thus, the difference due

to means (step 4) is subtracted from the observed difference in average wages (step 1).

$5,775.63 - $2,167.53 = **$3,608.10**

In sum, $2,167.53 of the $5,775.63 earnings gap between natives and second generation immigrants can be attributed to differences in characteristic averages. These may include different average levels of parental or respondent education, different probabilities of having a library card, different ratios of males to females, or different average number of siblings. This only makes up 37.5% of the earnings gap, so the reward structures (i.e., returns) must be operating differently for the two groups.

Table 5 summarizes the numerical results of the Oaxaca Decomposition. Over $3,500—62.5%— of the earnings gap is due to differences in the returns the children of natives and those of immigrants receives on the included variables. Somehow second generation immigrants acquire more from each additional unit of some or all of these characteristics than comparable natives. A likely explanation is that

Table 5: Oaxaca Decomposition among Natives and Second Generation Immigrants

Total Difference in Mean Earnings	$5775.63	100%
Difference due to Differences in Mean Characteristics	$2167.53	37.5%
Difference due to Differing Returns (Coefficients)	$3608.10	62.5%

they earn more money for each additional year of education they attain by supplementing that education (Chiswick & Miller, 2009). The reason for this cannot be tested within this analysis, but there are many hypotheses. One, working through the idea of an "American Dream," is that because the children of immigrants are grateful for their American opportunities, such as education, they work harder to ensure that they reap as much benefit from them as possible (Diajic, 2003). Native children, on the other hand, may see the same options of education as rights rather than privileges and may not be inclined to maximize their benefits. Another possible explanation relates to the inspiration of this paper: immigrants earn much less than comparable American-born workers. It is possible that the children of immigrants strive for higher returns on their investments so that they can financially support their parents. Contrariwise, the children of natives may not feel that responsibility, or to extend this reasoning, their parents may be able to support them financially so that they can accept less than optimal returns on previous investments.

Finally, two simple decompositions are executed to determine the effect of each of the education variables. To find the effect Respondent Education has on the earnings gap, the difference in averages (average Second Generation Immigrant Education – average Native Respondent Education) is multiplied by the coefficient obtained from the native regression. Again, the native regression is used. This (0.23*6,265.159) yields a positive $1,440.99, or 24.95% of the total earnings gap. Thus, Respondent Education is responsible for second generation immigrants earning approximately $1,500 more than natives. Using the same technique, the effect of Parental Education was found to be a negative $1,950.35, or -33.77% of the gap (-1.67*1167.876). The negative sign means that second generation immigrants earn about $2,000 less than natives because of this variable. This is largely due to the higher average of native Parental Education.

Path Analysis

Thus far, the Oaxaca Decomposition determined that most of the difference in earnings between second generation immigrants and natives is due to differing returns (rather than differing mean characteristic values). Further decompositions found parental and respondent education to both be highly responsible for these differing returns. Thus, the next step is to further investigate the path of returns by determining the relationship between Parental Education and Respondent Education in regard to Respondent Earnings.

The goal of this analysis is to measure the intergenerational transfer of human capital from parents to their children. Visually, the empirical design of this project can be illustrated with a triangle shown in Figure 1. The direct effect, running along the bottom of the triangle, maps the relationship between the parents' human capital to the respondent's 2006 earnings. This path indicates the effect that background variables, specifically parental education and characteristics of the respondent's childhood home, have on the respondent's future earnings. The upper path shows that background variables can influence the respondent's earnings indirectly by influencing the respondent's own investments in education.

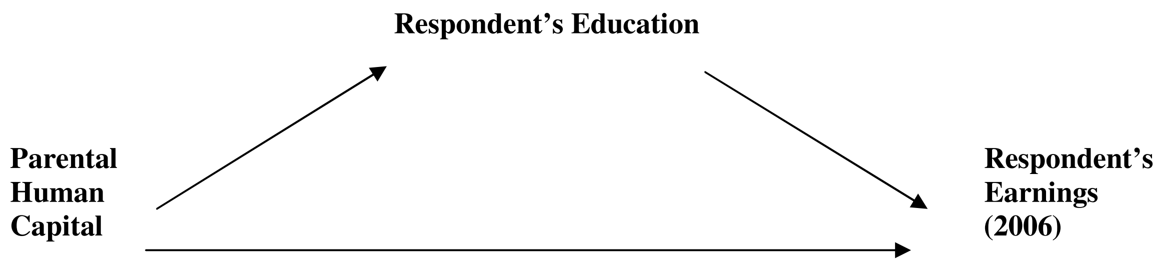

Figure 1: Direct and Indirect Path Model

The path analysis will identify both the direct and the indirect path mapped in Figure 1. The methodology for this analysis is based on the work of Israel and Seeborg (1998). While parental human capital does affect respondent earnings directly, it is likely that it also works through the intervening variable of respondent education to determine respondent earnings. This indirect path is mapped in two steps: the first step measures the effect of parental human capital on respondent education, and the second step measures the effect of respondent education (with parental capital characteristics held constant) on respondent earnings. Thus, there are two regressions needed to measure the indirect path and a single regression to measure the direct path. A path analysis will determine the importance of the indirect path as compared to the direct path for both natives and second generation immigrants.

A parent's human capital can affect his or her child's earnings either directly or indirectly. Directly, a parent may teach his or her child at home, thereby increasing the child's human capital. With increased human capital, the child will be more valued in the labor market and should earn more. Parents can also indirectly affect a child's earnings by affecting the child's educational attainment. A parent's high education level, for example, may increase the education level of the child. This may be due to advice or help the parent can offer throughout the child's schooling. The higher educational attainment of the child will, in turn, cause that child's earnings to be higher. Thus, the parent's education can indirectly influence the child's earnings by influencing the child's level of educational attainment, as shown in Figure 1. Because there are two effects (direct and indirect), it is important to acknowledge and analyze both. Since immigrant families are not typically expected to have as much U.S.-specific human capital to offer to their children, the direct effect of immigrant education on second generation immigrant earnings will probably be weaker than for natives.

While the basic paths for both immigrant and native families are fundamentally similar, the importance of each step of the path may differ. For example, the indirect path may be more important for immigrant families and the direct path is more important for natives. Econometric techniques will be used to estimate the direct and indirect effects of parental human capital (specifically Parental Education) on respondent education using three equations.

The first equation predicts Respondent Earnings from parental human capital background variables. In Figure 1, this equation represents the entire triangle. It accounts for both the direct and indirect paths of intergenerational transfer of human capital, thus offering an estimate of the overall effect of Parental Education on Respondent Earnings. Thus, this regression model focuses on the impact of background characteristics without controlling for the respondent's own investment in human capital (for example, their own education). By not controlling for Respondent Education, the coefficient of Parental Education will pick up its own effect on Respondent Earnings along with any indirect effect it might have through Respondent Education. The **Background Regression** is:

$$\textbf{Respondent Earnings} = \alpha + \beta_1 \textbf{(Parental Education)} + \beta_2 \textbf{(Library Card)} + \beta_3 \textbf{(Female)} + \beta_4 \textbf{(Family Size)} + \beta_5 \textbf{(Close)} + u$$

The second equation includes a control for Respondent Education. Visually, this regression is the direct path running along the bottom of Figure 1. It provides two important details. First of all, it gives an accurate prediction of the direct effect of Parental Education on Respondent Earnings because all other variables, including the respondent's own education, are controlled for. Secondly, the coefficient of Respondent's Education explains how much one year of respondent education affects his or her own earnings. This value will be crucial in translating years of education into earnings later on. The **Direct Effect Regression** is:

Respondent Earnings = $\alpha + \beta_1$ (Parental Education) + β_2 (Library Card) + β_3 (Female) + β_4 (Family Size) +β_5 (Close) + β_6 (Respondent's Education) + u

The final regression estimates the first part of the indirect path in Figure 1, running from Parental Human Capital to Respondent's Education. Predicting Respondent Education from background variables, this equation explains how Respondent Education reacts to one additional year of Parental Education. The **Intervening Regression** is:

Respondent Education = $\alpha + \beta_1$ (Parental Education) + β_2 (Library Card) + β_3 (Female) + β_4 (Family Size) +β_5 (Close) + u

The Path Analysis proceeds in four steps.

1. Estimate each of the three regressions (Background, Direct, and Intervening) for natives only.
2. Determine the direct effect of Parental Education on Respondent Earnings, which is simply the coefficient β_1 in the Direct Regression.
3. Multiply two coefficients to determine the indirect effect of Parental Education on Earnings. The coefficient for Parental Education in the Intervening regression is multiplied by the coefficient for Respondent Education in the Direct regression (i.e., β_1 in the Intervening Regression multiplied by β_6 in the Direct Regression). This calculation estimates the effect that one additional year of parental education has on the respondent's earnings through the parent's effect on the educational attainment of the child. This is the indirect effect of an additional year of parent's education (shown in Figure 1). For instance, if an extra year of parental education leads to two additional years of respondent education, and each additional year of respondent education is known to increase earnings by $500, the two years of respondent education caused by one year parental education leads to $1,000 of increased earnings.

4. Add the indirect effect calculated in step two to the coefficient of Parental Education from the Direct regression in step one. This adds the indirect to the direct effect and will yield an "overall effect."

After completing these four steps for natives, the same procedure is conducted for the second generation sample.

Because the Oaxaca Decomposition shows that much of the difference in mean earnings among natives and second generation immigrants is caused by differing returns, the path analysis becomes more important. The path analysis will give some insight on whether the differences in returns are caused by direct or indirect mechanisms (shown in Figure 1). For example, this process will weigh how important the indirect path of transmission is for natives and second generation immigrants. Because they have different returns (i.e. coefficients) it is expected that the indirect path of intergeneration transfer of human capital may also be different between second generation immigrants and natives. The regression results of all three equations (Direct, Controlled, and Intervening) for natives and second generation immigrants are displayed in Tables 6 and 7 respectively, and the empirical steps of the path analysis are carried out below each table.

The four steps of the path analysis for native respondents is outlined below:

1. Each of the three regressions (Background, Direct, and Intervening) is estimated for the native respondents and shown in Table 6.

Table 6: Path Analysis Regressions for Natives (t-statistic)

	Background (Earnings in $)		**Direct (Earnings in $)**		**Intervening (Education in years)**	
Constant	15865.71***	(4.65)	-42841.83***	(-10.27)	9.30***	(64.12)
Parental Education	3287.78***	(13.81)	1256.53***	(5.15)	0.32***	(31.26)
Library Card	7294.54***	(4.97)	4494.19***	(3.21)	0.52***	(8.33)
Female	-22086.04***	(-17.58)	-24391.92***	(-20.32)	0.33***	(6.04)
Close	4326.53	(1.83)	3311.83	(1.47)	0.09	(0.88)
Family Size	-1169.93***	(-4.47)	-700.18**	(-2.80)	-0.08***	(-6.91)
Respondent Edu			6256.94***	(22.46)		
Sample Size	4872		4872		6307	
Adjusted R^2	.125		.207		.220	
Durbin-Watson	1.82		1.87		1.72	

White's Test	253.34	384.89	113.53

*** significant at the .001 level
** significant at the .005 level
* significant at the .01 level

The Intervening D-W statistic was inconclusive at 5% and found autocorrelation at 1%
The White's test for the Intervening regression found heteroscedasticity at the 5% and 1% levels.

2. The direct effect of Parental Education (from the Direct Regression) is $1,256.53 of increased respondent earnings for every additional year of parental education.
3. For natives, the intervening regression model shows that one additional year of parental education causes about an additional one-third of a year of respondent education. Because one extra year of respondent education leads to a $6,000 increase in earnings, the additional one-third year of respondent education caused by the additional year of parental education translates into an estimated increase in earnings of: 0.32 years * $6,256.94 = **$2,002.22**.

   This is the calculated indirect effect for natives.
4. Adding the indirect effect of parental education on respondent earnings (calculated in step two) with the direct effect of parental education (from the Direct regression) yields the overall effect of parental education on respondent earnings. $2,002.22 + $1,256.53 = **$3,258.75**. This is slightly lower than the $3,287.78 effect predicted with the Background Regression.

In order to compare the path of transmission in native families with that in immigrant families, it is necessary to repeat the path analysis for second generation immigrants. The four steps are outlined below:

1. Each of the three regressions (Background, Direct, and Intervening) is estimated for the second generation respondents and shown in Table 7.

Table 7: Path Analysis Regressions for Second Generation Immigrants (t-statistic)

	Background (Earnings in $)		**Direct (Earnings in $)**		**Intervening (Education in years)**	
Constant	39896.26***	(3.60)	-46338.38***	(-3.17)	10.84***	(21.36)
Parental Education	2143.46***	(3.43)	997.51*	(1.68)	0.17***	(5.76)
Library Card	6410.23	(1.11)	-1907.85	(-0.35)	1.15***	(4.38)
Female	-30.179.47***	(-6.42)	-31686.79***	(-7.32)	0.27	(1.21)

Close	-1869.92	(-0.33)	-1853.36	(-0.02)	0.15	(0.59)
Family Size	272.43	(0.29)	287.21	(0.33)	-0.03	(-0.63)
Respondent Ed			7612.60***	(8.25)		
Sample Size	379		379		484	
Adjusted R^2	.140		.271		.144	
Durbin-Watson	2.02		2.06		1.69	
White's Test	40.93		74.66		14.04	

*** significant at the .001 level
** significant at the .005 level
* significant at the .01 level

The Intervening regression has autocorrelation (from D-W) at the 5% level and the D-W test for the Background regression is inconclusive at 5% and not autocorrelated at 1%.
All three equations have heteroscedasticity.

2. The direct effect of Parental Education (from the Direct Regression) is $997.51 of increased respondent earnings for every additional year of parental education.

3. For second generation immigrants, one additional year of parental education leads to an additional one-fifth of a year of respondent education. Because one extra year of respondent education leads to a $7,000 increase in earnings, the additional one-fifth year of respondent education caused by the additional year of parental education translates into an estimated increase in earnings of:

   0.17 years * $7,612.60 = **$1,294.14**.

   This is the calculated indirect effect for second generation immigrants.

4. Adding the indirect effect of parental education on respondent earnings (calculated in step two) with the direct effect of parental education (from the Direct regression) yields the overall effect of parental education on respondent earnings. $1294.14 + $997.51 = **$2291.65**. This is slightly higher than the $2143.46 effect predicted with the Background Regression.

Table 8: Comparison of Path Analyses for Natives and Second Generation Immigrants (effect of Parental Education on Respondent Earnings with the intervening variable Respondent Education)

	Native	Second Generation Immigrant

Direct	$1256.53	$997.51
Indirect	$2002.22	$1294.14
Overall	$3258.75	$2291.65
Percent Effect of Indirect (Indirect/Overall)	61.44%	56.47%

Table 8 summarizes the results of the Path Analysis for both natives and second generation immigrants. The direct effect of parental education on respondent earnings is larger for native than immigrant families. This signifies a difference in the effect of parent's education between natives and immigrants. An immigrant's additional year of education may lead to a lesser increase in children's earnings because the parent's education is not fully applicable to America. Knowing Mexican law or how to close a business deal in France may not be helpful in America, so a parent with human capital that is not based on U.S. institutions and culture may not be able to directly influence his or her child's earnings as much as a native parent.

The indirect effect of human capital transfer is also larger for natives. The main reason for this is that an additional year of education by immigrant parents causes a much smaller increase in the educational attainment of their children compared to the larger effect that native parents have on their children's educational attainment. This could easily be another argument for imperfect transferability of international human capital in America, but it may also have to do with preferences. Because many immigrant parents have relatively low levels of education, they may choose to stress aspects of their human capital other than education. Knowing that their education is lower than native averages, immigrants may transfer time management, work ethic, or motivation to their children that is independent of their own educational attainment. Native parents, however, may use their own education level as a goal for their children to meet or surpass.

This is an important conclusion because it requires further consideration of what causes second-generation immigrants to obtain higher levels of education than natives (Table 1), if it is not due to their parents' education levels. One possible explanation is that the children of immigrants are more likely to speak a foreign language, and that being multilingual is beneficial. Specifically, speaking a second language may increase verbal ability and, in the long run, make education easier or more available. High verbal skills can increase the probability that a student will attend college because he or she will likely be accepted to more schools, and possibly receive more or larger scholarships. Another explanation, and one borrowed from Diajic (2003), is that some sort of "American Dream" motivates immigrants and/or their children to try harder. If they believe that America offers more opportunity, first- and second- generation immigrants may feel obligated to take advantage of those opportunities, an important one being education.

Finally, the Path Analysis finds that for both groups the Indirect path of human capital transfer consists of more than half of the overall effect of parental education on respondent earnings. Both paths are stronger in the native population, due to the larger effect of native parental education on respondents in the United States. This further emphasizes the importance of culturally relevant human capital.

V. Conclusion

This study provides a detailed analysis of second-generation immigrant earnings compared to native earnings. Following Marshall's work, this project assumes that parents are motivated to invest in the human capital of their children, via their own human capital, in hopes of providing them with the means to be more successful in the future (Rosen, 2008). It also controls for cohort bias, a common confound in previous work (Borjas, 2006), by mapping each respondent earnings directly to his or her parent's human capital. Respondents with immigrant parents, and thus those who received human capital specific to a non-American culture, earn more, measured in wages and salaries, than natives. Though the exact reason for this is not identified, it is concluded that second-generation immigrants surpass their parents' levels of education and earnings, and also rise above native earnings (though not significantly so). This does not appear to be merely regression toward the mean because the analysis suggests that second generation immigrants actively pursue higher success (i.e. receive significantly more education than natives and reap greater returns from their investments), which entails more than simple statistical averaging. These results imply second-generation immigrants are economically efficient in America, and immigration policy makers should consider the favorable economic performance of second generation immigrants in the size and composition of immigration flows.

The Oaxaca Decomposition shows that the difference in earnings between natives and second generation immigrants is mostly due to differing returns, rather than different average characteristics. This may be because the two groups have different reward structures or, following Chiswick and Miller 's (2009) theory of under-education, because second generation immigrants learn to supplement their education with additional investments in human capital. They may also be more highly motivated to effectively apply their education in the labor market or be more obliged to financially support their parents, compared to natives.

Finally, the Path Analysis finds that both the Direct and Indirect paths of human capital transmission are stronger for native than immigrant families. While parental education is a good predictor of ultimate earnings for natives, the predictive power is not as strong for second-generation immigrants. There is a strategy among immigrant families that overcomes the low educational attainment of immigrants so that second generation immigrants regress beyond the native mean. Several plausible explanations are offered; including enhanced verbal abilities caused by multilingualism and a theory involving the "American Dream." Following Chiswick and Miller's (2009) argument, second generation immigrants may supplement their education to earn more. The Path Analysis also proves that the Indirect path is more important for both groups than the Direct path, emphasizing the importance of respondent educational attainment over the Direct effect of parental education on respondent earnings.

Intergenerational transfer of human capital among immigrant families is an important area of research and requires much more investigation before strong policy implications can be drawn. It is clear, however, that increased education leads to increased earnings for both second-generation immigrants and natives. Thus, increasing domestic education levels will benefit both American natives and the economy.

Though this study improved on previous designs by using longitudinal data, there are many restrictions and several improvements can be made. One restriction, due to the sample, is that foreign language could not be tested. Multilingualism may play a large role in the higher earnings second-generation immigrants' experience, but this study could only theorize about its function. If foreign language is a strong positive predictor of earnings, foreign language programs could be increased throughout the country so that natives could also benefit from this advantage. The data set also restricts the study due to the specific questions asked in 1979. There is no evidence of what country immigrants moved from, so conclusions could not be made about country-specific human capital and Roy's theory could not be fully tested. Knowing the country of origin would allow for other social factors that may influence personal immigration decisions, for instance income equality in the origin country, to be considered. Another disadvantage of the data set is that various measures of aptitude, standardized or IQ tests, are not recorded for very many respondents, thus making them impossible to include as controls in this study.

Future research could also explore the level of motivation of immigrant families compared to natives. Though it was not the main focus of this analysis, the existence of such an "American Dream" ideal may cause immigrant families to pursue more opportunities, feel obligated to try harder to be successful, or have better attitudes in general about their life goals. Assimilation could also be controlled for in future designs. Immigrants who have successfully assimilated should be able to offer their children American-specific human capital, which should have a positive effect on earnings. Finally, the social acceptance of immigrants and their families in America should be considered. There may be racial discrimination or discrimination based upon immigrant status regardless of country of origin. It is important to understand the role natives play in letting immigrant families have the same opportunities as natives and accepting them into society.

There is still much to be studied about the economic performance of second-generation immigrants, but this research hopefully provides a contribution by considering previous literature and improving upon the basic empirical design in using longitudinal data and studying the specific link of human capital transfer within families. The results are promising for America at a time when the immigrant population is growing and the second-generation immigrant population is booming.

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Appendix 1:

The data set contains approximately 49% "European" (English, French, German, Greek, Irish, Italian, Other Spanish, Polish, Portuguese, Russian, Scottish, and Welsh), 25% Black, 13% "Hispanic" (Cuban, Chicano, Mexican, Mexican-American, Puerto Rican, and Other Hispanic), 9% American (American and None), 3% other, and 1% Asian (Chinese, Filipino, Hawaiian, Pacific Islander, Asian Indian, Japanese, Korean, Vietnamese).

Because of the lack of diversity and the uncertainty of the question asked, these racial and ethnic identities were divided into "Close" and "Not Close" for second generation immigrants as well as natives. "Close" includes Cuban, Chicano, Mexican, Mexican-American, Puerto Rican, and Other Hispanic. All other responses are coded as "Not Close."

Appendix 2: Statistical Tests

Multicollinearity: This is not a threat to this analysis because correlations between independent variables are low. Furthermore, the regressions produced significant coefficients while R-squares are low.

Autocorrelation: The Durbin-Watson Test was run for each of the regressions presented. In most cases the null hypothesis of non-autocorrelation was not rejected at the 1% or 5% level. The regressions with autocorrelation are marked in their respective tables. Even with autocorrelation, the regression coefficients are unbiased and consistent. The danger in autocorrelation is that estimated variances are biased (usually lower), estimated standard errors of coefficients are biased (usually lower), and t-statistics are biased (usually higher). Thus, tests of significance are invalid. The regressions here were not altered because changing only some of the equations would make comparison difficult. Furthermore, the regressions are trustworthy in their theory.

Heteroscedasticity: White's Test was performed on each of the regressions presented. In several tests, the null hypothesis of non-heteroscedasticity was not rejected at the 0.1% level. The regressions with heterscedasticity are marked in their respective tables. With heteroscedasticity, regressions coefficients are still unbiased and consistent, but the estimated variances, estimated standard errors, and t-statistics are all biased. Thus, tests of significance are invalid. Again, these equations were not altered so that they could be compared to non-heteroscedastic regressions.