Differences in Returns to Education for First-Generation and Second-Generation Immigrants

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Abstract: Previous research has established that first-generation immigrants reach lower levels of education and earn less relative to domestically-born workers. However, the educational attainment and incomes of second-generation immigrants are notably comparable to those of natives. This study attempts to understand this discrepancy between first and second-generation immigrants by exploring the determinants of income and how their influence varies across immigrant groups. US Census data from the Annual Social and Economic Supplement to the Current Population Survey is utilized to compare income data for US workers over an 11-year period. The results offer statistical evidence that first-generation immigrants do experience lower returns to education.

Motivation and Research Focus

Most of the existing economic literature on immigration focuses on the wage gap between natives and immigrant workers, and studies are limited to analyzing first-generation immigrants, not born in the US. Yet with the percentage of the American population representing immigrants steadily rising, some researchers predict that a new generation of second-generation immigrants will soon become a large portion of the population. Born in the US but with parents from abroad, the second-generation immigrants are the first-generation's direct descendants. Although studies have illustrated that first-generation immigrants earn substantially less than native citizens, the second generation has proven to be notably more successful, with an average income rivaling that of the native-born population. One possible explanation could be variances in returns to education.

This proposed research will explore a potential reasoning for the income difference between first-generation and second-generation immigrants, by comparing their returns to education. As native-born residents, the second-generation has greater access to domestic educational resources, including federal financial aid. One study revealed that second-generation Hispanic and Asian immigrants enrolled in college full-time at higher rates than the corresponding first generations, with 54% of second-generation Asian undergraduates being full time in comparison to only 40% of first-generation Asian students (Staklis 17).

Evaluating and contrasting the effects of education on the personal incomes of first-generation and second-generation immigrants would provide more insight into the wage disparity between these groups. Furthermore, if returns to education vary depending on whether the education was completed in a domestic or foreign institution, then it could potentially explain the second generation's capability earning higher wages. So this research aims to identify whether there is a statistically significant difference in returns to education between the first generation of immigrants and the second-generation.

Literature Review

While there is no literature directly examining the returns to education for second-generation immigrants, there is extensive research on the topic of returns to education. Within that field are studies looking at the returns to education for first-generation immigrants, and others comparing immigrants' average educational attainment to that of other demographics in the US. Coelho and Liu (2017) recently studied factors that affect the rate of returns to education. Unlike previous analyses, they utilize college-level data rather than individual data, taking the aggregate values for each of the approximately 560 universities in the US. Furthermore, their model includes the colleges' most common academic majors as one of the explanatory variables for graduates' starting salaries and mid-career salaries. The findings reveal that college's acceptance rate, faculty's salary, average state income, and whether the school is public or private all had a modest effect on postgraduate salaries. However, of all the variables, course of study proved to have the largest effect on graduates' earnings, accounting for approximately 66% of the variation (Coelho and Liu, 2017, p. 610). Their study supports the claim that area of study has a significant effect on postgraduate earnings, and that the returns from postsecondary education in the US are only moderately affected by the quality of the institution.

Bartik and Hershbein (2018) look to examine the relationship between family income and returns to education. Using longitudinal data from the Panel Study of Income Dynamics, they calculated the average family income of about 4,400 individuals from when they were the ages of 13 to 17 and categorized the households as low-income, middle-income, or high-income based on the averages. Their regression results demonstrate that, overall, people from middle or high-income families had significantly greater returns to education at all levels of educational attainment. High school graduates from families with higher incomes earned about 39% more than those from lower income families. Similarly, people from upper-income families with a bachelor's degree earned 136% more than their highschool counterparts and nearly double the returns of low income individuals with bachelor's degrees (Bartik and Hershbein, 2018, p. 12). However, there was a large decrease in the earnings differentials after removing outliers from the middle or high-income group, specifically those that fell within the top 1% income bracket. Bartik and Hershbein also note that their findings are not significant enough to confirm family income has a direct effect on an individuals' returns to education.

Deutscher (2020) uses a combination of census data and survey data to test possible factors of increased intergenerational mobility of immigrants and compares the educational mobility rates for various migrant groups. The study attempts to capture cultural effects on education through the "epidemiological approach"- as developed by Raquel Fernández in her 2011 study. For each immigrant's country of origin the average test scores on the Programme for International Student Assessment (PISA) are included to "capture both institutional factors (e.g.,better schools) and cultural factors (e.g., values) that influence educational outcomes" (Deutscher, 2020, p. 1716). Results show that people from countries that performed better on PISA tests reached higher levels of educational attainment. Migrants from communities with a larger wage gap between the first-generation and similarly educated natives were also more likely to pursue greater education. Second-generation immigrants from Southeast Asian countries, where the first-generation earned 22% less on average than natives with the same educational attainment, were approximately 16% more likely to pursue college compared to those from the UK, where the wage gap was only 8% (Deutscher, 2020, p. 1719). Both results suggest that immigrants' educational attainment is moderately affected by country of origin and their surrounding culture.

Maja Melzer et al. (2018) compares the income disparity in Germany between natives and first-generation immigrants to that of natives and second-generation immigrants by utilizing cross-sectional data. Their argument is that the earnings discrepancies between either generation of immigrants and natives varies based on workplace contexts, specifically organizational differences between occupations. To evaluate their hypothesis, they include institutional characteristics, such as the percentage of immigrants in the workplace and the spread of immigrants across different roles, whether they are in supervisory positions, and divided occupations into primary or secondary. They find that the wage gap for first-generation immigrants is largely unaffected by different workplace structures. However, the differential for second-generation immigrants was found to vary depending on whether they worked in the primary or secondary labor market. In the primary labor market, individuals with the same amount of educational attainment as native Germans did not experience as large of an income gap as those in the secondary market. The authors conclude by stating that structural characteristics in the workplace could be a factor in the wage gap between immigrants and German natives but the scale of impact varies depending on the specific migrant group.

Coulumbe et al. (2014) introduces a new approach by which to compare wage differentials between native and immigrant workers that involves using nations' GDP per capita. The variable is introduced as a measure of immigrants' quality of education and human capital, and the authors justify its inclusion with previous empirical evidence showing a strong correlation between a nation's GDP per capita and returns to education within the country. By using OLS and data from the Canadian Census, they confirm the accuracy of GDP per capita as a measure of immigrants' human capital quality, as immigrants' work experience and returns to education were found to increase if their country of origin had a high GDP per capita. They also observed that differences in human capital accounted for a large portion of the immigrant wage gap, and after adding human capital to their model of wages, the unexplained aspect of the wage gap decreased by approximately 62% for male immigrants and essentially dissolved for female immigrants (Coulumbe et al., 2014, p. 16). The study included additional separate models for both genders to account for any potential wage discrimination.

Hudley (2016) analyzes differences in educational performance between native, first-generation immigrant, and second-generation immigrant black students, using ANOVA and survey data from the University of California. The study showed that second-generation students had the best average educational performance, but native men received the highest initial salaries after graduating. Yet the significance of immigration status as an explanatory variable decreases when family income and gender were added to the model. Although it should be noted the study had a limited sample size of 800, restricted only to students that identified as black to some degree.

Postepska (2019) aims to evaluate the role of ethnic capital over time, and the study applies the framework developed by George J. Borjas in 1992 to recent data gathered in the General Social Survey. She finds that, although there is inconclusive evidence on the significance of immigrants' ethnicity as a determinant of level of education, ethnic capital and the amount of parental education are found to have significant effects on the intergenerational transmission of education. For her study, ethnic capital refers to the overall human capital of a migrant group and their educational attainment and professional skills. In other words, these results suggest that parental education and ethnic capital both have a significant influence on second-generation immigrants' educational attainment.

Lancee and Bol (2017) examine the relationship between immigrant earnings and place of education. They hypothesize that immigrants' low wages are partially the result of an inability to utilize skills gained abroad in another country's labor market and thus seek to study whether an immigrant's place of education has an effect on the transferability of their human capital. After running multiple regressions with employment data from eleven Western European countries, they found that country of origin is strongly correlated to immigrants' wage discrepancies. The findings show that workers in Western Europe with a foreign, non-Western degree earned substantially less than their counterparts with a Western but foreign degree, and even after accounting for area of study and occupation-specific skills, those with a non-Western degree earned about 7.7% less than the average immigrant (Lancee and Bol, 2014, p. 709). These results present a challenge to the basic credential theory- which states that workers' wages increase with their level of education- and suggest that returns to foreign and domestic education are inconsistent. However, Lancee and Bol note the discrepancy in returns could potentially be explained by varying quality of education, but further research would be required.

Hardoy and Schøne (2014) provide additional insights into returns to education for non-Western immigrants by analyzing immigrants in the Norwegian labor market. Their study uses a distinct method to quantify educational attainment, entitled the "Over-Required-Under" approach to education. Individuals are categorized as overeducated, required, or undereducated, depending on how well their level of education matches the average education requirement for their occupation, and their model included dummy variables for each group. This method offers a contrast to other studies that only measure educational attainment based on years of education.

Their regression results show that there is a notable discrepancy between returns to domestic, Norwegian education and returns to foreign education. Norwegian natives received an average increase of 6.8% in their income with every year of domestic education, and non-Western immigrants had a marginal increase of 5.8%. Yet with foreign education, non-Western immigrants only received a 2.5% increase per year of education (Hardoy and Schøne, 2014, p. 59) . Their study offers further evidence that returns to foreign education are significantly lower, potentially due to difficulty transferring skills between national labor markets or discrimination.

El-Araby Aly and Ragan (2010) then seek to analyze the returns to education for Arab immigrants, and this study is one of the few that focuses on the American labor market. They utilize US Census data and a multiple regression model to estimate and compare the wage outcomes for immigrants from various Arab nations, and each countries' development is measured through the Human Development Index (HDI), created by the UN Development Program. The study reveals that the returns to education for Arab immigrants are minimal for the first twelve years of education. Yet for every year beyond that period, they receive an increase in wages of approximately 10.8% per year of education, based on data from the 2000 Census year (El-Aly and Ragan, 2010, p. 530). Furthermore, they discover that, after controlling for country of origin, the origin country's level of development has a significant impact on immigrants' wages, with the two being positively correlated. Their results align with previous studies' conclusions about the influence of country of origin on immigrants' wages.

Ultimately, there are multiple theories regarding returns to education. According to the credential theory, earnings should rise with education, and the increase in earnings should scale exponentially with higher levels of education. However, economic literature comparing the wages of immigrants and natives reveals that immigrants experience smaller returns to education, which is unexplained by the credential theory. Hardoy and Schøne (2014) and Lancee and Bol (2017) find that country of education has a significant effect on returns to education, which suggests the difference could be explained by varying quality of education. In comparison, the human-capital theory states that returns differ based on social characteristics. Studies such as Coulumbe et al. (2014) and Deutscher (2020) accounted for immigrants' countries of origin and found that people from the same migrant group earned similar returns. The logic is that these individuals receive the same quality of education and possess similar cultural values, which affect their educational attainment and returns to education. Researchers also considered nativist bias as a potential cause of the difference in returns.

Data Description and Research Methodology

The purpose of this research is to identify whether second-generation immigrants experience different returns to education in comparison to first-generation immigrants. My hypothesis is that the second generation will have higher returns to education, given that previous literature has found that returns to domestic education are larger than returns to foreign education. I expect the estimated coefficient for years of education to be statistically significant for all regressions.

This study will use data from the Current Population Survey (CPS) and the corresponding Annual Social and Economic Supplement (ASEC). The CPS contains microdata from 1994 to the present and has a thorough record of individuals' educational attainment and sources of income. The additional data from ASEC then can be used to identify whether those individuals have parentage of foreign birth, which will be used to distinguish between specifically second generation immigrants. For my research, I intend to use CPS and ASEC data from **2009 to 2019**, and **each year** contains approximately **90,000** observations. About 17,000 of the observations are for first-generation immigrants, and 8,000 are for the second generation. The large number of observations then allows me to run separate regressions for each immigration group. I plan to run four regressions: one with the overall model using all observations and one for each of the three immigration groups. By including all observations in one model, I can account for discrimination based on immigration status. I also chose to use data from an eleven-year period to account for any time effects on income.

For my model, I plan to regress the real value of total personal income against annual unemployment rate, average annual productivity, years of education, immigration status, GDP per capita of the origin country, supervisory status, race, age, and gender, using the Stata software program. I also constructed an overqualified measure based on individuals' level of educational attainment. I compared the respondent's education level to the average educational requirement of their occupation, and if their individual educational attainment exceeded the requirement, they are marked as overqualified. The data for occupational education requirements is taken from the BLS. The dependent variable is the inflation-adjusted value of the individual's total personal income, and I plan to take the natural log to better estimate the proportional effect of each variable. The model to be used is as follows:

$$\ln(\text{Total Personal Income}) = \beta_1 \text{ YEAR} + \beta_7 \text{ UNEM} + \beta_7 \text{ PRODC} + \beta_7 \text{ IMMIG} + \beta_7 \ln(\text{GDPC}) + \beta_2 \text{ EDUC} + \beta_3 \text{ SPVSR} + \beta_4 \text{ QUAL} + \beta_5 \text{ RACE} + \beta_6 \text{ AGE} + \beta_7 \text{ SEX} + \varepsilon$$

with ε as the random error term.

- YEAR is a discrete numerical variable that identifies which year of the CPS and ASEC the respondent's data was recorded. It is taken from the CPS and provided in numerical form.

- Unemployment (UNEM) is a continuous variable that provides the unemployment rate for the year of observation. This variable will be used as a measure of economic performance for the year. A period of economic downturn would cause lower wages, and so this measure is used to account for this effect. It is taken from the St. Louis Federal Reserve Database and recorded in numerical form.
- Productivity (PRODC) is a continuous variable that measures the average labor productivity for laborers in the nonfarm business sector. This variable is included as a measure of the average work done by an individual, which affects wages. In years of high productivity, workers will subsequently earn more, and this variable is included to account for that effect. It is taken from the St. Louis Federal Reserve Database and provided in numerical form.
- Immigrational Status (IMMIG) is a categorical variable that indicates the immigration status of the respondent, whether they are a first-generation immigrant, second-generation, or a native. This variable will be used to identify wage discrimination between the three groups. The data includes the respondents' country of birth and their parents' countries of birth. Individuals born outside the US will be categorized as first-generation immigrants. Immigrants from the US but with parents born outside the US will be labeled as second-generation immigrants, and the remaining with parents native to the US will be categorized as natives. The data is taken from the CPS and will be provided in numerical form.
- GDP per Capita (GDPC) is a continuous variable that gives the GDP per capita of a respondent's country of origin. Previous economic literature on immigrant wages has found country of origin to be a significant factor. One potential explanation is that nations

with a higher GDP per capita offer different resources that affect worker productivity. Therefore, this variable is included to account for national differences in education quality and human capital. The data is taken from 2014, around the middle of the observation period, and it is provided in constant 2010 dollars. The values will also be logged to better measure the proportional effect on immigrants' income. It is taken from World Integrated Trade Solution and provided in numerical form.

- Years of Education (EDUC) is a discrete variable that measures the highest level of education completed by the respondent. It is taken from the CPS and provided in numerical form. The estimated coefficient for this variable will be used to measure the returns to education for each immigration group.
- Supervisory Role (SPSVR) is a dummy variable that indicates whether the respondent's occupation puts them in a supervisor position over others. Previous economic literature has shown that people in a supervisory position tend to have a higher income than those in non-supervisory roles, so this variable is included to control for that effect. The data is taken from the CPS and provided in binary form.
- Educational Qualification is a dummy variable that indicates whether the respondent meets or exceeds the average education requirement for their occupation. At present, I have CPS data on respondents' level of education and their occupations, according to the 2010 Census occupation codes. There is also a table created by the Bureau of Labor Statistics that indicates the average educational requirement for each occupation, and it contains data for each of the occupations included in the 2010 Census, i.e. all the occupations recorded in the CPS. As part of my research, I plan to compile all the data and identify whether the respondent has the education levels required for their

occupation. This variable could have a significant impact on income, allowing for analysis of the credential theory.

- RACE is a categorical control variable that indicates the respondent's race. Previous economic literature has established that race has a significant effect on personal income, and this variable will help control for that effect. The data is taken from the CPS and provided in nominal form.
- AGE is a continuous control variable that indicates the respondent's age. Previous economic literature has established that personal income is more likely to increase, as they gain experience and spend more time in their field, and this variable will help control for that effect. The data is taken from the CPS and provided in numerical form.
- SEX is a binary control variable that indicates the respondent's sex. Previous economic literature has established that personal income varies greatly depending on gender, and this variable will help control for that effect. The data is taken from the CPS and provided in nominal form.

Results

The following model was used to compare variables' effects on incomes from all immigrant groups:

$$\log(\text{Total Personal Income}) = \beta 1\ AGE + \beta 2\ FEMALE + \beta 3\ RACE + \beta 4\ EDUC + \beta 5\ SPVSR$$
$$\beta 6 \log(LGDP) + \beta 7\ UNEM + \beta 8\ OVQUAL + \beta 9\ GEN1 + \beta 10\ GEN2 + \varepsilon$$

with the residual, ε, assumed to be normal.

The expected sign of each variable varies based on the existing literature. Human capital variables include age, which is predicted to have a positive effect on income, as individuals gain experience over time, improving their productivity. Education is expected to have a positive sign, both because of productivity benefits and as a credential granting access to higher-paying jobs. In the literature (Columbe et al., 2014; Lancee and Bol, 2017) GDP per capita is used as a proxy measure for resources brought from immigrants' origin countries, including work habits, some means, and educational quality. Therefore it is predicted to have a positive sign, leading to employment with better wages.

This study adds a few productivity controls. It includes a dummy variable for workers in supervisory roles, since such appointments distinguish both skill and talent, and the potential productivity provided by such positions translates to higher wages. The dummy variable for overqualified is an indicator for workers whose individual educational attainment exceeds the requirement for their occupation, meaning that they are not fully utilizing their education. The overqualified variable is then expected to have a negative sign.

Macroeconomic circumstances may also affect income growth over time. The sign for the unemployment rate should be negative, as high unemployment signals an economic downturn where average work hours may drop, and wage growth is constrained.

Demographic controls were also included. These capture associated characteristics not measured in our model, but may also reflect discrimination. The variable for females should have a negative sign, since studies like Hudley (2016) and Deutscher (2020), have shown that women earn notably less than men, even controlling for other variables. Similarly, previous research (El-Araby Aly and Ragan, 2010; Lancee and Bol, 2017) demonstrates that white workers have the highest incomes, controlling for other determinants, so all race variables are expected to have negative signs. Finally, the first-generation variable and the second-generation variable should both have negative signs, as the literature (Coulumbe et al., 2014; Maja Melzer et al., 2018) finds that each generation of immigrants has lower incomes compared to natives, ceteris parubus.

Given the prevalence of heteroskedasticity in previous panel income studies, the regression was checked and corrected for heteroskedasticity. The results of the Wooldridge test also indicated the presence of moderate autocorrelation, so it was further corrected for autocorrelation.

The regression results for the full dataset are presented in Column 1 of Table 1. The R-squared value is approximately 0.262, and the F-statistic for the equation is significant. Age and years of education are both significant at the 1% level and have strong positive effects. These results are consistent with previous findings that the two variables are positively correlated to income.

This study went beyond the variables provided by the Census in identifying determinants of income. Employment in a supervisory role is significant at the 1% level and has a strong positive effect on personal income. The change in income from employment in a supervisory role is comparable to the income increase from an additional three years of education. This finding suggests that individuals in supervisory positions earn significantly more than non-supervisory workers.

The overqualified measure, which is a dummy that identifies if an individual's educational attainment exceeds the average educational requirement for their occupation, has a negative coefficient and is significant at the 1% level. This result shows that when an individual's occupation does not utilize their level of education, they will earn less. It supports the theory that returns to education are limited by whether one can fully apply their education in the workplace.

The log of GDP per capita for the individual's country of origin is used to measure if the resources in their home country have an effect on earnings. This variable is logged to better estimate the change in income proportional to the change in GDP per capita. However, it is not significant. The insignificant results may be because the data does not control for where the individual was educated. It is possible that some immigrants came as youths and received their education in the US.

The unemployment rate is significant at the 1% level and is negatively correlated to personal income. It also accounts for the cyclical effects on income.

The results provide further evidence that women are much more likely to have smaller incomes, even controlling for these factors, as was demonstrated in previous literature. That coefficient is significant at the 1% level and has a coefficient of -0.424. According to these results, women are estimated to make 52.8% less than men on average. It is unlikely this discrepancy is due to lower education, as the data shows women reach higher levels of educational attainment. The percentage of men in the sample with a college degree is 32.24%, whereas for women it is 35.84%. A potential explanation could be that women are less likely to be employed in high-paying positions. 11.71% of male workers are in supervisory roles, but in comparison the percentage for females is only 8.14%.

All race indicators also have a negative effect on income, with one exception. Compared to all racial variables, Native American has the largest negative coefficient with a value of -0.153. The estimated coefficients for Black and Mixed race are similar, -0.1 and -0.118 respectively. It is worth noting that the Black variable has a notably higher t-value of -27.56, implying that black workers are consistently more likely to earn less. While significant at the 1% level, the coefficient for Asian is smaller in absolute terms, and it has a smaller t-value. This finding suggests that Asian employees' incomes are closer to the average, and they experience less of a discrepancy compared to other racial groups.

Contrary to expectations, the results show that Hispanic people are likely to have higher incomes, and the relationship is significant at the 1% level. Similarly, first-generation immigrants are expected to earn more, as the variable for the first generation also has a positive coefficient that is significant at the 1% level. These results are unusual and inconsistent with existing literature that demonstrates lower earnings for Hispanic workers and immigrants. Furthermore in the regression, second-generation immigrants are found to have smaller incomes, as expected, with a negative coefficient of -0.001 that is significant at the 5% level, suggesting that immigrants are more likely to earn less.

One potential explanation for the results of the Hispanic and first-generation variables is sample-selection bias. The ASEC data used for this regression is gathered by conducting surveys and relies on willing participation. It is possible that Hispanic people or immigrants with little to no documentation were less likely to respond to the survey due to personal concerns, and this behavior resulted in unrepresentative data. That is, the data regarding Hispanic workers and first-generation immigrants may not accurately represent the full population. Kissem (2017) argues that the methods of the U.S. Census led to the repeated undercounting of the Hispanic population. He estimates that the 2000 Census undercounted the Hispanic population that lived in the US for five or less years by 17.7% (Kissem, 2017, p. 807).

To discern different pay experiences, three additional regressions were run using the same model, one for each immigrant group. By separating the data, it is possible to identify whether each generation experiences different returns to education, or if one group is characteristically overeducated for the jobs they can access. A potential issue could be that one generation is restricted in their ability to utilize their education, either due to limited number of appropriate jobs or discrimination, and this behavior would result in an overeducation dilemma for that specific generation.

Having separate regressions makes it easier to identify if the effect of a certain variable differs based on the generation of immigrants. Each regression utilized the same model but with different data. The first regression was limited to individual data on US natives. The second regression used data solely from first-generation immigrants, and the third regression focused on second-generation immigrants. The following model was used for all three regressions:

$$\log(\text{Total Personal Income}) = \beta 1\ AGE + \beta 2\ SEX + \beta 3\ RACE + \beta 4\ EDUC + \beta 5\ SPVSR$$
$$\beta 6\ LGDP + \beta 7\ UNEM + \beta 8\ OVQUAL + \varepsilon$$

with ε as the random error term, and the same expected coefficient signs as in Equation 1. However, the variable for country of origin's GDP per capita was eliminated in the US native regression, as the value was identical across all observations. The results for the US native regression, the first-generation immigrant regression, and the second-generation immigrant regression are displayed in Columns 2, 3, and 4 respectively of Table 1.

Comparison of the separate regressions shows that the segregated results resemble the findings of the combined model. The negative correlation between unemployment and personal income is consistent in all three regressions, but there is some variance in coefficient value. The coefficient for unemployment in the first-generation regression is -0.0323, whereas the coefficient in the US native model is -0.0218 and even lower for the second generation at -0.0181. These findings imply that changes in unemployment have a greater effect on first-generation immigrants' income compared to other groups. This indicates that they work in more cyclically-sensitive occupations, especially blue-collar positions.

Age, education, and supervisory employment are all positively correlated with income and significant at the 1% level. In the US Native model, the coefficient for education is 0.181, which is similar to the coefficient value of 0.182 in the second-generation regression. Yet for the first-generation regression, the education coefficient is only half as large, at 0.0923. This result provides evidence that first-generation immigrants experience lower returns to education than US natives, but that difference diminishes by the following generation. This has not been explored by previous research

Age also has a much lower impact on the incomes of first-generation immigrants, with a coefficient value of 0.0141 compared to 0.2145 for US natives. The limited effect of age suggests that first-generation immigrants have fewer opportunities for career advancement, as it shows their incomes increase minimally over time. The coefficient is even higher for second-generation than for native-born.

For employment in a supervisory position, the coefficient for both immigrant groups is larger than that of US natives. This increased difference could be because of the lower percentage of immigrants in supervisory positions: only the exceptional immigrant or child of immigrants gets promoted, and their income is correspondingly higher.

In the first-generation immigrant model, GDP per capita for country of origin is significant at the 1% level with a coefficient of 0.019, whereas in the second-generation model, the estimated coefficient is near zero. This decrease implies that the resources in an immigrant's country of origin have a much greater impact on the first generation than the second generation. This finding makes sense, as the first generation must directly utilize their home country's resources before immigrating, in comparison to the second generation that is born in the US.

Alternatively, if the significance for the first generation in any way reflects prejudice against immigrants from poor countries, that discriminatory effect wanes by the next generation.

The overqualified measure is significant at the 1% level in all regressions. However, it has a positive effect on income in the first-generation but a negative effect in the other two regressions, which is consistent with the combined model. The positive correlation in the first-generation model is surprising. In Hardoy and Schøne (2014), the results for the overqualified measure were negative across all observations. Perhaps first-generation workers with higher educational attainment are paid more as an incentive to stay with their current employment, or that education is a proxy for talent or hard work that is reflected in pay. It demonstrates that overqualification can have multiple effects on earnings and requires a two-tailed test. The first generation of immigrants may be excluded from Native career ladders, so they earn recognition as exceptionalist.

The findings regarding race vary notably across immigrant groups. The indicator for black workers is significant at the 1% level across all regressions and has a negative effect on income. Its coefficient value is the highest in the second-generation model, -0.132, and lowest in the one for US natives, -0.081. It shows that- for black employees- second-generation immigrants experience the largest earning discrepancy compared to others in their immigrant group. The combination of Blackness and immigrant parents appears to slow the integration into the US economy. Likewise, the indicator for Hispanic workers is negatively correlated and is significant at the 1% level in all regressions. However, it has the highest coefficient value in the model for first-generation immigrants, with an estimated coefficient of -0.111.

The variable for American Indians is significant at the 1% level in the US native model, at the 5% level in the first-generation immigrant model, and at the 10% level in the second-generation model. The coefficient for this variable also changes from -0.134 in the US native regression to 0.066 in the first-generation. The positive effect of Native American status on income in the first-generation regression contradicts previous findings, but could be explained by a limited number of observations or measurement error. Only about 10,000 of the 912,600 observations in the full dataset are from Native Americans. Lower-income immigrants from Mexico, for instance, might not identify as Native American, despite having indigenous ancestry.

The significance of being Asian varies in a similar manner. It is significant at the 10% level in the US native regression, at the 5% level in the first-generation regression, and at the 1% level in the second-generation regression. It is the only racial variable to be positively correlated to income in all three regressions, and it has the largest coefficient value in the second-generation regression among the racial dummy-variables, meaning that second-generation Asian workers earn more compared to other second-generation immigrants. The mixed-race indicator has negative significance at the 1% level in the US native regression, but positive significance at the 5% level in the first-generation regression. The inconsistent results for this variable are in line with previous findings from established literature.

Conclusion

The original purpose of this study was to compare the returns to education for first-generation and second-generation immigrants. The results from the separate regressions for each immigrant group provide statistical evidence that first-generation immigrants experience significantly lower returns to education compared to both second-generation immigrants and US natives. This finding supports the initial hypothesis that the second generation would have higher returns to education. It also reveals that the second generation experiences the same returns as those native-born. In itself, this suggests relative rapid access to lucrative career ladders for the more-educated, despite having immigrant parents.

The models used in this study also included variables that measure the GDP per capita for immigrants' origin countries and identify overqualified workers. GDP per capita for origin countries was significant in the first-generation model, which supports the theory that immigrants from wealthier countries experience higher returns to education. The overqualified measure was significant in all models. These two results are consistent with previous literature.

However some findings were unexpected and require further research. Although consistently significant, the sign for the overqualified measure becomes positive in the first-generation model, which differs from the existing literature. Given the lower educational attainment of first-generation immigrants and the fewer number of overqualified first-generation workers compared to other immigrant groups, it is possible that employers are more willing to offer greater wages to the highly educated first generation. One unique aspect of this study is a combined model with data from natives, first-generation immigrants, and second-generation immigrants. In this full model, the variable for first-generation immigrants has a positive effect on income. The hispanic variable in the first-generation model is also positively correlated to income. It is proposed that these unusual results are due to sample-selection bias from the US Census and a lack of information on low-income households. However additional research with different income data is needed to confirm this theory.

This research provides more information on the characteristics shaping second-generation immigrants' income and offers a potential explanation for the lower incomes of the first generation. The results from the separate models show that the income effects of certain attributes, such as age or supervisory employment, vary even between first and second-generation immigrants. Furthermore, the lower returns to education for the first generation demonstrate that even with similar levels of educational attainment, first-generation immigrants will still earn less than second-generation immigrants or US natives. This result implies that the incomes of first-generation immigrants are influenced by numerous factors and that their fewer earnings may not be entirely explained by a lack of education. Therefore, it emphasizes the need for additional research regarding determinants of immigrants' income.

There are multiple research opportunities to expand on this work. One option is to recreate this study with data from a wide range of households. Researchers could identify whether these results are still attainable when there is a wider proportion of lower-income households. Another possibility is to include a direct measure of the quality of education. In this study, GDP per capita was used as a proxy measure for the resources brought from outside countries, but there could be another variable directly related to foreign education that would offer more information. Yet overall, this research offers further insight into the factors affecting immigrants' income and highlights the distinction between the first and second generation.

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Appendix

Table 1: Summary Data

Variable Name	Description	Mean	Standard Deviation	Data Source
tpinc	The log of the respondent's total Personal Income	10.36	1.15	https://www.census.gov/data/datasets/time-series/demo/cps/cps-asec.2019.html
year	The year the observation was taken	2013.84	3.21	https://www.census.gov/data/datasets/time-series/demo/cps/cps-asec.2019.html
age	The respondent's age	41.95	13.83	https://www.census.gov/data/datasets/time-series/demo/cps/cps-asec.2019.html
educ	Years of education received	10.63	2.64	https://www.census.gov/data/datasets/time-series/demo/cps/cps-asec.2019.html
spvsr	Whether the respondent is in a supervisory role for their occupation	0.11	0.31	https://www.census.gov/data/datasets/time-series/demo/cps/cps-asec.2019.html
lgdpc	The log of GDP per capita for the respondent's country of origin	10.47	0.97	https://wits.worldbank.org/CountryProfile/en/Country/BY-COUNTRY/Sta

				rtYear/2014/EndYear/2014/Indicator/NY-GDP-PCAP-KD#
ovqual	Whether the respondent exceeds the average education requirement for their occupation	0.31	0.46	https://www.bls.gov/emp/tables/education-and-training-by-occupation.htm
unem	The average unemployment rate for the year of observation	6.64	2.16	https://fred.stlouisfed.org/series/UNRATE
gen1	Whether the respondent is a first-generation immigrant	0.18	0.39	https://www.census.gov/data/datasets/time-series/demo/cps/cps-asec.2019.html
gen2	Whether the respondent is a second-generation immigrant	0.08	0.27	https://www.census.gov/data/datasets/time-series/demo/cps/cps-asec.2019.html
female	Whether the respondent is female	0.48	0.5	https://www.census.gov/data/datasets/time-series/demo/cps/cps-asec.2019.html
black	Whether the respondent's race is Black	0.1	0.3	https://www.census.gov/data/datasets/time-series/demo/cps/cps-asec.2019.html
hspnc	Whether the respondent's race is Hispanic	0.17	0.38	https://www.census.gov/data/datasets/time-

				series/demo/cps/cps-asec.2019.html
asian	Whether the respondent's race is Asian	0.06	0.24	https://www.census.gov/data/datasets/time-series/demo/cps/cps-asec.2019.html
natam	Whether the respondent's race is Native American	0.01	0.1	https://www.census.gov/data/datasets/time-series/demo/cps/cps-asec.2019.html
mixed	Whether the respondent is mixed race	0.02	0.13	https://www.census.gov/data/datasets/time-series/demo/cps/cps-asec.2019.html

Table 2: Summary Statistics for US Natives

Variable Name	Mean	Standard Deviation
tpinc	10.39	1.16
year	2013.79	3.21
age	42.3	12.02
educ	10.86	2.29
spvsr	0.12	0.32
lgdpc	N/A	N/A
ovqual	0.32	0.47
unem	6.67	2.15
female	0.49	0.5
black	0.12	0.32
hspnc	0.06	0.23
asian	0.01	0.1
natam	0.01	0.11
mixed	0.02	0.13
Observations	737,859	

Table 3: Summary Statistics for First-generation Immigrants

Variable Name	Mean	Standard Deviation
tpinc	10.27	1.09
year	2013.94	3.2
age	42.61	12.4
educ	9.64	3.63
spvsr	0.08	0.27
lgdpc	8.87	1
ovqual	0.25	0.43
unem	6.57	2.15
female	0.44	0.5
black	0.08	0.26
hspnc	0.51	0.5
asian	0.24	0.43
natam	0	0.04
mixed	0	0.08
Observations	183,561	

Table 4: Summary Statistics for Second-generation Immigrants

Variable Name	Mean	Standard Deviation
tpinc	10.28	1.23
year	2014.07	3.21
age	37.33	14.33
educ	10.84	2.41
spvsr	0.1	0.3
lgdpc	9.78	0.99
ovqual	0.32	0.47
unem	6.48	2.15
female	0.48	0.5
black	0.04	0.2
hspnc	0.47	0.5
asian	0.13	0.33
natam	0	0.06
mixed	0.03	0.16
Observations	81,409	

Table 5: Robust Regression Results

	1 - Full Dataset	2 - US Natives	3 - First-Generation Immigrant	4 - Second-Generation Immigrant
age	0.02121 *** (241.54)	0.02145 *** (211.77)	0.01399 *** (48.45)	0.02638 *** (46.82)
educ	0.15278 *** (292.14)	0.180473 *** (262.64)	0.09232 *** (76.92)	0.18198 *** (51.05)
spvsr	0.38786 *** (112.52)	0.356827 *** (90.21)	0.4636 *** (36.53)	0.412653 *** (17.4)
lgdpc	0.00243 (1.01)		0.01941 *** (4.79)	0.00649 (0.7)
ovqual	-0.02993*** (-11.89)	-0.06043 *** (-20.81)	0.05248 *** (5.77)	-0.02637 (-1.63)
unem	-0.0233 *** (-44.24)	-0.0218 *** (-35.07)	-0.03232 *** (-20.38)	-0.01809 *** (-5.25)
gen1	0.40416 *** (6.87)			
gen2	-0.00973 * (-1.85)			
female	-0.42396 *** (-191.11)	-0.4372 *** (-167.09)	-0.41117 *** (-59.98)	-0.32697 *** (-22.96)
black	-0.10015 *** (-27.56)	-0.0811 *** (-20.33)	-0.098 *** (-5.87)	-0.13229 *** (-3.27)
hspnc	0.00938 *** (2.33)	-0.00455 (-0.77)	-0.11129 *** (-10.12)	0.06795 *** (3.43)
asian	-0.02935 *** (-5.01)	0.005623 (0.44)	0.0144 (1.15)	0.07698 *** (2.74)
natam	-0.15327 *** (-12.91)	-0.13442 *** (-10.73)	0.06643 (0.79)	-0.0454 (-0.26)
mixed	-0.1175 *** (-12.28)	-0.12407 *** (-11.31)	0.04616 (1.14)	0.007 (0.15)
_cons	8.1523 *** (301.78)	7.875792 *** (777.6)	9.01 *** (206.98)	7.528149 *** (135.69)
R-sq	0.2618	0.2782	0.2102	0.2938
F-statistic	17271.61	15889.46	1813.92	665.73
Prob > F	0.0000	0.0000	0.0000	0.0000

*Note: * - .10 significance, ** - .05 significance, *** - .01 significance with two-tailed test*