THE UNIVERSITY OF CHICAGO

Immigrant Intergenerational Mobility: Effect of Parental Income Trajectory

By

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Abstract

This paper contributes to the literature on immigrant mobility in the US context by examining how immigrant parents' income trajectory impacts the early-career income and educational achievement of their children. Through analyzing a custom-built panel dataset made of two immigrant cohorts, I hope to estimate the effect of parental income growth rate on the children's outcomes. To achieve this, I utilize the OLS slope of both parents' income over time to operationalize the rate of change during the child's development, controlling for a range of individual and family factors. Under the "role model" hypothesis, an upward income trajectory of immigrant parents can signal successful integration and provide motivation for the second generation. However, common sociological barriers such as social class may still limit the mobility of immigrant children. After a comprehensive analysis of data from the Panel Study of Income Dynamics, I did not observe a robust effect of parental income trajectory that spans the first 18 years of child growth. However, evidence suggests that parental income growth during teenage years can potentially have a positive influence on total years of schooling completed by the child. Average parental income appears to be a much more reliable predictor of child outcomes, pointing to a stratification of social class within the immigrant community.

Keywords: Immigration; Intergenerational Mobility; Parental Income Trajectory; PSID

1 Introduction

Immigration in the US has been an important area of research for social scientists and policy-makers. While there are many factors behind the growing number of immigrants, one common motivation for immigration is to seek better economic opportunities and pursue the American dream. Intergenerational mobility, which refers to the changes in "individual status" across generations, provides a very useful lens to look at the social standing of immigrants. In a just society, we would see the children of immigrants achieve upward movement even when their parents have limited resources. While there has been a vast literature on the intergenerational correlations of income and education, the mechanisms of the process are yet to be fully understood. Immigrants as a group also received relatively less scholarly attention than the native population. This project aims to draw on existing literature on income and education mobility to examine how income trajectory of immigrant parents impacts their children's outcomes. I introduce parental income slope as a measurement of temporal income changes, utilizing a wide range of specifications to probe the complex processes of intergenerational correlations within the immigrant community.

My research question is: Does parental income trajectory affects immigrant children's early-career earnings and educational attainment? I hypothesize that immigrant parents who experience greater income growth during the child's development window (0 - 18 years old) serve as a positive "role model", motivating their children to achieve higher income and educational level. I will study this question by building a sequence of models that account for family influence and individual attributes.

2 Literature Review

The study of intergenerational mobility has produced two core empirical measures: the intergenerational elasticity of earnings (IGE) and the rank-rank slope. Both consider the full income distribution to capture how children's earnings relate to their parents' position. However, these estimators impose a linear relationship that can be misspecified, since children from high-earning families have limited room for upward movement relative to children from low-income backgrounds (Deutscher & Mazumder, 2023). The literature on education mobility has similarly relied on linear or log-linear regression (Black & Devereux, 2011; M. Hill & Duncan, 1987; Torche, 2011), which may obscure causal mechanisms. More recent work has introduced nonparametric models to capture nonlinear processes of intergenerational transmission (Chang et al., 2025b), though this line of research remains in its early stages. By treating parental income trajectory as a main predictor of child outcome, we can bypass the specification problem in mobility research, as children's income level is not inherently bounded by parental income growth rate.

Some mobility scholars have focused on the temporal dimension of parental income. Rather than treating parental earnings as a fixed snapshot, they track the child's exposure to income over time, contributing to a trajectory-based framework of mobility. Research has shown that the timing of parental income during a child's formative years leads to heterogeneous effects on future earnings (Carneiro et al., 2021; Chang et al., 2023). There is evidence suggesting that income and family structure trajectories have the strongest influences in middle childhood and adolescence, rather than early childhood (Chang et al., 2025a). However, the alternative pattern can also be observed in young children, where early economic disadvantage can undermine educational outcomes despite later improvement of family income (Riser et al., 2022). Other work has examined how the duration of neighborhood poverty exposure shapes children's outcomes (Wodtke, 2016) and how parents' intragenerational income trajectories are linked to children's own trajectories across life stages (Cheng & Song, 2019). While this body of work establishes the importance of the temporal dimension of parental income, it has not directly examined the rate of parental income growth as a distinct channel.

Many studies have also documented the importance of neighborhood context for intergenerational outcomes. Chetty et al. (2014) and Chetty and Hendren (2018) established that geography exerts an independent and irreducible influence on mobility. Studies of neighborhood effects have further shown that residential conditions—including poverty concentration and exposure to disadvantaged peers—shape children's long-run attainment (Harding, 2003; Wodtke et al., 2023). For immigrant families, the racial composition of neighborhoods is especially relevant: racial enclaves may provide co-ethnic social capital and cultural resources, though their relationship to intergenerational mobility is not fully understood.

In recent years, researchers have shown increased attention to intergenerational mobility among immigrant families. Early work in this tradition grew out of the labor economics framework, examining the income correlations between first-generation immigrants and their native-born children across ethnic groups (Borjas, 1993). More recent scholarship has used large-scale administrative data to identify long-term trends, compare immigrant and native families, and map geographic variations in upward mobility (Abramitzky et al., 2022). Sociological studies have expanded the outcome space beyond income to include health, education, and occupational attainment (Feliciano, 2020), and an expanding literature identifies differential mobility mechanisms across ethnic groups (Aydemir et al., 2013; Kim, 2006) or even adopts a multigenerational perspective (Hammarstedt, 2009). Despite this progress, there is still a conceptual gap in terms of the exact mechanisms behind immigrant mobility.

This project is inspired by the intellectual frameworks listed above and aims to move forward the research on what parental factors may influence child outcomes. Theoretically, my work is grounded in the family investment model (Becker & Tomes, 1979), which holds that parents' monetary resources shape children's human capital and future earnings. I extend this framework by treating parental income growth, aside from income level, as a distinct mechanism. In doing so, I operationalize the "role model hypothesis" from M. Hill and Duncan (1987): upward movement of parents may serve as a source of motivation for their children beyond the material resources. The intuition is that a promising income trajectory of parents can signal underlying behaviors that facilitate integration, which can encourage positive behavioral measures in children that are conducive to higher income and educational attainment. In fact, there is some evidence from past studies suggesting that income trend may have modest beneficial associations with measures of behavior in children (H. D. Hill, 2021), but alternative findings suggest that class reproductions can override individual efforts (Feliciano & Lanuza, 2017). Using PSID data on immigrant households, this project will expand on the temporal frameworks of mobility and explore the influences of parents' income trajectory. Through implementing various specifications of regression models, I will examine the effect of parental income slope on child income and education, while controlling for family and individual factors. I hope that my work can draw scholarly attention to the unique patterns of mobility among US immigrants and encourage future research on the topic.

3 Data

3.1 Overview

This study draws on data files from the Panel Study of Income Dynamics (PSID) to construct an intergenerational dataset with rich information about the income, education, and demographics of immigrant households. PSID is a nationally representative longitudinal survey since 1968, which provides individual and family-level details about survey households. It is supplemented by two immigrant refresher samples that form the basis of my analysis. The 1997 New Immigrant Sample (Tier 1) added 1,391 heads of household, and the 2017 Immigrant Refresher (Tier 2) contributed an additional 608 individuals. Together, these two cohorts constitute the universe of immigrant parents used in all models.

I merge four types of PSID files to build my custom dataset. The cross-year individual file uniquely identifies each survey respondent and contains individual information including age, sex, sample-member status, and educational level for each survey wave. Education is measured in the number of grades completed. Age is used to recover the birth year for each individual. The family files supply household-level economic and demographic variables for each survey wave. I use the combined income of both parents for all parental income constructions. Income of the children is directly available in the files if the child is head of the household. Otherwise, I calculate it by subtracting income of household head from the combined income of head and spouse. I then deflate all the income variables to 2024 dollars using the CPI-U-RS research series (Stewart & Reed, 1999). In the cases where race of the child is ambiguous or not directly observable, I impute it from the race of his/her parents. The individual file and family files have annual data from 1968 to 1997 and then becomes biennial from 1999 to present. The parent identification file provides child-parent linkages, which allows me to map each child to their biological father and mother using a unique identifier.

The final dataset consists of pairs of immigrant parents and children, where each pair links a child to his/her parents. Every pair contains a full set of variables including income, education, and demographic information. Parental income is measured using the log of the combined annual labor income of both parents for all observable waves. This will later be used to calculate the OLS income slope and average parental income over a designated number of survey waves. I define parental education as the maximum number of grades completed between both parents as of the latest wave. As for the child outcomes, I compute the average (log) annual labor income of the child between 24 and 27 years old, the maximum number of grades completed as of the latest wave (for children above 24 years old), a boolean variable for high school completion by age 19, and a boolean variable for college completion by age 23. The choice of age thresholds aims to provide a decent coverage of early-career income and educational achievement without truncating the sample size too much, as many children in the survey cohorts are relatively young by the time of this study. When race of the child needs to be imputed from the parents, I assign the parents' race to the child if both parents share the same race. If the parents are not of the same race, a child with a Black parent is coded as Black, a non-Black child with a White parent is coded as White, and for all other combinations, the race is coded as Other. If race is only available for one parent, I assign it to the child directly.

I have acquired expedited IRB approval from the University of Chicago for the use of de-identified secondary data that can contain geographical identifiers at Census-tract level. The protocol number is IRB26-0154.

3.2 Summary Statistics

The dataset contains 2,324 pairs of immigrant parents and children. In terms of family structure, 81% of children have an immigrant father and a native-born mother, while 11.7% of them have both parents classified as immigrants. 87.1% of children share parents with at least one other child in the dataset, as there are 299 children who are the only child in their households.

As for the variables that are used in the analysis, parents generally see better coverage compared to the children partially because they are older and appear in more survey waves. Among all the 2,324 observations, 98.1% have parental education, 87.2% have a race code for at least one parent, and 52.41% have parental income for at least 3 survey waves. 77.2% of children have a specific race assigned to them, 28.4% have observed education when they are 24 or older, and 12.6% have observed income between 24 and 27 years old.

Most parents in the sample arrived in the US as an adult, as only 8.3% of them arrived before the age of 9 (Figure 1). This implies that they would likely face cultural and language barriers when they raised their children. While an immigrant who arrived at a very young age may have a more ambiguous status of the 1.5 generation, my sample mostly consists of parents who clearly belong to the first generation of immigrants.

The distribution of parental income roughly follows a bell curve, with the mean and median income around $60,000 (Figure 2, Figure 3). On the other hand, the children's mean income between age 24 and 27 is much smaller on average. The distribution is left skewed and has more outliers in the lower income bracket. This could be due to the limited age window of 24 to 27 years old, when some children may still be in school or have not secured stable employment.

As for the distribution of educational level, a high school degree is most common among the parents and children, with a bachelor's degree as the second most common (Figure 4, Figure 5). Compared to the children, the parents see a higher number of individuals with little education, suggesting a potential generational gap.

The racial composition of the PSID sample seems to diverge from the contemporary US demographics, with an oversampling of White immigrants as well as an undersampling of Hispanic and Asian immigrants (Figure 6). It is possible that the category "Other" contains Hispanic immigrants, but the precise makeup is not identifiable. The sample appears to have a generally balanced male-to-female ratio.

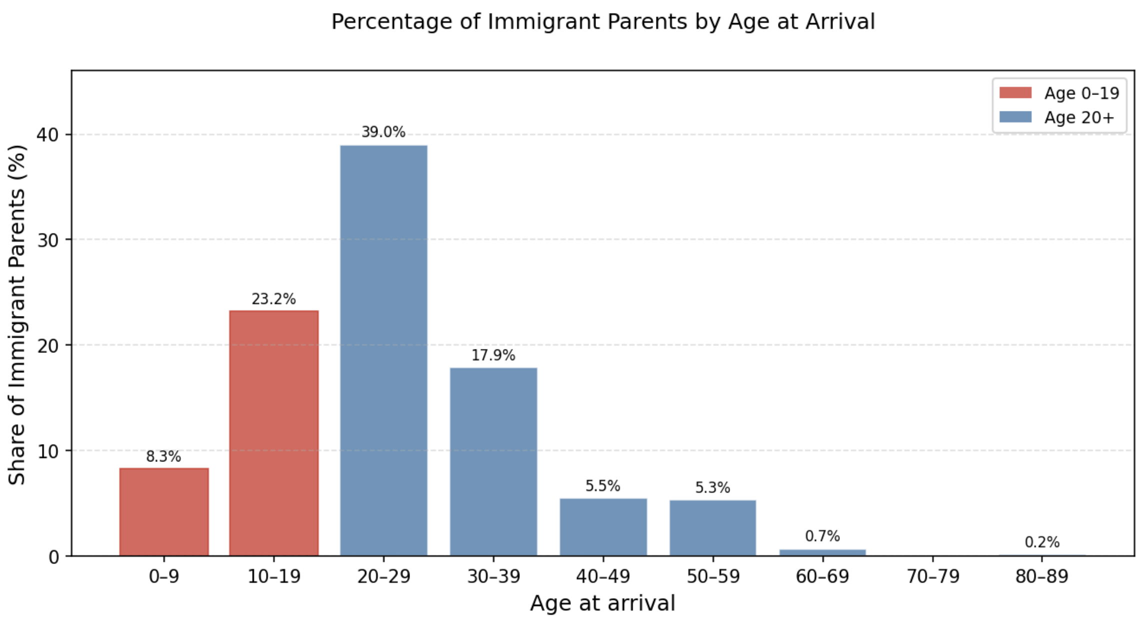

Figure 1: Distribution of Age at Arrival for Parents

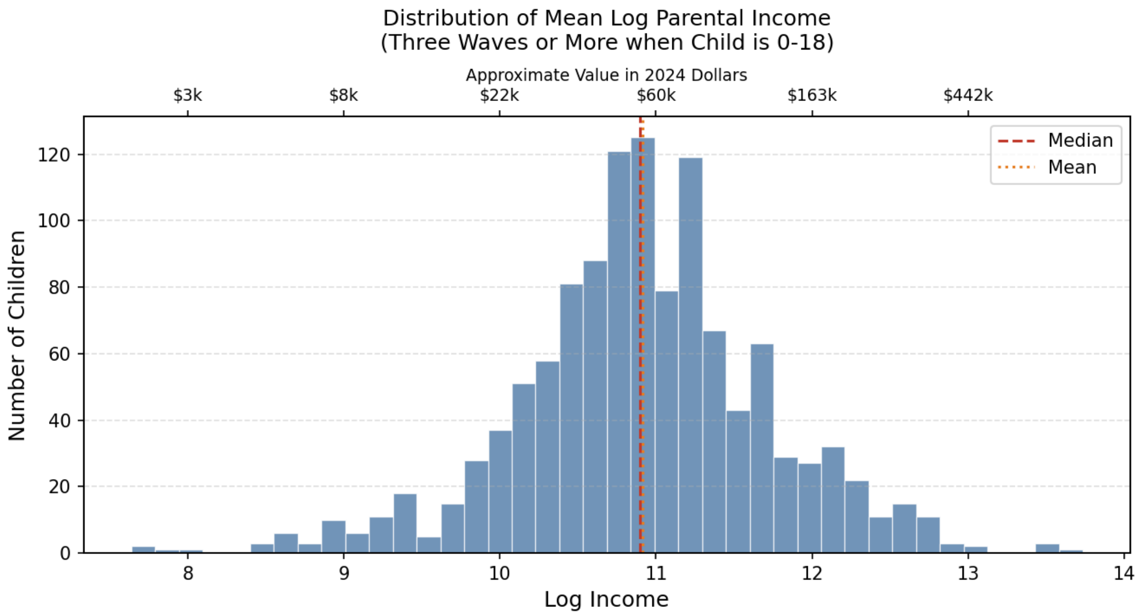

Figure 2: Distribution of Mean Parental Income

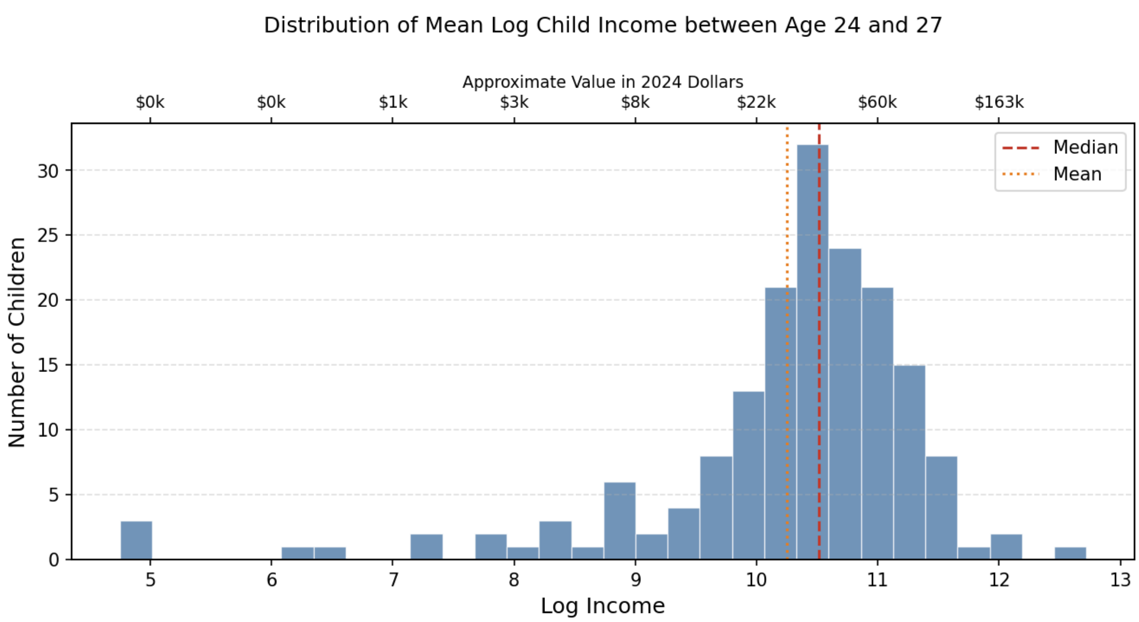

Figure 3: Distribution of Mean Child Income (Log, Ages 24–27)

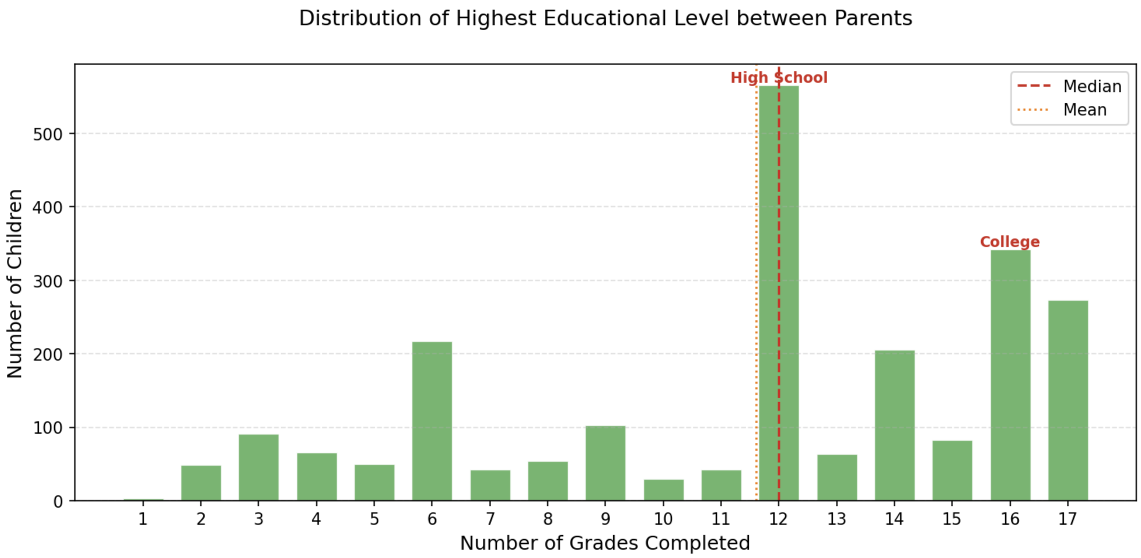

Figure 4: Distribution of Maximum Parental Education

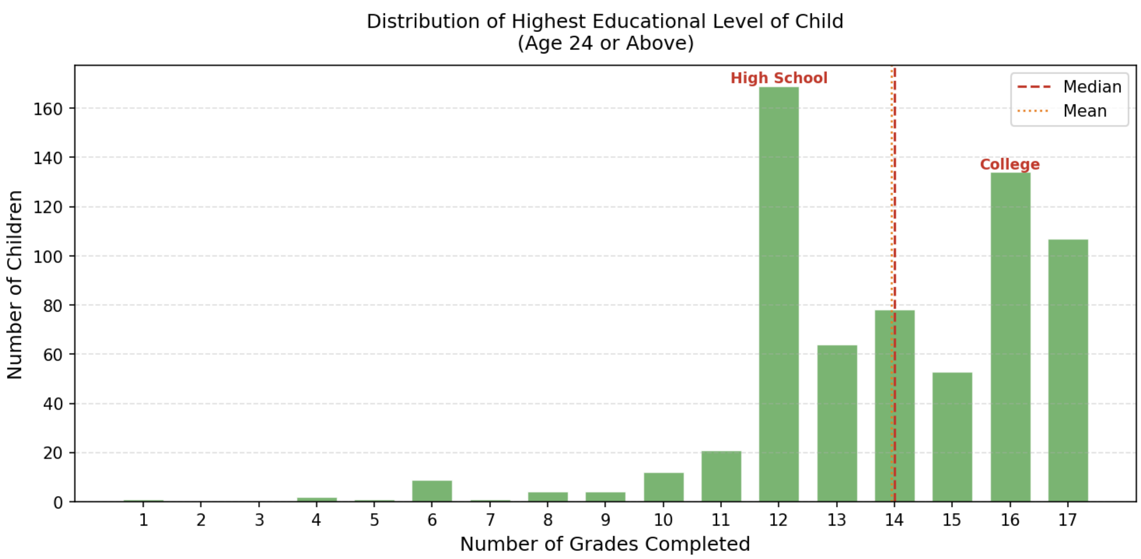

Figure 5: Distribution of Maximum Child Education

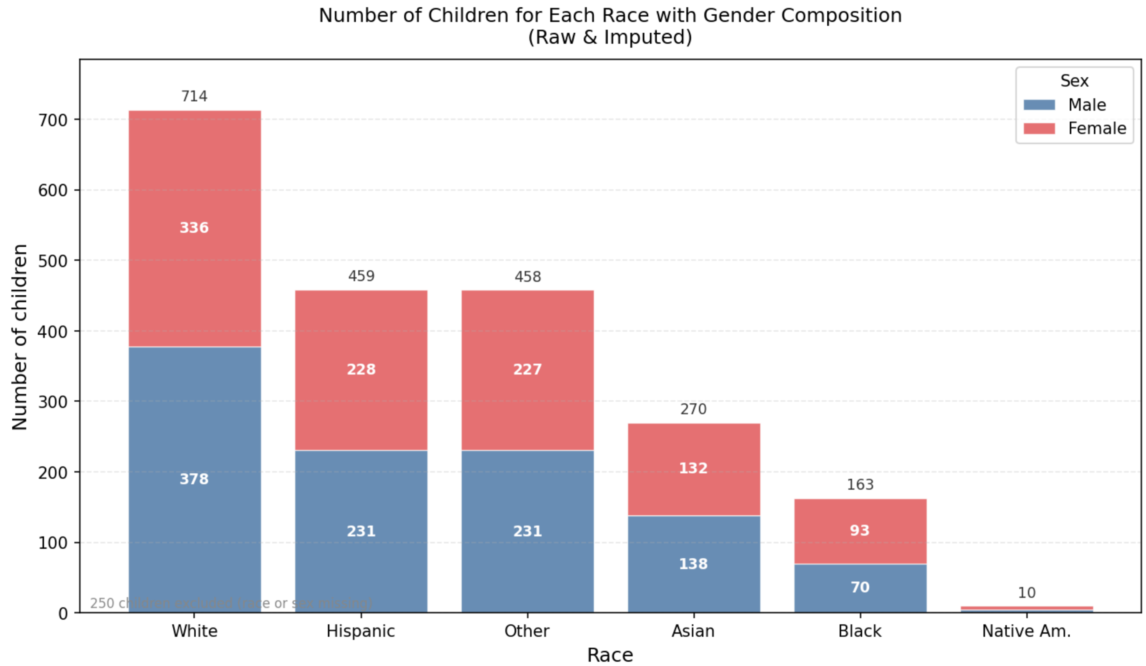

Figure 6: Distribution of Child Race and Sex

4 Methods

To examine the role of parental income trajectory in immigrant mobility, I implement a sequence of OLS regressions with child income or education as the dependent variable. I start with the child income models, followed by the child education models. Then I perform a series of robustness checks on the main specifications.

For the baseline specification, I calculate average parental income as well as parental income slope using at least 3 waves of income observations. Because the survey waves are biennial, this implies that each of the two variables are derived from a window of at least 5 years when the child is 0 to 18 years old. While a wider time span can reduce first-stage estimation error and have better coverage of child development, this is a practical choice given the trade-off between precision and sample size (or statistical power). I will test the validity of this construction in section 6. I implement clustered standard errors for all specifications because as shown in section 3, the majority of the children in my dataset share parents with at least one other person. These siblings will share social and genetic similarity. I also calculate the variance inflation factor for my main specifications and report it if it is high.

The parental income slope serves as an approximation of the rate of parents' income growth (or decline) during child development. I define it as the OLS slope of both parents' income over survey wave years. Because the slope and the average parental income are derived from the same series of income observations, I demean it to avoid collinearity and inflated standard errors, which provides a clearer separation of income level and income trajectory. The equation is shown below:

$$\Theta_{p(i)} = \frac{\sum_{t \in \mathcal{T}_{p(i)}} (t - \bar{t}_{p(i)})(\ln y_{p(i),t} - \overline{\ln y}_{p(i)})}{\sum_{t \in \mathcal{T}_{p(i)}} (t - \bar{t}_{p(i)})^2} \tag{1}$$

where $\Theta_{p(i)}$ is the demeaned income slope, $\mathcal{T}_{p(i)}$ is the set of waves with positive observed income, $\bar{t}p(i)$ is the mean wave year, and $\overline{\ln y}p(i)$ is the mean log income. $\Theta p(i)$ is orthogonal to $\ln(\bar{y}p(i))$ by construction.

4.1 Child Income

Income is a crucial indicator of the well-being of an immigrant child. I use early-career income of the child as the dependent variable. I implement a model that regresses child income over parental income slope, while controlling for both parents' attributes and individual traits of the child:

$$\ln(\bar{Y}_i) = \beta_0 + \beta_1 \Theta_{p(i)} + \beta_2 \ln(\bar{y}_{p(i)}) + \beta_3 E_{p(i)} + \beta_4 \text{Male}_i + \boldsymbol{\beta}_5^\top \mathbf{R}_i + \beta_6 S_i + \varepsilon_i \tag{2}$$

where $\ln(\bar{Y}_i)$ is the average income of the child between 24 and 27 years old, β_0 is the constant term, $\Theta_{p(i)}$ is the parental income slope, $\ln(\bar{y}_{p(i)})$ is the average income of both parents during child development, $E_{p(i)}$ is the maximum number of grades completed between two parents, Male_i is a dummy variable that equals 1 if the child is male, $\mathbf{R}_i$ is a race vector that consists of 5 race dummies including White, Black, Asian, and Latino, with Other as the reference category, S_i is the maximum number of grades completed by a child who is at least 24 years old, and ε_i is the stochastic error term.

4.2 Child Education

The use of early-career income, as measured by average annual income between 24 and 27 years old, can greatly reduce the sample size and introduce noise due to the small age window. Thus, I use child education as an additional dependent variable to further explore the effect of parental income trajectory on future achievement of the child, as the literature has commonly linked education to income. Child income is not suitable as a control variable because it can be the downstream outcome driven by education. Again, I start with a model that regresses the number of grades completed by the child over parental income slope, controlling for both parents' attributes and individual traits of the child:

$$S_i = \beta_0 + \beta_1 \Theta_{p(i)} + \beta_2 \ln(\bar{y}_{p(i)}) + \beta_3 E_{p(i)} + \beta_4 \mathrm{Male}_i + \boldsymbol{\beta}_5^\top \mathbf{R}_i + \varepsilon_i \tag{3}$$

where I use the same set of variables as the income model, with education now as the outcome of the child. I then use linear probability models to explore the probability of high school completion or college completion respectively, allowing me to examine two educational milestones of the child:

$$\Pr(\mathrm{HS}_i = 1) = \beta_0 + \beta_1 \Theta_{p(i)} + \beta_2 \ln(\bar{y}_{p(i)}) + \beta_3 E_{p(i)} + \boldsymbol{\beta}_4^\top \mathbf{R}_i + \beta_8 \mathrm{Male}_i + \varepsilon_i \tag{4}$$

$$\Pr(\mathrm{COL}_i = 1) = \beta_0 + \beta_1 \Theta_{p(i)} + \beta_2 \ln(\bar{y}_{p(i)}) + \beta_3 E_{p(i)} + \boldsymbol{\beta}_4^\top \mathbf{R}_i + \beta_8 \mathrm{Male}_i + \varepsilon_i \tag{5}$$

where $\Pr(\mathrm{HS}_i = 1)$ is the probability that the child has completed high school by the age of 19, $\Pr(\mathrm{COL}_i = 1)$ is the probability that the child has completed high school by the age of 23. All the other variables have been previously defined. It is worth noting that I assume the effect of income slope is linear throughout the child's growth, which I will test in section 6.

5 Results

5.1 Income

The regression results from child income models are shown in Table 1. The sample size is not large mostly because parental income measures require at least 3 waves, and child income requires at least one positive value between the age of 24 and 27. I acknowledge that the operationalization of child income implies the existence of attenuation bias due to the volatility of early-career earnings, but it is rare to have intergenerational data on US immigrant households that have wide coverage of lifetime income.

Parental income slope does not seem to have a significant effect on child income, and the large standard errors mean that the true effect is not clearly identifiable. Average parental income has generally weak associations with income of the child, which could be driven by the measurement noise on the children's side. Parental education, however, remains statistically significant across all relevant specifications, and the magnitude of the coefficient experiences very small changes even with additional controls. This suggests that immigrant parents with more education are likely to raise children with higher early-career income, though the actual causal mechanism would require further examination. The fact that parental education is still influential after controlling for child education implies that the children of highly educated parents benefit from channels other than their own education. Gender is shown to be another significant regressor, suggesting a divergence of income level between male children and female children within the immigrant community. All of the coefficients for race dummies have negative values, but this is not a robust observation given the large standard errors and the small reference group. Finally, child education appears to be a strong predictor of income, which is consistent with the common findings in labor economics.

TABLE 1
PARENTAL INCOME SLOPE AND CHILD INCOME

Dep. var.:	Log child income (mean, 24–27)				
	(1)	(2)	(3)	(4)	(5)
Parental income slope	−0.419	−0.260	−0.260	−0.379	−0.346
	(0.557)	(0.554)	(0.624)	(0.665)	(0.640)
Avg. parental income	0.058	−0.053	−0.075	−0.072	−0.102
	(0.066)	(0.076)	(0.070)	(0.078)	(0.077)
Parental education		0.181**	0.201**	0.221**	0.187**
		(0.086)	(0.081)	(0.088)	(0.089)
Male			0.501***	0.481***	0.557***
			(0.140)	(0.142)	(0.149)
Race: White				−0.263	−0.259
				(0.182)	(0.196)
Race: Black				−0.515	−0.551
				(0.487)	(0.444)
Race: Asian/Pacific Islander				−0.340	−0.428
				(0.304)	(0.312)
Race: Latino				−0.405**	−0.360*
				(0.193)	(0.213)
Child education					0.220**
					(0.098)
R^2	0.004	0.025	0.086	0.097	0.136
Observations	170	170	170	170	170

Notes. Each column reports coefficients from an OLS regression with standard errors clustered at the family level in parentheses. Continuous covariates are standardized to mean zero, unit variance within the estimation sample; the parental income slope and all binary covariates are in original units. Sample restricted to observations with at least three positive parental income waves when the child is 0 to 18 years old and at least one observed child income wave between 24 and 27 years old. Educational level is measured in terms of years of schooling. Log transformation has been applied to parental income. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Education

Now I present the regression results from the models where education is the outcome variable, as shown in Table 2. Sample size is clearly larger because child income is removed from the specifications, providing more statistical power. Compared to the child income models, child education generally has less noise as a dependent variable.

Similar to the previous section, parental income slope is subject to large standard errors and does not have any identifiable effect on child education. However, average parental income is statistically significant across all specifications, suggesting that high-income households are more likely to provide children the resources to achieve better educational outcomes. This is consistent with the assumptions of the Becker-Tomes model, where parents invest in the human capital of their children. Parental education has weak associations with child outcome in the second and third specifications, and the pattern diminishes after controlling for race. It is possible that educational level of parents absorbs some of the income effect. Again, gender seems to be a strong predictor of child outcome among immigrant households. The race dummies do not seem to hold much explanatory power except for Asian/Pacific Islander, which may have some positive associations with education. However, we can only reject the null hypothesis at the 10% level, so it is hard to frame the racial difference as a robust finding.

The results from the linear probability models are shown in Table 3. Sample size is even larger than the models for years of schooling, a result of the lower age threshold. Rather than examining the incremental changes in child education, the family of models listed here aims to provide a general sense of how family and individual factors impact educational milestones of immigrant children.

The findings for high school completion see a significant relationship between parental income slope and child outcome, indicating that an upward income trajectory of both parents during child development may have a positive association with the probability of high school graduation. The pattern persists when controlling for race. Average parental income and parental education appear to be trivial, which could be caused by sample noise. Gender is still a powerful indicator of outcome. While Black children seem to be associated with a higher chance of finishing high school among all immigrant children, the actual relationship needs further examination with a more robust reference group.

The findings for college completion, however, suggest a very different set of correlations. The influence of parental income slope is now unidentifiable given the standard errors. Average parental income becomes strongly associated with college graduation. As a college degree is often viewed as a passport to middle-class stability, it is likely that immigrant children from relatively well-off families are more likely to have the resources to maintain their status through college education. The coefficient for parental education is generally

Table 2
Parental Income Slope and Child Education

Dep. var.:	Child education (24 or above)			
	(1)	(2)	(3)	(4)
Parental income slope	0.480	0.425	0.332	0.209
	(0.535)	(0.535)	(0.541)	(0.524)
Avg. parental income	0.311***	0.238***	0.245***	0.210***
	(0.050)	(0.056)	(0.055)	(0.062)
Parent education		0.145*	0.130*	0.108
		(0.078)	(0.077)	(0.077)
Male			−0.355***	−0.376***
			(0.114)	(0.112)
Race: White				0.069
				(0.197)
Race: Black				−0.061
				(0.332)
Race: Asian/Pacific Islander				0.445*
				(0.259)
Race: Latino				0.038
				(0.184)
R^2	0.098	0.114	0.145	0.164
Observations	355	355	355	355

Notes. Each column reports coefficients from an OLS regression with standard errors clustered at the family level in parentheses. Continuous covariates are standardized to mean zero, unit variance within the estimation sample; the parental income slope and all binary covariates are in original units. Sample restricted to observations with at least three positive parental income waves when the child is 0 to 18 years old and at least one observed child income wave between 24 and 27 years old. Educational level is measured in terms of years of schooling. Log transformation has been applied to parental income. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

negligible, potentially absorbing some income effect. Gender still has a significant association with outcome, and Asian children seem to have a higher chance of college completion than the reference group.

6 Robustness Checks

I perform 4 separate robustness checks to test the validity of my sample construction and analytical methods.

6.1 Parental Income Waves

In my main analysis, parental income slope and average parental income are derived from at least 3 waves of income when the child is 0 to 18 years old. This operationalization aims to ensure that I have a decent sample size for each specification without introducing too much noise. As a result, the minimum observational window only spans 5 years during

Table 3
Parental Income Slope and Degree Completion

Dep. var.:	HS completion (19 or above)		College completion (23 or above)	
	(1)	(2)	(3)	(4)
Parental income slope	0.399***	0.408***	0.143	0.046
	(0.153)	(0.155)	(0.271)	(0.252)
Avg. parental income	0.001	0.001	0.129***	0.106***
	(0.014)	(0.016)	(0.028)	(0.030)
Parent education	0.012	0.009	0.071*	0.053
	(0.015)	(0.015)	(0.038)	(0.036)
Male	−0.080***	−0.076***	−0.150***	−0.164***
	(0.025)	(0.024)	(0.050)	(0.050)
Race: White		0.046		0.023
		(0.044)		(0.085)
Race: Black		0.095**		0.044
		(0.042)		(0.169)
Race: Asian/Pacific Islander		0.027		0.266**
		(0.063)		(0.115)
Race: Latino		0.036		−0.019
		(0.048)		(0.077)
R^2	0.051	0.055	0.159	0.192
Observations	483	483	376	376

Notes. Each column reports coefficients from a linear probability model (OLS) with standard errors clustered at the family level in parentheses. Continuous covariates are standardized to mean zero, unit variance within the estimation sample; the parental income slope and all binary covariates are in original units. Sample restricted to observations with at least three positive parental income waves when the child is 0 to 18 years old. Educational covariates are measured in terms of years of schooling; educational outcomes are binary variables that equal to 1 for degree completion. Log transformation has been applied to parental income. Columns (1)–(2) and (3)–(4) are estimated on different subsamples restricted to non-missing values of the respective outcome. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

child development, serving as a basic approximation of parental income trajectory. Including more waves for parental income measures can potentially help with convergence to the true trajectory. Plus, a more precise first-stage estimation can also reduce the errors of my models. To address the noisy estimations of income slope and average income, I test the main specifications against a higher threshold, 4 income waves or at least 7 years. The results are shown in Table 4.

Compared to the three-wave model from my main analysis, the four-wave model shows similar results when the outcome is child income. The coefficient for parental income slope is still negative, and the magnitude further increases. While it is not clear why parental income trajectory operates in the opposite direction of child income, the standard error renders this coefficient uninterpretable. Results are also similar when child education is the outcome. We see some increase in magnitude for the positive coefficient of income slope, though it remains statistically insignificant. It is worth noting that the linear probability model for high school graduation no longer displays the income slope as a significant predictor, with

Table 4
Robustness: Parental Income ≥4 Waves

Dep. var.:	Income	Education	HS completion	College completion
	(1)	(2)	(3)	(4)
Parental income slope	−1.616	0.673	0.279	0.354
	(1.154)	(0.769)	(0.205)	(0.369)
Avg. parental income	−0.134	0.211***	0.003	0.108***
	(0.102)	(0.073)	(0.018)	(0.036)
Parental education	0.234*	0.113	0.014	0.056
	(0.127)	(0.083)	(0.017)	(0.041)
Male	0.649***	−0.285**	−0.062**	−0.126**
	(0.183)	(0.123)	(0.027)	(0.057)
Race: White	−0.285	0.132	0.040	0.059
	(0.240)	(0.224)	(0.055)	(0.099)
Race: Black	−0.122	0.201	0.080	0.132
	(0.300)	(0.353)	(0.050)	(0.195)
Race: Asian/Pacific Islander	−0.429	0.494*	0.027	0.297**
	(0.339)	(0.280)	(0.078)	(0.128)
Race: Latino	−0.435*	0.211	0.051	0.056
	(0.254)	(0.202)	(0.055)	(0.088)
Child education	0.185*			
	(0.102)			
R^2	0.164	0.148	0.032	0.180
Observations	128	284	381	303

Notes. Each column reports coefficients from a separate regression (OLS for Income/Education, LPM for HS/College completion) with standard errors clustered at the family level in parentheses. Continuous covariates are standardized to mean zero, unit variance within the estimation sample; the parental income slope and all binary covariates are in original units. Parental income slope and average income are recomputed requiring at least 4 (rather than the baseline 3) positive income waves during ages 0–18. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the coefficient closer to 0. On the contrary, the model for college graduation shows an increase in magnitude for the positive coefficient of income slope. Overall, the four-wave specifications confirm my findings from the main analysis except for the role of parental income trajectory in high school graduation. It suggests that the previous significance of the income slope may be an artifact of the three-wave construction, rather than a signal of the underlying mechanism of mobility.

6.2 Immigrant Status of Parents

Among the 2324 pairs of parents and children in my dataset, 1883 pairs have an immigrant father and a native-born mother, which means that my results may not reflect immigrant households where both parents are immigrants. I run the main specifications on a subset of my data with families that are purely immigrants. Due to the size of this subsample, the results should not be treated as standalone findings.

Table 5
Robustness: Both Parents Immigrant

Dep. var.:	Income	Education	HS completion	College completion
	(1)	(2)	(3)	(4)
Parental income slope	0.500	−0.271	0.887**	0.004
	(1.895)	(1.633)	(0.383)	(0.737)
Avg. parental income	−0.265	0.260**	0.039	0.119**
	(0.230)	(0.127)	(0.027)	(0.051)
Parental education	0.405***	0.265**	0.064**	0.149***
	(0.156)	(0.119)	(0.032)	(0.053)
Male	0.423	−0.580***	−0.130**	−0.138*
	(0.392)	(0.186)	(0.051)	(0.081)
Race: White	−0.553*	−0.365	−0.068	−0.146
	(0.329)	(0.252)	(0.046)	(0.102)
Race: Black	−0.607	0.771**	0.047	0.567***
	(0.493)	(0.344)	(0.077)	(0.137)
Race: Asian/Pacific Islander	−0.922	−0.317	−0.328***	−0.089
	(0.665)	(0.514)	(0.115)	(0.207)
Race: Latino	−0.596*	−0.388	−0.010	−0.172
	(0.354)	(0.289)	(0.052)	(0.130)
Child education	0.251			
	(0.287)			
R^2	0.184	0.332	0.228	0.355
Observations	45	88	113	93

Notes. Each column reports coefficients from a separate regression (OLS for Income/Education, LPM for HS/College completion) with standard errors clustered at the family level in parentheses. Continuous covariates are standardized to mean zero, unit variance within the estimation sample; the parental income slope and all binary covariates are in original units. Sample restricted to the 174 (of 1,218) parent–child pairs in which both parents are immigrants (baseline sample also includes single-immigrant-parent pairs). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As shown in Table 5, the coefficients for race dummies shifted when compared to the baseline results, but this is likely caused by the aggressive truncation of my dataset. For the child income model, parental education is still a strong indicator of early-career income of the child. As for the education models, gender appears to be a persistent predictor of educational outcomes. Parental education also becomes a significant regressor, but this is only suggestive given the sample size. Average parental income still has a strong association with the years of schooling. Once again, the coefficient for income slope is significant in the model for high school graduation, while the model for college graduation supports the significance of average parental income. There do not seem to be meaningful differences between the results from the full sample and those from the subset.

6.3 Race-stratified Sample

The two PSID immigrant cohorts oversample White households and undersample Asian and Latino households, as shown in Figure 6. This could lead to imprecise estimates of coefficients for race dummies, bias the regression results towards White immigrants, and undermine the external validity of my findings. To construct a sample that is representative of the racial composition during the survey years, I resample the PSID cohorts using weights derived from the ACS data on racial distribution within the immigrant community. Given that the original cohorts were sourced in 1997 and 2017 respectively, I retrieve the ACS 5-year data of 2014/2017 for foreign-born individuals with children and split it into pre-1997 and post-1997 subsamples through year of arrival. I then calculate the weighted average of the racial percentages from the subsamples based on the relative size of the two PSID cohorts, which gives me an approximation of the racial composition if the PSID immigrant households were representative of the true population. Finally, I randomly resample the PSID households using the new weights while maximizing overall sample size. I test the main models on the resampled dataset.

Just like the results from my main analysis, gender is strongly indicative of child outcomes across all 4 specifications, as shown in Table 6. For the child income model, child education still shows a significant association with early-career income, but parental education has a weaker role. We also see the relative influence of race coefficients change, where White children seem to have the most advantage, followed by Asian/Pacific Islander, Latino, and Black. For the child education model, the significance of parental income persists, but the coefficients for race dummies do not have meaningful changes. As for the model of high school graduation, income slope is no longer significant. In addition, the relative influence of race coefficients remains mostly unchanged despite some signs of statistical importance. As for the model of college graduation, parental income and the dummy for Asian households appear to be significant regressors, as seen in the main analysis. White households also seem to have a larger advantage. In general, the results from the resampled dataset do not show large deviation from my main analysis, except for the income slope estimate for high school graduation and some changes regarding the race dummies. It is also worth noting that while resampling addresses the bias related to racial composition, the much smaller sample size implies that the reference group for race dummies may be unstable, which could introduce additional errors.

6.4 Age of Childhood Exposure

My models assume that exposure to parental income has a uniform impact throughout the child development window of 0 to 18 years, so I did not differentiate between income observations based on the child's age. However, it is possible that some years matter more in terms of future outcomes of the child. To examine whether the effect of parental income has temporal variance, I select the observations where at least 3 waves of income can be observed both before and after the child turns 9. I then calculate an early income slope

Table 6
Robustness: Race-Stratified Sample

Dep. var.:	Income	Education	HS completion	College completion
	(1)	(2)	(3)	(4)
Parental income slope	−0.107	0.132	0.180	−0.151
	(0.800)	(0.787)	(0.212)	(0.352)
Avg. parental income	−0.031	0.256***	0.019	0.118***
	(0.095)	(0.082)	(0.025)	(0.039)
Parental education	0.024	0.061	−0.008	0.048
	(0.129)	(0.098)	(0.020)	(0.046)
Male	0.760***	−0.373***	−0.063**	−0.136**
	(0.179)	(0.136)	(0.028)	(0.059)
Race: White	0.269	0.342	−0.036	0.272*
	(0.195)	(0.334)	(0.033)	(0.140)
Race: Black	−0.206	0.099	−0.037	0.194
	(0.513)	(0.461)	(0.029)	(0.224)
Race: Asian/Pacific Islander	−0.040	0.573	−0.107*	0.424***
	(0.358)	(0.350)	(0.060)	(0.151)
Race: Latino	−0.092	0.151	−0.094***	0.137
	(0.214)	(0.275)	(0.024)	(0.102)
Child education	0.186*			
	(0.111)			
R^2	0.182	0.186	0.032	0.225
Observations	104	229	306	244

Notes. Each column reports coefficients from a separate regression (OLS for Income/Education, LPM for HS/College completion) with standard errors clustered at the family level in parentheses. Continuous covariates are standardized to mean zero, unit variance within the estimation sample; the parental income slope and all binary covariates are in original units. Sample re-weighted from 1,001 pairs with known child race down to 559 by downsampling each race group to match ACS-derived immigrant-parent population shares (weighted average of Tier 1 pre-1997 and Tier 2 1998–2017 arrival cohorts). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and a late income slope, respectively. I re-run the main specifications with the two types of income slopes, which allows me to check if the timing of income trajectory affects child outcomes.

As a result of the filtering, the specification for child income has a very small eligible sample. Despite the standard error, the late income slope may have a positive association with early-career income, as shown in Table 7. For the models that examine child education, the coefficient for gender is not longer significant, suggesting that it might previously absorb some of the temporal differences of income slope. In fact, the model for years of schooling and the model for college graduation both suggest that late income slope may have a larger positive association with child outcomes. A Wald test of two different income slope coefficients also shows that for years of schooling, the timing of parental income trajectory can potentially lead to meaningfully different outcomes, with a p-value of 0.027.

Table 7
Robustness: Age of Exposure

Dep. var.:	Income	Education	HS completion	College completion
	(1)	(2)	(3)	(4)
Income slope, early (age 0–9)	−0.226	−0.652	0.041	0.024
	(0.948)	(0.728)	(0.128)	(0.387)
Income slope, late (age 10–18)	0.286	2.021*	0.178	0.887*
	(1.752)	(1.087)	(0.199)	(0.471)
Avg. parental income	−0.121	0.223*	−0.040	0.122**
	(0.177)	(0.120)	(0.025)	(0.057)
Parental education	0.342*	0.163	0.046*	0.061
	(0.178)	(0.134)	(0.025)	(0.065)
Male	0.693***	−0.173	−0.050	−0.103
	(0.247)	(0.182)	(0.037)	(0.084)
Race: White	−0.508	−0.157	0.110	−0.145
	(0.390)	(0.288)	(0.095)	(0.148)
Race: Black	−0.639	−0.396	0.079	−0.143
	(0.578)	(0.679)	(0.089)	(0.447)
Race: Asian/Pacific Islander	−0.723	0.081	0.133	0.024
	(0.489)	(0.360)	(0.113)	(0.189)
Race: Latino	−0.602	0.135	0.114	−0.066
	(0.437)	(0.260)	(0.095)	(0.139)
Child education	0.219			
	(0.180)			
R^2	0.210	0.200	0.064	0.193
Observations	58	123	187	136

Notes. Each column reports coefficients from a separate regression (OLS for Income/Education, LPM for HS/College completion) with standard errors clustered at the family level in parentheses. Continuous covariates are standardized to mean zero, unit variance within the estimation sample; the two income slopes and all binary covariates are in original units. Sample restricted to the 260 (of 1,218) pairs with at least 3 positive parental income waves in *both* the early (child age 0–9) and late (age 10–18) windows; mean waves observed are 3.7 (early) and 3.6 (late). Avg. parental income is the pooled 0–18 average, not window-specific. Wald tests of $H_0 : \beta_{\text{early}} = \beta_{\text{late}}$ are not rejected at 5% except for Education ($\chi^2 = 4.893$, $p = 0.027$). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To further examine the effect of late-stage parental income trajectory on years of schooling of the child, I regress the number of grades completed over the late income slope, controlling for family influence and individual traits. This specification is the same as Equation 3 except for the construction of income trajectory. The resulting coefficient of parental income trajectory is 1.658, with a p-value of 0.067. At a similar sample size, this coefficient is almost 8 times larger than the baseline specification. The coefficients for average parental income and child gender are also significant at the 5% level, just like the baseline results.

7 Discussion

The results from the main analysis and robustness checks suggest that parental income trajectory spanning child development does not have a robust effect on early-career earnings and educational attainment of immigrant children. As illustrated by the models of various specifications, the coefficients for parental income slope have unstable signs and magnitude, and the true effect is mostly unidentifiable given the large standard errors. While the baseline linear probability model for high school completion produces a statistically significant coefficient for the slope, the correlation dissolves into near randomness when 1) parental income requires at least 4 survey waves or 2) the sample is re-stratified to approximate realistic racial composition. This suggests that the initial observation of a positive association between income trajectory and high school graduation is sensitive to operationalization and sample selection. Rather than a signal of the true mechanism of immigrant mobility, the influence of parental income trajectory on high school completion appears to be an artifact of empirical bias.

However, there is evidence suggesting that late-stage parental income growth rate may have a positive association with children's years of schooling. After reconstructing Equation 3 with a two-stage setup for parental income slope, the Wald test shows that the coefficients for early-childhood income trajectory and teenage income trajectory differ at the 5% level, with a p-value of 0.027. When restricting parental income slope to a narrower child development window of 10 to 18 years old, I found that the coefficient of income growth rate is almost 8 times larger than the baseline result and significant at the 10% level with a p-value of 0.067. While this is not a definitive finding, it implies that an upward income trajectory of parents during teenage years of the child may potentially lead to higher educational attainment, relative to early-childhood income growth. In addition, results from Table 7 suggest that when controlling for early-childhood income growth rate, the late-stage growth rate may still have a positive association with years of schooling and probability of college graduation. The coefficients are significant at the 10% level. However, this pattern does not apply to high school graduation and requires further examination of its validity.

While the evidence on parental income trajectory is generally thin, stratifications of income and educational attainment seem to have a stronger association with child outcomes. Parental average income and child education show a positive relationship with early-career income of immigrant children at the 10% level, though the results become negligible when tested with four-wave income slope or race-stratified sample. Parental average income is also a significant indicator for years of schooling and probability of college graduation. Overall, immigrant parents with higher income appear to raise children with better outcomes, which could be evidence for stratification within the immigrant community. Because income can be viewed as a signal of social class, it is likely that class differences play a major role in the income and education level of immigrant children.

There also seems to be large differences in outcomes across demographic groups. For instance, the dummy variable for gender is significant at the 5% level for most models of early-career income, suggesting a male income advantage among immigrants. However, the opposite effect exists for child education, where being male is often associated with a negative coefficient. Some specifications, including the race-stratified models for high school and college completion, show that the Asian dummy variable has a strong positive correlation with education. However, due to the sample constraint, it is not possible to present this as a robust finding.

8 Limitations

A few limitations may introduce bias to my findings. First, the sample size is small. This is especially problematic for the child income models, as the minimum age threshold of 24 for early-career income leads to a large decrease in the size of eligible sample. For linear regression models, such a constraint can cause the lack of statistical power to effectively estimate the regressors and identify the true effect. As seen in Section 5 and Section 6, the coefficients for parental income slope generally have large standard errors, which could mask the actual value if there is any effect. The relative shortage of immigrant households in PSID data imposes a trade-off between empirical soundness and statistical power. A more comprehensive model often comes at the cost of sample size. Second, the PSID immigrant cohorts are rather recent, so many children are too young to manifest meaningful outcomes. The measurement of child income will be subject to life-cycle bias because it only captures a small window of lifetime income. Additionally, the age composition can bias the coverage of parental income trajectory, as some children have not reached 18 years old as of the last wave of parental income. While Section 6 provides initial evidence on the role of late-stage parental income growth rate, the relevant sample will be distorted due to the cohort structure. Third, the linear probability models have theoretical limitations, as it allows for negative predictions and assume a linear relationship, which can be inconsistent with real mechanisms. Fourth, I did not account for the neighborhood effect that could affect children's growth and outcomes. While I hypothesize that racial composition of the neighborhood also influences child outcomes, I will leave this question to future research.

9 Conclusion

This study utilizes a custom-built intergenerational dataset to examine the effect of parental income trajectory on immigrant children's early-career income and educational attainment. I estimate immigrant parents' income trajectory using an OLS slope of both parents' income over time, which is used to test the ”role model” hypothesis. Specifically, I am interested in whether a positive income growth rate from parents can lead to better child outcomes. After implementing a sequence of regression models and robustness checks, I did not find substantial evidence that supports a positive influence of parental income trajectory during the first 18 years of child development. However, the results suggest that late-stage income trajectory (when the child is 10 to 18 years old) may be associated with more schooling and higher chance of college completion. While the temporal heterogeneity of income effect needs further research, it is likely that immigrant children react to parental income growth differently at different ages.

Although parental income trajectory does not seem to be a prominent factor in immigrant children's outcomes, average labor income of both parents tends to be a much more reliable regressor for both early-career income and educational attainment. This suggests that parents with higher income are more capable of raising children with better outcomes. It also hints at the persistence of social class in immigrant mobility relative to an upward income trajectory of parents. As discussed earlier, the data constraint has limited the statistical validity of this study, but I hope that my findings can encourage more research on immigrant mobility with fine-grained intergenerational data. I propose that future research should explore the influence of parental income growth at different developmental stages of children. Additionally, we should also dissect the mechanisms that lead to differential group outcomes among immigrant children, incorporating individual, family, and neighborhood variables.

Data and Code Availability Statement

Panel Study of Income Dynamics, public use dataset. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI (2026).

Steven Ruggles, Sarah Flood, Matthew Sobek, Daniel Backman, Grace Cooper, Julia A. Rivera Drew, Stephanie Richards, Renae Rogers, Jonathan Schroeder, and Kari C.W. Williams. IPUMS USA: Version 16.0 [dataset]. Minneapolis, MN: IPUMS, 2025. https://doi.org/10.18128/D010.V16.0. IPUMS USA is a harmonized extract of American Community Survey microdata provided by the U.S. Census Bureau; used in Section 6.3 to construct ACS-derived race-composition benchmarks for the race-stratified resampling.

Here is the link to my GitHub repo.

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