Relative and Absolute Income Mobility Variation in the United States: 1968-1997

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April 3, 2017

Abstract: Decades of literature have attempted to estimate intergenerational income mobility levels in the United States, but less research has examined how income mobility varies by gender, race, and education backgrounds. In this study, I use the Panel Study of Income Dynamics (PSID) and multivariate OLS regressions with interactions to estimate gender, race, and college education effects on mobility. I find that females, especially those with low childhood incomes are less mobile than males. Blacks are less mobile than whites, and this disparity persists across all levels of childhood income. People with lower education levels are less mobile than those with higher education levels, especially among those with low childhood incomes. In fully adjusted models with state fixed effects, disparities in mobility by gender and race do not vary significantly by level of education attained. This analysis indicates that being college educated contributes to mobility, but college education does not differentially benefit females or blacks. Strategies other than college education may be needed to address gender-related and race-related disparities in income mobility.

I. Introduction:

The American Dream is the ideology that through hard work, people from all social classes can succeed in American society. This framework is a foundation for how people understand our capitalistic society, and yet empirically, evidence indicates that mobility is not fluid in 20th century United States. Those who are born into low-income households are significantly less likely to move into higher income quintiles than those who are born into high-income households (Kane 2004; Eagle 1989). Similarly, those born to the top 1% of earners are not likely to fall to the bottom on the income distribution (Kane 2004). These relationships demonstrate that the assumption of free mobility is false in the United States.

Much economic and sociological research published in recent decades examine how adulthood income varies by childhood income, gender, race, education level, and other individual characteristics. Estimating the relationship between adulthood income and childhood income in particular has been a large part of the literature. Few studies, however, examine how the relationship between adulthood income and childhood income, which I refer to as income mobility for the purposes of this study, varies by gender, race, and education level. To fill this gap in the literature, I assess the variation in mobility by gender, race, and education level in the United States from 1968-1997 using the PSID, which is a longitudinal data set that starts in 1968. The PSID begins with 4,800 families and collects data each year from the original families as well as any families newly established by members of the existing sample. My sample includes 6,172 individuals who are observed both as a child in a family in the PSID and as a head of household or a spouse in a family in the PSID from 1968-1997. The analysis proceeds in five parts.

In Part 1 of the analysis, I present full sample baseline statistics of mobility, following a similar procedure to Chetty (2014)[1]. I estimate the intergenerational elasticity of income (IGE) by using OLS to regress log adulthood income on log childhood income, which is the canonical method of measuring mobility in the literature (Solon 1999). This relationship is sensitive to the measure of income used, age at which income is measured, data set, sample, and point in the childhood income distribution the IGE is measured. This sensitivity has led to large variation in the IGE in the literature with estimates ranging from 0.2-0.6. I also estimate the Intergenerational Rank Association (IRA), which Dahl and DeLeire (2008) introduced into the literature as a more stable measure of mobility than the IGE. For the IRA measure, each individual receives a childhood income rank and an adulthood income rank based on his/her percentile in the respective income distributions. The IRA estimates the slope of the joint distribution between adulthood income rank and childhood income rank using OLS regression. The IRA slope is highly linear and consistent across income measures, points in the distribution, and age at income measurement (Dahl & DeLeire 2008; Chetty 2014), thus making it a more stable measure of mobility than the IGE. For a third measure of mobility, I generate the quintile transition matrix for the full population. The transition matrix displays the probability of being in each adulthood income quintile, given one's childhood income quintile.

The results from Part 1 of my analysis reveal that the IGE for the full sample is 0.549, whereas the IGE for the sample restricted to those who fall between the 10th and 90th percentile is 0.607. The IRA for the full sample is 0.546 and is highly linear throughout the childhood income distribution. The entries of the transition matrix indicate that individuals are most likely to

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[1] Chetty (2014) examines variation in mobility by county in the United States. Refer to the literature review for a more detailed discussion of this paper.

[2] I use both log and rank measures of income as dependent variables.

remain in their childhood income quintile as adults, and this trend is especially strong for those in the top and bottom childhood income quintile.

In Part 2 of my analysis, I estimate the impact of childhood income, gender, race, and education level on adulthood income using multiple multivariate OLS regression models with both log adulthood income and adulthood income rank as dependent variables. I include parent college education status, parent marital status, individual marital status, average age in adulthood, parent's average age in childhood, and individual's average age in childhood as control variables in the fully adjusted models in this section and throughout the analysis.

The results from Part 2 of my analysis, consistent with previous literature, indicate that females have 13.3% less adulthood income than males, and blacks have 29.0% less adulthood income than whites, with all controls included. High school graduates, individuals with some college, and college graduates, compared with non high school graduates, have 28.5%, 40.9%, and 62.5% higher adulthood incomes respectively. A positive association between adulthood income and childhood income exists as well, with a 10% increase in childhood income leading to a 3.2% increase in adulthood income.

In Part 3 of my analysis, I study whether mobility also varies by gender, race, and education level. I characterize mobility by gender, race, and education level by regressing adulthood income on childhood income[2], gender, race, educational attainment, and interaction terms between each of these three variables and childhood income, controlling for the same background characteristics as in Part 2. I assess mobility in two way estimated by the both the slope and intercept results from OLS regressions. Relative mobility refers to the difference in outcomes between individuals at the top versus the bottom of the childhood income distribution,

[2] I use both log and rank measures of income as dependent variables.

and is measured by slope estimates. Absolute mobility refers to the absolute changes in an individual's income status from childhood to adulthood, which I estimate using both the slope and the intercept. OLS regressions between adulthood income and childhood income[3] result in both slope and intercept parameters. Both the IGE and the IRA are slope estimates, and thus measure relative mobility because they show the difference in adulthood income for individuals born into high-income and low-income environments. A smaller IGE indicates higher relative mobility because the difference in adulthood income between those with high childhood incomes and low childhood incomes is small. The intercept is the expected adulthood income at the bottom of the childhood income distribution. Using both the slope and intercept, I can estimate the expected adulthood income at any point in the childhood income distribution, which is one way to measure absolute mobility. A second measure of absolute mobility is the probability that an individual is in the top adulthood income quintile, given being in the bottom childhood income quintile.

The results from Part 3 of the analysis suggest that both relative mobility and absolute mobility vary by gender, race, and education level. Females have lower relative mobility than their male counterparts. Females who are born to a family in the bottom quintile of childhood income face a large penalty in absolute mobility whereas females who are born in the top income quintile do not face this penalty. Relative mobility does not vary by race, but blacks have lower absolute mobility than their white counterparts, regardless of their childhood income. People with lower education levels have lower relative mobility and lower absolute mobility, particularly at the bottom of the childhood income distribution.

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[3] I use both log and rank measures for income.

In Part 4 of my analysis, I examine whether the gender disparity in mobility differs for those with a college education compared to those without a college education. I tested this by including a three-way interaction term between college education status, childhood income and gender in the previous models.

The results from Part 4 of the analysis indicate that the interaction between female and childhood income does not vary significantly by college education, meaning that females do not receive a larger increase in relative mobility than males by graduating from college. Also, the gender disparity in absolute mobility is not significantly different by college education status. These results suggest that college education may not be the most effective solution to gender disparities in mobility.

In Part 5 of my analysis, I assess whether the racial disparity in mobility varies by college education by including a three-way interaction term between college education status, childhood income and race in the previous models.

The results from Part 5 of the analysis are similar to the Part 4 results in that the three way interaction is not significant, suggesting that the interaction between black and childhood income does not vary significantly by college education. These results suggest that college education may not be the most effective solution to racial disparities in mobility.

This paper proceeds as follows. In Section II, I review the literature pertaining to intergenerational mobility in the United States, the effects of gender, race, and education on adult income, and the variation of intergenerational mobility in the United States. In Section III, I discuss the methods used for measuring relative and absolute mobility in the analysis. In Section IV, I describe the PSID data set and the variables included in the analysis. In Section V, I implement the analysis described in five parts above. Section VI concludes and suggests areas of future related research.

II. Literature Review

a. Intergenerational Mobility

Estimation: A majority of economics scholarship surrounding intergenerational mobility focuses on estimating the relationship between childhood income and adulthood income. The most common measurement of intergenerational mobility is the IGE, which is estimated by regressing

Table 1: Review of Past IGE Estimates

Paper	IGE	Data Set	Outcome Variable	Child's Age Range	Parent Income Measure
Couch and Dunn 1997	0.13	PSID	Multiyear Average of earnings (6 years maximum)	Not Specified	Multiyear Average of earnings (6 years maximum)
Eide and Showalter 1997	0.34	PSID	1991 log annual earnings	24-40	Log 3-year average of father's earnings
Minicozzi 1997	0.42	PSID	Log 2 year average of annual earnings	28-29	Log estimate of present value of father's lifetime earnings
Levine and Mazumder 2002	0.391	NLS	Earnings	28-36	Earnings
Mayer and Lopoo 2008	0.408	PSID	Log family income at age 30	30	2 year average when child is 15-17
Dahl and DeLeire 2008	0.26-0.63	SSA	Varies	Varies	Varies
Hertz 2003	0.534	PSID	Log age adjusted average family income	Not specified	Log age adjusted average family income
Grawe 2004	0.154	NLS	Log average earnings 1978-1981	Under age 19 in 1966	Log average earnings 1965-1970
Jantti 2006	0.517	NLSY	Average log earnings 1995-2001	Not specified	Log family income in 1978
Chetty 2014	0.344	Administrative Tax returns	2 year average family income at 15-17	29-30	4 year average family income 1996-2000

log adulthood income on log childhood income. This process of estimation receives a lot of consideration in the literature partly because of the large variance in estimates, ranging from 0.2-0.6, reviewed in Table 1.

Part of the variation in estimates comes from use of different data sets and income measures. For instance, the PSID has higher estimates for the IGE than the National Longitudinal Study of Youth, which is another longitudinal study commonly used to study intergenerational mobility (Grawe 2004). Some researchers measure economic status with earnings while others use family income, which can also lead to varying IGE estimates (Solon 1999; Mayer and Lopoo 2005).

Bias from transitory shocks in income causes some of this variation in IGE estimates in the literature. In each study, individuals are observed for a number of years in childhood (T_c) and a number of years in adulthood (T_a). Suppose $Y_a = Y + v_a$ where a is the age of the parent, Y is permanent income, and va is deviation of measured income from permanent income at age a. Assuming that v is a transitory shock, then expression 1 is the attenuation bias.

$$\frac{Var(Y)}{Var(Y) + Var(v)} \qquad (Expression\ 1)$$

which means:

$$plimB = \frac{Var(Y)}{Var(Y) + Var(v)} B \qquad (Equation\ 1)$$

When parent's income is averaged over multiple years, the attenation bias then becomes (Black and Devereux 2011):

$$\frac{Var(Y)}{Var(Y) + Var(v)/T_c} \qquad (Expression\ 2)$$

Therefore, as T_c increases, the attenuation bias shrinks. Mazumder (2005) provides empirical estimates of the IGE using 1984 SIPP data and Social Security Administrative Records that show as T_a increases, so does the IGE. When T_a=2, the IGE=0.25, and when T_a=16, the IGE =0.61.

Lifecycle bias is a third cause of variation in IGE estimates in the literature. Lifecycle bias refers to relationship between age of father/age of son and the IGE estimate. The IGE tends to decrease with father's age at measurement (Nilson 2008, Haider and Solon 2006) and increase with son's age at measurement (Reville 1995). Grawe (2006) finds that father's age at measurement accounts for 20% of the variance in IGE estimates. This bias occurs because deviation of observed earnings from permanent earnings is correlated with the level of observed earnings, due to larger wage growth for workers with high lifetime earnings in the beginning of their careers. Correcting this bias fully requires a full lifetime of income data, but measuring income for both parents and children near midlife for as many years as possible reduces the bias (Grawe 2006).

In response to this variation in IGE estimates, Dahl and DeLeire (2008) proposes an alternative measure for intergenerational mobility, the Intergenerational Rank Association (IRA). The IRA measures the association between an individual's position in the childhood income distribution and adulthood income distribution. The IRA is robust across samples, definitions of income, age of parent's income measurement, and number of years parent's income is collected. (Dahl and DeLeire 2008). Because the IRA is less sensitive to these variables than the IGE, researchers have begun to employ the IRA more frequently in studies of mobility (Chetty, 2014, Grawe 2004).

Despite the rigor and novelty of each of these studies, they focus predominantly on the transmission of status from white fathers to white sons. This is partly because females often have zero earnings in adulthood because they are more likely to be unemployed than males. A few studies examine intergenerational transmission of status from parents to daughters (Minicozzi 1997; Shea 1997), with one including women with zero earnings and also taking into account husband's earnings **(**Chadwick and Solon 2002)**.** The IGE estimates for daughters are generally higher than the IGE estimates for sons. Less work exists comparing IGE estimates by race, but studies do show that blacks are less likely to escape poverty than whites (Kearney 2006; Hertz 2003).

b. Determinants of Income

Race and Gender:

Race and gender are associated with income. White females and black males both earn about 2/3 of what white males earn in general, and black women earn about ½ of what white males earn (Altonji and Blank 1999). These earnings differentials lead to income inequality between demographic subgroups in the United States. These differences come from differences in employment as well as employer discrimination (Altonji and Blank 1999).

Education:

Policymakers often claim higher education is a solution to escaping poverty, and a large literature targets understanding whether empirical evidence exists for this claim. Large labor markets returns exist to graduating from college (Grogger and Eide 1995; Averett 1996). The correlation between college degree attainment and labor market outcomes is higher than ever at this moment in time (Goldin and Katz 2007). The share of national income going to high school graduates declined by 15% from 1991-2012(Fry and Taylor 2012), illustrating that not obtaining a college degree has an increasingly negative effect on future outcomes.

Research also analyzes whether these positive returns to college education vary by gender and race. Multiple studies find higher returns to education for females than for males (Dougherty, 2005; Charles and Luoh 2003; Diprete and Buchmann, 2006), and one study finds that the wage premium for college-educated women isn't higher than it is for men. With respect to race, income returns to higher education are no significantly different for blacks and whites. (Ashenfelter and Rouse, 1999; Barrow and Rouse, 2005).

c. Variation in Mobility

A few studies examine variation in mobility by certain characteristics. A large literature exists comparing IGEs from multiple countries to understand which societies are most mobile (Corak 2006; Blanden 2013; Solon 2002). Similarly, Chetty (2014) analyzes variation in mobility by geographical area in the United States, and Mayer and Lopoo (2008) examines variation in mobility by government spending in different geographical areas. Hertz (2003) compares mobility trends by race and finds that blacks are less mobile than whites. A few papers estimate the IGE for females as well as males, but these papers are limited in their analysis of absolute mobility (Minicozzi 1997; Shea 1997). This paper fills this gap in the literature by studying variation in both relative and absolute mobility by gender, race, and college education status across the childhood income distribution.

III. Method

a. Relative Mobility

Intergenerational Elasticity of Income: I use OLS to regress log adulthood income on log childhood income. The resulting coefficient is the IGE.

$$log(Y_a) = \alpha + \beta log(Y_c) + \varepsilon \qquad \text{(Equation 2)}$$

In this equation, Y_a is adulthood income, Y_c is childhood income, and β is the intergenerational income elasticity (IGE). The IGE measures of relative mobility because it shows the difference in adulthood income between children from top childhood income families and bottom childhood income families. β can be interpreted as the percentage change in adulthood income given a certain percentage change in childhood income. The IGE specification requires that no one had zero income, which can skew the sample depending on the data set. In my sample, no one had zero income, so this is not a problem for my analysis.

$$\beta = IGE = corr(LogY_a, LogY_c)\frac{SD(LogY_a)}{SD(LogY_c)} \qquad (Equation\ 3)$$

Intergenerational Rank Association: A second measure of mobility is the IRA, proposed by Dahl and DeLeire (2008). With this method, each individual is ranked with respect to both the childhood income distribution and adulthood income distribution. Adulthood rank is then regressed on childhood rank using equation 4.

$$Rank(Y_a) = \nu + \varphi Rank(Y_c) + \upsilon \qquad \text{(Equation 4)}$$

φ is the correlation between the childhood income rank and the adulthood income rank. The rank-rank relationship is highly linear, unlike the log-log joint distribution.

Interaction Effects: To understand how mobility varies by gender, race, and college education status, I use interaction effects in the OLS regressions. Y_{ai}

$$log(Y_{ai}) = \alpha + \beta_1\, log(Y_{ci}) + \beta_2 x_{2i} + \beta_3\, log\,(Y_{ci})x_{2i} + X_i + \varepsilon \qquad \text{(Equation 5)}$$

$$Rank(Y_{ai}) = \nu + \varphi_1\, Rank(Y_{ci}) + \varphi_2 x_{2i} + \varphi_3\, Rank(Y_{ci})x_{2i} + X_i + \upsilon \qquad \text{(Equation 6)}$$

Where x_{2i} represents a dummy variable for being female, being black, or being college-educated and X_i represents a vector of control characteristics. ($\varphi_{2} + \varphi_3$ Rank(Y_{ci})) represents the partial effect of being female (or black/college educated). ($\varphi_1 + \varphi_3\, x_{2i}$) represents the partial effect of childhood income. If $x_{2i} = 0$ then the partial effect would be φ_1. If the interaction coefficients are significantly different from zero, then the joint distribution between log adulthood income and log childhood income (or adulthood rank and childhood rank) has a significantly different slope for females and males. In Part 4 and Part 5 of my analysis, I use three way interactions between childhood income, gender/race, and college education status to understand whether the two-way interactions between gender/race and college education vary by college education status. In order to implement a three-way interaction, all combinations of two-way interactions of the three variables as well as the individual three variables must be included in the regression.

State Fixed Effects:

Because the PSID includes individuals from all states in the United States, I include state fixed effects to control for unobservable state level trends in mobility. This technique allows me focus on variation in mobility at intra-state levels, and it reduces the potential for omitted variable bias. Because my data set functions as a cross sectional data set, no assumptions need to be made about unobservable factors being time-invariant. I tested two models: one with childhood state fixed effects and one with adulthood state fixed effects. In Equation 7, d_s represents a dummy variable for state fixed effects.

$$log(Y_{ai}) = \alpha + \beta_1 log(Y_{ci}) + \beta_2 x_{2i} + \beta_3 \log(Y_{ci}) x_{2i} + X_i + d_s + \varepsilon \ \ (Equation\ 7)$$

b. Absolute Mobility

Absolute mobility measures the outcomes of individuals with a given childhood income in absolute terms. To compare absolute mobility at the bottom and the top of the distribution, I generate two statistics for subsamples of the data set: expected adulthood income in the lowest childhood income quintile and expected adulthood income in the highest childhood income quintile. A second measure of absolute mobility is the probability that an individual ends in the top quintile given that they were born into the bottom quintile.

Transition Matrices:

The IGE and IRA are summary measures of mobility in a sample, thus they mask details about mobility at different points of the childhood income distribution. I use transition matrices to understand the relationship between childhood income and adulthood income across the childhood income distribution. Adulthood income quintiles are the columns of the matrix and childhood income quintiles are the rows of the matrix. Each entry in the matrix represents the probability that an individual is in a certain adulthood income quintile given that he/she were in a certain childhood income quintile.

IV. Data

a. Description of PSID

I analyze the relationship between childhood income and adulthood income using the Panel Study of Income Dynamics, a nationally representative survey of socioeconomic outcomes often used for intergenerational studies. The study began in 1968 with 18,000 individuals living in 4,800 families in the United States. When individuals in the original sample establish their own households, the members of that new household are added to the sample. The survey has since expanded to 7,000 families and more than 70,000 people across four generations of families have been interviewed for the PSID since its inception (Hill 1992). The PSID contains information from every individual in the family, although the head of the household and their spouse receive more detailed profiles. The data set originally started in order to evaluate Lyndon B Johnson's War on Poverty, which was a set of legislation aimed at targeting poverty in the United States. Because of this goal, it surveys a disproportionate number of low-income households, which also leads to an oversampling of blacks and non-college educated individuals. This allows for more statistical precision in examining black-white differences in mobility. Sampling weights are provided to ensure that the sample is representative of the United States population.

A majority of studies examining intergenerational mobility use the PSID because it follows the children from the original sample and collects annual family income from them as adults, so it is possible to relate the income reported by parents at the beginning of the survey to the income reported later by the children with small measurement error for both variables. An exception to this practice is Chetty (2014), a paper that shares similar motivations and methods to this study. Chetty (2014) uses administrative records from federal income tax returns from 1996-2012, which allows for a much larger sample size than the PSID, and provides data on every county in the United States. Although the sample size and spatial variation are benefits of administrative data, these data limit the number of years income data is observed. Chetty (2014) only observes the individuals' income in their upper teenage years from 1996-2000 and at age thirty from 2011-2012. With the PSID, I build a sample that takes into account many years of an individual's life as a child and as an adult, and thus generate a more robust measure of income than is possible with the administrative data. [4]

b. Construction of the Sample

To generate the study sample, I retain all individuals who are observed both as a child and as a head of household or the spouse of a head of household between the years of 1968-1997 and are either black or white. The data set did not contain enough observations of individuals of other races or ethnicities to study their outcomes with statistical precision. 16,323 people were observed at children at some point, and 7,616 of these individuals were then also observed as a

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[4] See literature review section for a more extensive description of the bias introduced by only using singular years for income measurement.

head of household or the spouse of the head of a household. After retaining only black participants and white participants 6,172 people remained in the sample.

Table 2: Individual Descriptive Statistics[5]

Individual Descriptive Characteristics						
Characteristic	Percent	Freq	Mean	SD	Max	Min
GENDER						
Male	48.44	3003				
Female	51.56	3196				
RACE						
Black	43.72	2710				
White	56.28	3489				
EDUCATION						
No HS	21.85	1304				
HS	37.08	2213				
Some Coll	23.32	1392				
Coll	17.74	1059				
INCOME						
Child			10269.92	8646.42	656.23	123095.3
Adult			15726.28	12705.87	1.11	357286
Log Child			8.96	.75	6.49	11.72
Log Adult			9.37	.84	.105	12.79
MARITAL STAT						
Married	72.11	4470				
Not Married	27.89	1729				
PARENT MARITAL STAT						
Married	78.31	4833				
Not Married	21.69	1339				
AGE						
Adult			28.46	4.94	16.5	51.75
Parent			43.18	8.57	18	83.8
Child			14.300	4.01	1	24.67
PARENT EDUCATION						
No HS	17.07	577				
HS	34.79	1176				
Some Coll	24.50	828				
Coll	23.64	799				

To construct the income variable I used the measure of total net family income. Studies in the past have used wages to assess the transmission of earnings from parent to child, but I

[5] Income is adjusted to 1997 dollars.

consider the full financial profile of the household. Because family income includes income transfers and assets, it is a more accurate indicator than wages of financial well-being, which is the outcome of interest. Another reason I use family income is to include females in the analysis who are unemployed, and thus have zero earnings. By using family income, I gain understanding of how economic status in childhood affects economic status in adulthood, regardless of employment. To measure childhood income, I average total net family income over all the years that an individual appears in the data set as a minor in a family under the age of 25 and divide by the number of people in the family to account for the higher consumption needs of larger families. I apply the same process for average income in adulthood. Income is adjusted to 1997 dollars throughout the analysis using the CPI deflator. To measure educational attainment, I generate four categories: no high school, high school degree, some college, college graduate. This variable exists for both the individual and for the head of the household that that individual was a child in. Average age in adulthood is the mean of the ages in the years that the individual is observed in the data set as an adult. Average age in childhood is the mean of the ages in the years that the individual is observed in the data set as a child. Average age of parent is the mean age of the head of the household across the years that the individuals is observed in the data set as a child. Race is defined as the race of the head of household one grew up in because there is no individual race variable in the PSID. Childhood state and adulthood state are the states where the individual resided for the longest period of time in childhood and adulthood respectively.

The average family income in childhood is 9749.46$. The average income in adulthood is 12,989.58$ dollars. The difference between average childhood family income and average adulthood family income is similar to the overall real income growth over the latter half of the twentieth century, particularly in the 1960’s and 1970’s (Gottschalk 1997). Table 2 contains simple descriptive statistics for the final sample. My sample consists of slightly more females than males and slightly more whites than blacks. The percentage of college graduates is 17.74%, which is significantly lower than the national average in the 1980s, which was 34% for whites, 30% overall, and 7% for blacks. This lower college graduation rate is logical in the context of this sample, which oversamples blacks and people with low-income status. 72.11% of the sample was a part of a married household in adulthood. Out of those who were not married, the most common status was "single", followed by "divorced", "separated", and finally "widowed".

Table 3: Lifecycle Bias and Transitory Shock Income Bias[6]

	Female	**Male**	**Black**	**White**	**College**	**No College**
Average Age - Child	28.12	28.81	28.59	28.34	28.04	30.4
	(0.086)	(0.09)	(0.097)	(0.082)	(0.068)	(0.141)
Average Age - Parent	42.7	43.71	43.17	43.20	44.96	42.82
	(8.69)	(8.41)	(8.84)	(8.36)	(7.84)	(8.67)
# of years – Child	12.36	12.81	12.22	12.84	12.5	12.95
	(0.107)	(0.113)	(0.113)	(0.106)	(0.208)	(0.083)

c. Attrition and Bias

This study is primarily concerned with examining the variation in the IGE estimate by gender, race, and college education. In order for the conclusions to be valid, the lifecycle bias and transitory shock income bias[7] must not have differential impacts on females vs. males, blacks vs. whites, and college educated vs. non-college educated people. Table 3 contains summary statistics for average parent's age and average individual adult age as well as the

[6] Standard deviations are in parentheses. All differences in outcomes by gender, race, and college education are statistically significant.
[7] See Section II for further discussion of these biases.

average number of years income data is collected for childhood and adulthood by gender, race and college education.

Lifecycle bias does not differentially affect any subgroup of interest. Although the differences in average age of child and average age of parent by gender, race, and college education status are statistically significant, they are not practically important. Mean adulthood income at age 28 is not statistically significantly different from mean income at age 30, and mean childhood income at age 42 is not statistically different from mean adulthood income at age 45, so lifecycle bias does not differentially impact any gender, race, or college education group.

Transitory shock bias is also unlikely to bias the results. As number of years that an individual is observed in childhood increases, the IGE increases.[8] Males, whites, and college-educated individuals are observed for slightly longer on average than females, blacks, and non-college-educated individuals respectively. Therefore, if transitory shock bias affects the analysis, it would increase males', whites', and college educated individuals' IGEs. Because these groups have lower IGEs than their respective counterparts, if there is transitory shock bias, my estimates of disparities in mobility underestimate the real disparities.

Although neither lifecycle bias nor transitory shock bias affects my analysis, I include IRA estimates throughout the analysis as a robustness check because lifecycle bias and transitory school bias do not affect the IRA (Dahl and DeLeire 2008).

One thing that is necessary to consider when using longitudinal data is sample attrition. The PSID tries to minimize attrition by adding incentive payments, tracking, and respondent letters. Even so, the attrition rate for the first year was 11 percent and after that it is about 2-3

[8] See Section II for a further explanation of this relationship.

percent each year. Weights are provided that are updated each year to account for this attrition. I use the individual weights associated with the last year that someone appeared in the data throughout the analysis, as recommended by Hill (1992).

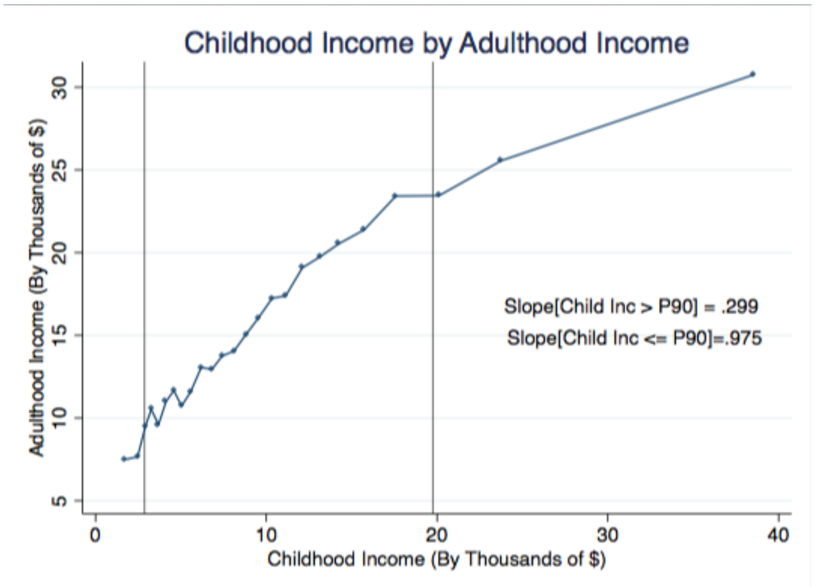
V. Results

Part 1 of my analysis examines the national baseline statistics of intergenerational mobility using the IGE estimates, IRA estimates, and transition matrices described in Section III. Part 2 analyzes the associations between adulthood income and childhood income, gender, race, and college education. Part 3 studies the variation in mobility by gender, race, and college education, and finds a negative association between being female and mobility, particularly at the bottom of the childhood income distribution, a negative association between being black and mobility across the entire childhood income distribution, and a negative association between lower levels of education and mobility throughout the entire childhood income distribution. Part 4 assesses whether college education modifies the gender effect on mobility. Part 5 assesses whether college education modifies the race effect on mobility. Together these findings indicate that although college has a positive association with mobility for the full sample, it does not erase gender or race disparities in mobility.

a. Part 1 - Full Sample Baseline Statistics

Figure 1 is a binned scatter plot of childhood income versus adulthood income. This graph visually represents the conditional expectation of adulthood income given childhood income $E[Y_a|Y_c=y]$. The relationship between childhood income and adulthood income is concave, meaning that the impact of one extra dollar in childhood depends on an individual's childhood income. Under the 90^{th} percentile, 1 extra dollar leads to .975 extra dollars in adulthood. Above the 90^{th} percentile:,1 extra dollar leads to 0.299 extra cents in adulthood.

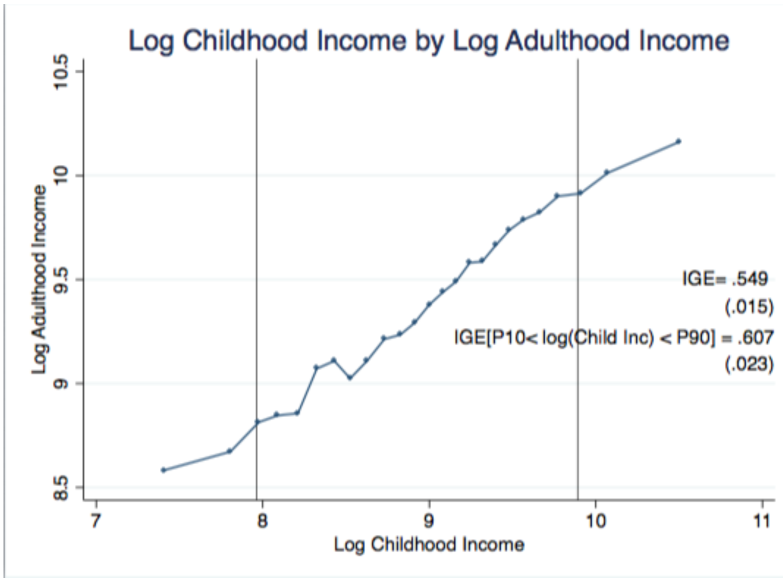
Figure 1:Childhood Income By Adulthood Income (Full Sample)[9]



Because both the childhood income and adulthood income distribution skew towards large values, I use log adulthood income and log childhood income for a majority of my models, resulting in the IGE estimate for mobility. The IGE estimate for this full sample is 0.549, indicating that if childhood income increases by 10%, then adulthood income increases by 5.49%. My estimate for overall IGE is slightly higher than most of the estimates in the literature, which could be due to a number of factors. First, my sample includes both males and females while most studies only include males, who have lower IGE estimates than females. Second, I use the PSID, which generally results in higher estimates of the IGE than other data sets. Third, I observe individuals for long periods of time in both adulthood and childhood, which increases the IGE estimate (Grawe 2006). When I limit my sample to only males, the IGE estimate

[9] The binned scatter plot divides the x-axis into 25 sections and plots the mean childhood income vs. mean adulthood income for each section (See Appendix A, Figure 1a for 100 bin scatter plot). The vertical lines mark the 10th percentile and the 90th percentile respectively. The slope estimate come from bivariate OLS regressions.

Figure 2: Log Childhood Income by Log Adulthood Income (Full Sample)[10]



decreases to 0.47, which is similar to other PSID estimates. Figure 2 is a binned scatter plot of log childhood income by log adulthood income. Although the joint distribution of log childhood income and log adulthood income is approximately linear between the 10th percentile and the 90th percentile, the slope flattens both above the 90th percentile and below the 10th percentile. The IGE varies by point in the childhood income distribution.

The IRA for the full population is 0.546. Figure 3 is a binned scatter plot of individual's childhood income rank and adulthood income rank, which visually represents the conditional expectation of rank in adulthood given rank in childhood, $E[R_a|R_c=r]$. The IRA is the slope of this highly linear relationship. Limiting the sample to only those between the 10th and 90th percentile does not change the IRA significantly, indicating that the IRA is not sensitive to point of measurement in the childhood income distribution.

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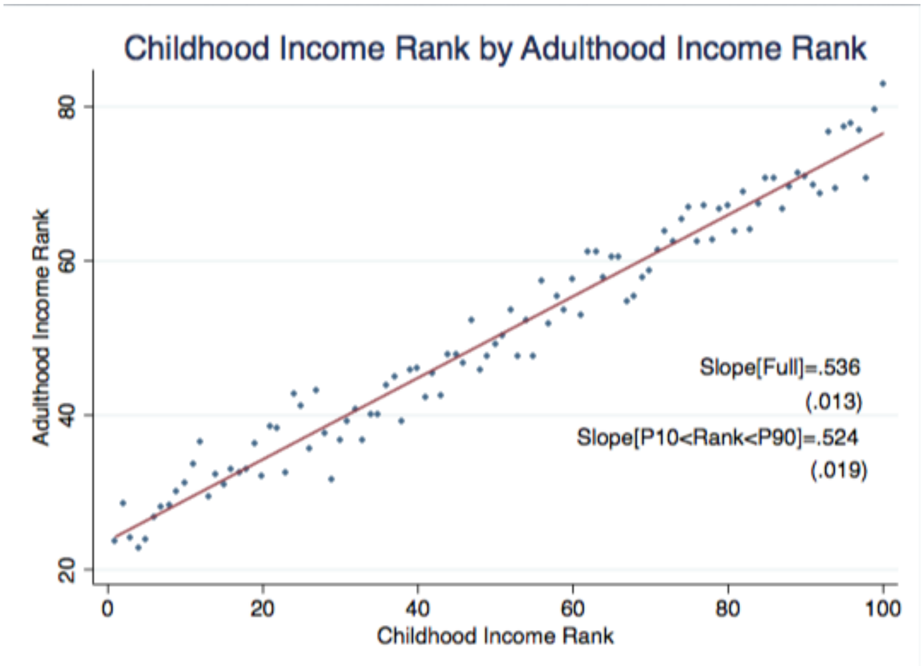
[10] This is a binned scatter plot, 25 bins. The vertical lines mark the 10th percentile and 90th percentile of log childhood income. These estimates are regression coefficients from running bivariate OLS regressions on the underlying data.

Figure 3:Childhood Income Rank By Adulthood Income Rank (Full Sample)[11]



Lastly, I display the transition matrix for the full sample in Table 4. The largest probabilities exist on the diagonal of the transition matrix, indicating that an individual's childhood income quintile is the most likely of any to be his/her adulthood income quintile. This effect is particularly strong for those in the first childhood income quintile, who have a 47.06% chance of being in the first adulthood income quintile, and those in the fifth childhood income quintile, who have a 45.65% chance of being in the fifth adulthood income quintile, suggesting that the ends of the income distribution are particularly sticky. Individuals in the third childhood income quintile are most mobile, with similar probabilities of being in all five adulthood income quintiles.

[11] This is a binned scatter plot, 25 bins. These estimates are regression coefficients from running bivariate OLS regressions on the underlying data.

Table 4:Quintile Transition Matrix[12]

	Adult 1	Adult 2	Adult 3	Adult 4	Adult 5
Child 1	46.81	24.14	15.38	9.17	4.5
Child 2	27.5	27.99	21.72	15.46	7.32
Child 3	16.3	22.71	24.49	21.98	14.52
Child 4	7.35	16.16	21.06	26.69	28.73
Child 5	3.01	9.66	16.39	25.73	45.21
Total	20.07	20.07	19.8	19.85	20.2

b. Part 2 - Variation in Income

Significant associations exist between adulthood income and race, gender, college education, and childhood income respectively. As Table 5, Column 3 displays, females have 13.3% lower adulthood incomes and 4.88 lower adulthood ranks than males, blacks have 29.0% lower adulthood incomes and 8.85 lower adulthood ranks than whites. High school graduates, individuals with some college, and college graduates have 28.5%, 40.9%, and 62.5% higher adulthood incomes and 9.99, 14.97, and 24.82 higher adulthood ranks than non high school graduates, all else being held equal. In the fully adjusted model, a 10% increase in childhood income leads to a 3.18% increase in adulthood income and a 1 percentile rank increase in childhood leads to a .33 rank increase in adulthood. These results are consistent with previous literature. These results remain consistent with the addition of both childhood and adulthood state fixed effects (See Appendix D).

c. Part 3 - Variations in Mobility

Gender:

Females face lower levels of relative mobility than males. The interaction term between female and log childhood income, displayed in Table 6, is positive and significant (interaction=0.163)

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[12] The rows of Table 4 represent individuals' childhood income quintile, and the columns of Table 4 represent individual's adulthood income quintile.

after including all controls, signifying that females have a larger IGE than males, and thus have lower relative mobility. Figure 4 is a binned scatter plot that shows log childhood income versus adulthood income for both males and females, and it visually represents the significant interaction between childhood income and gender. Although both lines demonstrate that childhood income and adulthood income are positively related, the slope of the joint distribution is larger for females than males. As a robustness check, I do an analogous analysis replacing log childhood and adulthood income with rank income measurement and achieve consistent results (See Appendix A, Figure 2a for plot of ranks). These results remain consistent with the addition of both childhood and adulthood state fixed effects (See Appendix D).

As childhood income increases, the disparity between male and female absolute mobility decreases. The mean log adulthood income for those in the bottom quintile of the childhood income distribution is 9.05 for males as opposed to 8.54 for females, which is a 0.51 log income disparity. For individuals in the top quintile of childhood income, the mean log adulthood income is 9.96 for males and 9.93 for females, which is a 0.03 log income disparity that is statistically insignificant. Females born in the bottom quintile have a 2.59% chance of ending in the top quintile. Males have a 7.01% chance of ending in the top quintile if they were born in the bottom quintile (See Appendix B, Table 1b and Table 2b for transition matrices by gender).

For a more detailed description of how the gender disparity in mobility varies by childhood income, I generate dummy variables for each childhood income quintile, and I regress log adulthood income on these quintiles as well as interactions between the income quintiles and gender. The resulting coefficients for these models appear in Table 7. For those in the poorest

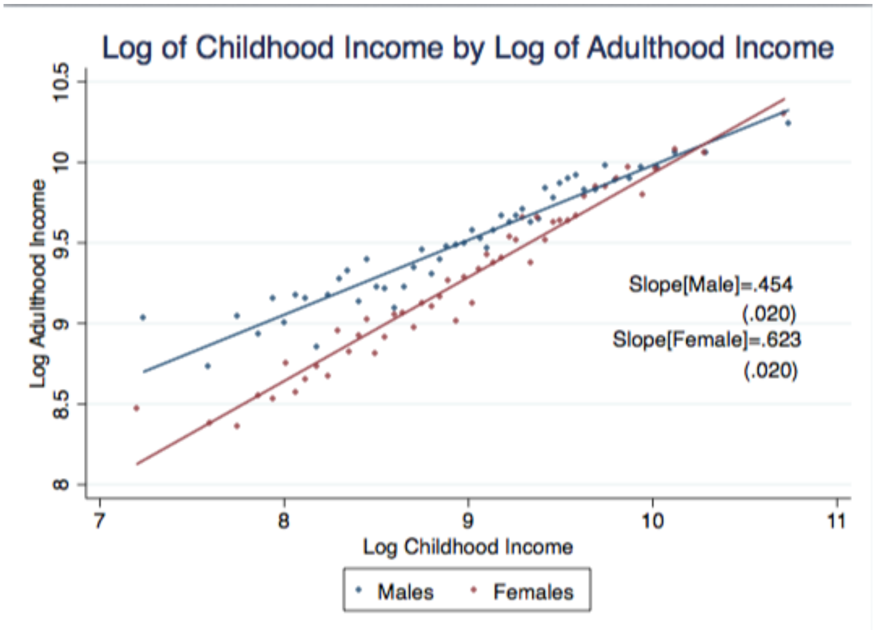
Table 5: Linear Regression Results: IGE and Rank-Rank Estimates[13]

VARIABLES	(1) Log(Ya)	(2) Log(Ya)	(3) Log(Ya)	(4) Ranka	(5) Ranka	(6) Ranka
Log(Yc)	0.529***	0.338***	0.318***			
	(0.0145)	(0.0163)	(0.0166)			
Gender (Female=1, Male=0)		-0.153***	-0.133***		-5.647***	-4.882***
		(0.0180)	(0.0183)		(0.713)	(0.726)
Race (Black=1, White=0)		-0.236***	-0.290***		-6.576***	-8.853***
		(0.0294)	(0.0303)		(1.091)	(1.119)
High School		0.276***	0.285***		9.482***	9.997***
		(0.0283)	(0.0287)		(1.071)	(1.084)
Some College		0.404***	0.409***		14.51***	14.97***
		(0.0303)	(0.0306)		(1.193)	(1.204)
College		0.619***	0.625***		23.73***	24.82***
		(0.0308)	(0.0413)		(1.213)	(1.611)
Single - Parent			-0.00688			0.119
			(0.0324)			(1.303)
Parent College Status			-0.0283			-1.822
			(0.0372)			(1.452)
Average Age (Adult)			0.0129***			0.430***
			(0.00361)			(0.141)
Average Age (Child)			0.00701			0.287*
			(0.00428)			(0.171)
Single – Child			0.162***			6.995***
			(0.0337)			(1.371)
Average Age (Parent)			-0.00231			-0.0749
			(0.00142)			(0.0542)
Rankc				0.528***	0.351***	0.331***
				(0.0133)	(0.0166)	(0.0169)
Constant	4.698***	6.242***	5.940***	25.19***	27.81***	10.44***
	(0.135)	(0.151)	(0.163)	(0.902)	(1.304)	(3.039)
Observations	6,198	6,198	5,970	6,198	6,198	5,970

[13] All education variables are dummies that are equal to one to indicate an individual's highest level of education. No High School is the comparison group. Single – Parent = 1 if an individual was raised by a single parent. Single – child = 1 if an individual is single as an adult. Sampling weights are used. Robust standard errors are in parenthesis.

*** p<0.01, ** p<0.05, * p<0.1

Figure 4: Log Childhood Income by Log Adulthood Income (By Gender)[14]



twenty percent of households as children, females have 42% less adulthood income and a 12.30 lower rank than their male counterparts, which is much larger than the 13.1% income penalty and 4.88 rank penalty that females face on average. This mobility penalty for females decreases as childhood quintile increases, and for those in the top childhood income quintile, the female adulthood income penalty is no longer significant, indicating that males and females do not have significantly different adulthood income for the same childhood income.

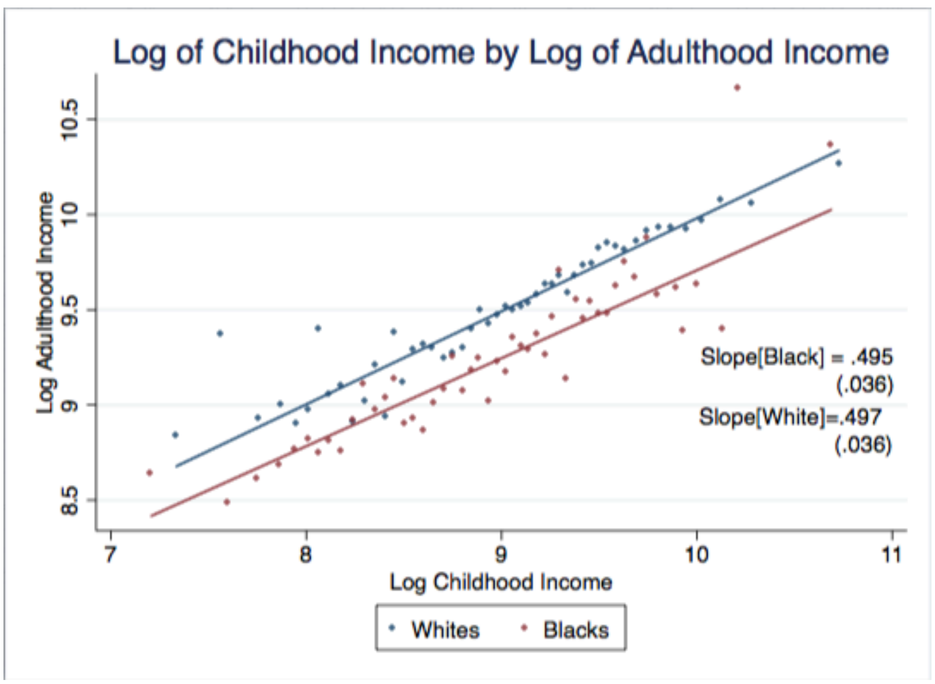
Race:

Relative mobility does not vary significantly by race. The interaction effect between race and childhood income is not significant for either the models using the rank measurements for income or the log measurements for income, indicating that blacks and whites have the same relative mobility. Figure 5 is a binned scatter plot that shows the joint distribution of log childhood income and log adulthood income separately for blacks and whites, and it visually

[14] This is a binned scatter plot, with 25 bins. Slope estimates come from OLS bivariate regressions for females and males separately on underlying data.

represents the insignificant interaction term. The IGE has a similar slope for blacks and whites. Unlike the analogous plot for gender, the negative black effect on log adulthood income does not attenuate as one moves up the childhood income distribution, but rather remains constant. As a robustness check, I run the same analysis except with rank measurements instead of log estimates for income. The IRA estimates and graph display a similar trend (See Appendix A, Figure 3a). These results remain consistent with the addition of both childhood and adulthood state fixed effects (See Appendix D).

Figure 5: Log Childhood Income by Log Adulthood Income (By Race)[15]



Although relative mobility does not vary by race, absolute mobility does. For all levels of childhood income, the expected value of adulthood income is lower for blacks than whites. The expected log adulthood income for individuals born in the bottom income quintile is 9.04 for whites and 8.73 for blacks, which is a 0.29 disparity. The expected log adulthood income for

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15 This is a binned scatter plot, with 25 bins. Slope estimates come from OLS bivariate regressions for blacks and whites separately on underlying data.

those individuals born in the top income quintile is 9.97 for whites and 8.65 for blacks, which is a 0.32 disparity. The racial disparities in mobility at the top and bottom of the childhood income distribution are very similar, and both are statistically significant. See Appendix B, Table 3b and Table 4b for transition matrices by race.

Education:

Relative mobility varies by education level. The interaction terms between the high school graduate, some college, and college graduate dummies and log childhood income are -0.110, -0.231, -0.257 (Displayed in Table 6) respectively, and are statistically significant. These negative interaction terms indicate that each group has a significantly different relative mobility than those who did not graduate high school. Individuals who did not graduate high school have a larger IGE and thus have a lower relative mobility. Those who have at least some level of college have higher levels of relative mobility than those who only have a high school degree. Figure 6 visually represents these interaction terms because the slope of the line varies with level of education. The slopes for those without a high school degree and with only a high school degree are steeper than those with some college or a college degree. The IRA plot shows similar trends (See Appendix A, Figure 4a). These results remain consistent with the addition of both childhood and adulthood state fixed effects (See Appendix D).

Absolute mobility varies by education group and childhood income. For those born in the bottom income quintile, college educated individuals have an expected log adulthood income of 9.50 and non-college educated individuals have an expected log adulthood income of 8.73, which is a 0.77 disparity. For those born in the top income quintile, college educated individuals have an expected log adulthood income of 10.16 and non-college educated individuals have an

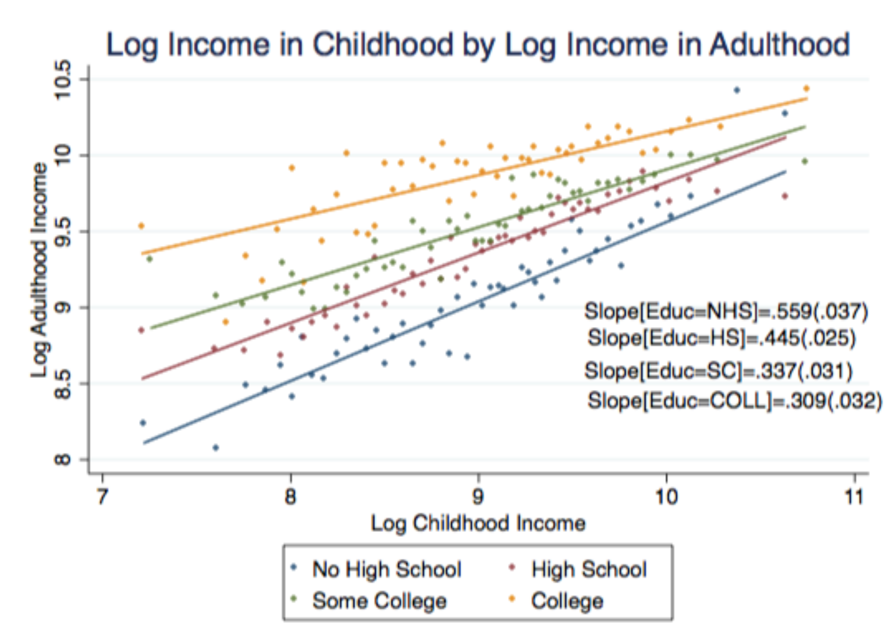
Table 6: Linear Regression Results: IGE and IRA estimates with Interactions [16]

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (Y_a)	Log (Y_a)	Log (Y_a)	Log (Y_a)	$Rank_a$	$Rank_a$	$Rank_a$	$Rank_a$
Log (Yc)	0.445**	0.484**	0.560**	0.366**				
	(0.0208)	(0.0179)	(0.0339)	(0.0392)				
Child Rank	-				0.465***	0.511***	0.488***	0.357***
					(0.0198)	(0.0171)	(0.0330)	(0.0385)
Gender	-1.656**			-1.788**	-12.81***			-13.77***
	(0.270)			(0.257)	(1.826)			(1.773)
Race	-	-0.368		-0.752**		-3.229*		-7.922***
		(0.342)		(0.341)		(1.939)		(1.934)
College	-		2.987**	2.470**			34.83***	33.87***
			(0.432)	(0.426)			(3.179)	(3.245)
High School	-		1.243**	1.390**			11.01***	12.66***
			(0.382)	(0.374)			(2.163)	(2.113)
Some College	-		2.504**	2.537**			22.35***	24.32***
			(0.420)	(0.426)			(2.778)	(2.809)
Fem*log(Y_c)	0.163**			0.179**				
	(0.0289)			(0.0276)				
Black* log(Y_c)	-	0.0166		0.0549				
		(0.0386)		(0.0387)				
Coll* log(Y_c)	-		-0.257**	-0.203**				
			(0.0465)	(0.0461)				
Hs* log(Y_c)	-		-0.110**	-0.125**				
			(0.0422)	(0.0415)				
Sc* log(Y_c)	-		-0.231**	-0.233**				
			(0.0458)	(0.0465)				
Fem*$rank_c$					0.119***			0.143***
					(0.0268)			(0.0260)
Black*$rank_c$						-0.0640		-0.00835
						(0.0413)		(0.0418)
Coll*$rank_c$							-0.176***	-0.160***
							(0.0467)	(0.0475)
Hs* $rank_c$							-0.0468	-0.0659
							(0.0406)	(0.0404)
Sc*$rank_c$							-0.141***	-0.164***
							(0.0456)	(0.0465)
Constant	5.564**	5.155**	4.130**	5.459**	32.26***	27.45***	16.95***	7.274**
	(0.195)	(0.168)	(0.305)	(0.360)	(1.394)	(1.243)	(1.640)	(3.307)
Observation	6,151	6,151	6,151	5,927	6,151	6,151	6,151	5,927

[16] Robust standard error are in parentheses. Log(Ya)=log adulthood income, Log(Yc)=log childhood income, Rankc=childhood rank, Ranka=adulthood rank, race(black=1, white=0), gender(female=1, male=0). No high school is the omitted education status group for comparison. Controls and sampling weights are included but not displayed in the table. *** p<0.01, ** p<0.05, * p<0.1

expected log adulthood income of 9.79, which is a 0.37 disparity. College educated individuals born in the bottom income quintile have a 18.18% chance of ending in the top income quintile, whereas non college educated individuals born in the bottom quintile have a 3.86% chance of ending in the top income quintile. See Appendix B, Table 5b and Table 6b for transition matrices by college education status.

Figure 6:Log Adulthood Income by Log Childhood Income (Education)



As childhood income increases, the disparity in absolute mobility by different levels of education decreases. Similar to my analysis for gender, I interact the childhood income quintile dummies with a dummy variable for college education to gain a more detailed understanding of how the association of college education and adulthood income varies across the childhood income distribution. The resulting coefficients appear in Table 7. The interaction terms are significantly positive for the bottom quintile and the third quintile, but they are not significant for

Table 7: Linear Regression Results: Quintile Dummies and Female/College Interactions[17]

VARIABLES	(1) $Log(Y_a)$	(2) $Log(Y_a)$	(4) $Rank_a$	(5) $Rank_a$
2.quint_child	0.158**	0.304***	5.492**	9.043***
	(0.0660)	(0.0467)	(2.434)	(1.554)
3. quint_child	0.337***	0.501***	13.41***	17.01***
	(0.0633)	(0.0466)	(2.363)	(1.626)
4. quint_child	0.520***	0.718***	22.00***	26.65***
	(0.0636)	(0.0458)	(2.315)	(1.608)
5. quint_child	0.602***	0.856***	24.48***	32.12***
	(0.0625)	(0.0470)	(2.291)	(1.675)
female	-0.0128	-0.133***	-0.502	-4.962***
	(0.0321)	(0.0186)	(1.257)	(0.733)
black	-0.243***	-0.248***	-7.596***	-7.699***
	(0.0313)	(0.0314)	(1.185)	(1.187)
College	0.357***	0.329***	14.80***	13.07***
	(0.0352)	(0.0433)	(1.368)	(1.669)
1q*fem[18]	-0.421***		-12.30***	
	(0.0788)		(2.670)	
2q*fem	-0.198***		-6.888***	
	(0.0588)		(2.235)	
3q*fem	-0.150***		-5.902***	
	(0.0520)		(2.116)	
4q*fem	-0.133***		-5.781***	
	(0.0484)		(1.932)	
5qo.fem				
	-		-	
1q*college		0.383***		10.89*
		(0.130)		(5.659)
2q*college		0.100		4.360
		(0.0739)		(3.342)
3q*college		0.102*		5.985**
		(0.0592)		(2.401)
4q*college		-0.0376		-0.0610
		(0.0502)		(2.037)
5oq.college				
		-		-
Constant	8.638***	8.466***	20.79***	16.49***
	(0.0876)	(0.0770)	(3.240)	(2.872)

17 Robust standard errors are in parenthesis. Controls and sampling weights are included in regression, but they are not shown here., *** p<0.01, ** p<0.05, * p<0.1

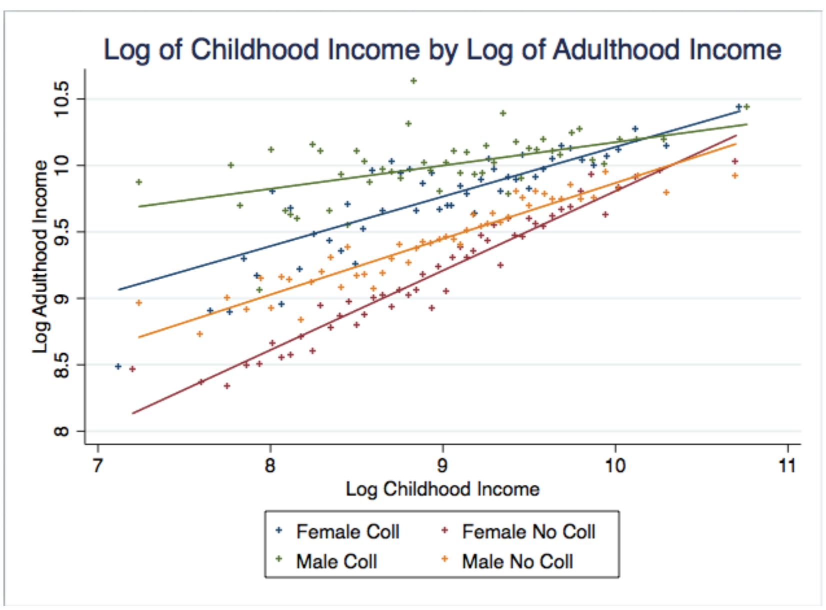
18 These represent the interactions of the quintile dummies with female dummy, The fifth quintile dummy interaction is omitted because of collinearity.

the second, fourth and fifth quintile. In addition to the 33% increase in adulthood income and 13.07 increase in rank that college brings, for individuals in the bottom quintile it brings a 38.3% increase in adulthood income and a 10.89 increase in rank. This indicates that the negative interaction term between childhood income and college attendance mostly stems from individuals at the bottom of the childhood income distribution receiving a much larger mobility reward from college than others.

d. Part 4 - Education and Gender

The gender mobility in disparity does not vary significantly by college education. The three-way interaction between log childhood income, gender and college education status is insignificant, signaling the interaction between log childhood income and gender does not differ by college education. Although the relative mobility increases for all college educated individuals (as can be seen by the significant interaction between college education and

Figure 7: Log Childhood Income by Log Adulthood Income (By Gender and Education)[19]



[19] Binned scatter plot, 25 bins.

childhood income, discussed in Part 3), it does not increase differentially for females. Figure 7 represents this trend visually. The smaller slopes for college educated females and males than their counterparts indicate that college education increases relative mobility for both females and males. It does not, however, increase females' relative mobility more than it increases males' relative mobility. These results remain consistent with the addition of both childhood and adulthood state fixed effects (See Appendix D).

College education also does not increase females' absolute mobility more than it increases male's absolute mobility. Although the interaction term between college and female is significant in a simple regression, after controlling for the interaction between childhood income and female as well as other controls, the female/college interaction term becomes insignificant, indicating that females do not receive a larger adulthood income bump through college education than males do. Among college-educated individuals who were born in the bottom income quintile, females have an expected adulthood log income of 9.31 and males have an expected adulthood log income of 9.86, which is a 0.55 gender disparity. Among non college educated individuals who were born in the bottom income quintile, females have an expected log adulthood income of 8.51 and males have an expected log adulthood income of 9.02, which is a 0.51 gender disparity. The gender disparity in mobility does not vary by college education. Although college education has a positive effect on both relative and absolute mobility for females, it does not have a larger of a positive effect in these areas on females than males. Therefore, although college education can elevate a female's income status in adulthood, it cannot help with the inequalities that exist between male and female mobility.

Table 8: Linear Regression Results: Interactions with College Status[20]

VARIABLES	(1) Log(Ya)	(2) Log(Ya)	(3) Ranka	(4) Ranka
Log(Yc)	0.368***	0.298***		
	(0.0167)	(0.0268)		
Black*College	0.238***	0.998	5.571	4.058
	(0.0803)	(0.971)	(3.460)	(6.529)
Fem*College	0.0732*	0.833	2.916*	0.137
	(0.0408)	(0.641)	(1.579)	(5.639)
Fem*Log(Yc)		0.188***		
		(0.0331)		
Black*Log(Yc)		0.0281		
		(0.0449)		
College*Log(Yc)		-0.0990*		
		(0.0553)		
Coll*Fem*Log(Yc)		-0.0898		
		(0.0673)		
Coll*Black*Log(Yc)		-0.102		
		(0.110)		
Rankc			0.381***	0.345***
			(0.0167)	(0.0259)
Fem*Rankc				0.135***
				(0.0316)
Black*Rankc				-0.0382
				(0.0452)
College*Rankc				-0.147**
				(0.0581)
College*Fem*Rankc				-0.00424
				(0.0721)
Coll*Black*Rankc				-0.0638
				(0.119)
Constant	5.677***	6.309***	14.43***	16.40***
	(0.165)	(0.252)	(2.849)	(3.034)
Observations	5,970	5,970	5,970	5,970
R-squared	0.333	0.342	0.341	0.346

[20] Controls and sampling weights are included in the regressions, but they are not displayed in the table., *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parenthesis.

e. Part 5 - Education and Race

The racial disparity in mobility does not vary significantly by college education. The three-way interaction between log childhood income, race, and college education status, signaling the interaction between log childhood income and race does not differ by college education. Although the relative mobility increases for all college education individuals, it does not increase differentially for college-educated blacks.

The disparity in absolute mobility by race also does not vary by college education. Although the race/college education interaction is significant in a simple regression, in a fully adjusted model, this interaction is no longer significant. This indicates that college education does not increase blacks' adulthood income more than it increases whites' adulthood income on average. Although college education has a positive effect on both relative and absolute mobility for blacks, it does not have a larger of a positive effect in these areas on blacks than whites. Therefore, although college education can elevate a black's income status in adulthood, it cannot help with the inequalities that exist between black and white mobility. These results remain consistent with the addition of both childhood and adulthood state fixed effects (See Appendix D).

VI. Discussion and Conclusion:

Females, blacks, and lower educated individuals have lower adulthood incomes than their respective counterparts. These trends extend to mobility as well. Females are less mobile than males, particularly females born into born households. Blacks are less mobile than whites regardless of childhood income. Individuals with lower levels of education are less mobile the those with higher levels of education, particularly among those who are born into poor households.

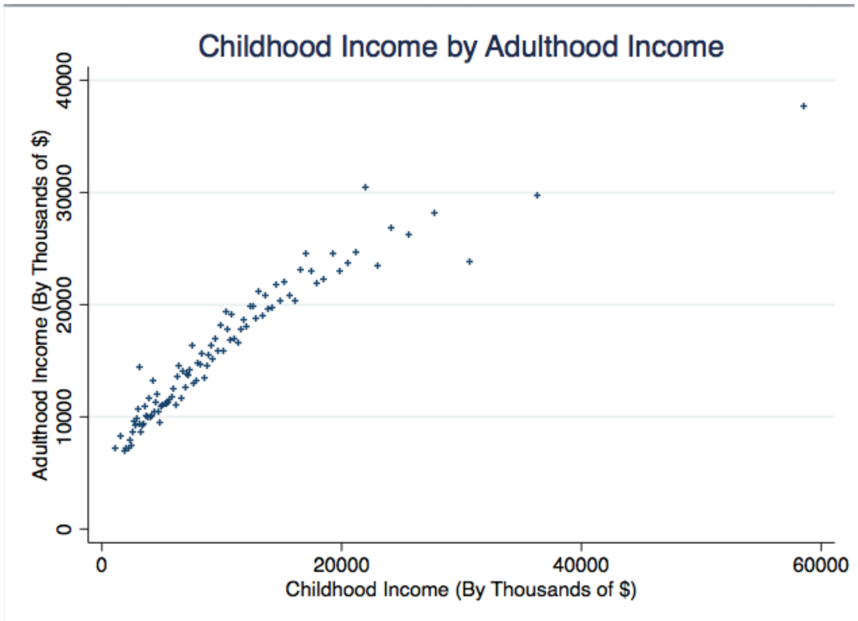
In fully adjusted models with state fixed effects, I find no evidence that college has a differential impact on the mobility of females or blacks. Although college education increases mobility for everyone, it does not increase mobility more for females than for males, and it does not increase mobility more for blacks than for whites. Thus, college education may not be the solution to closing the gender and racial gap in income mobility.

The results should be interpreted in light of some limitations. First, my results cannot be interpreted causally because of the many unobserved neighborhood, family, and individual characteristics that are not included in the analyses. Nevertheless, because of the large gap in the literature pertaining to intergenerational mobility, the descriptive analyses developed in this study lays important groundwork for future research in causal mechanisms of intergenerational mobility and frame the discussion of such topics in the literature. Second, the data used for this paper come from 1968-1997, so results may vary with more contemporary data. I use data from this time period to compare my estimates to existing research in the field, which primarily has been done with data from the second half of the twentieth century. Third, the education data available are not comprehensive and do not include information on college quality or on early childhood education. Given current results, future research that includes measures of college quality as well as early childhood education is warranted.

In summary, females are less mobile the males, especially those who are born poor, blacks are less mobile than whites regardless of childhood income, and individuals with lower levels of education are less mobile than those with higher levels of education. The gender and racial disparities in mobility still exist among those who are college educated, indicating that college education may not be the most effective way to reduce gender and race based inequalities in mobility. Other strategies for solving this problem should be explored.

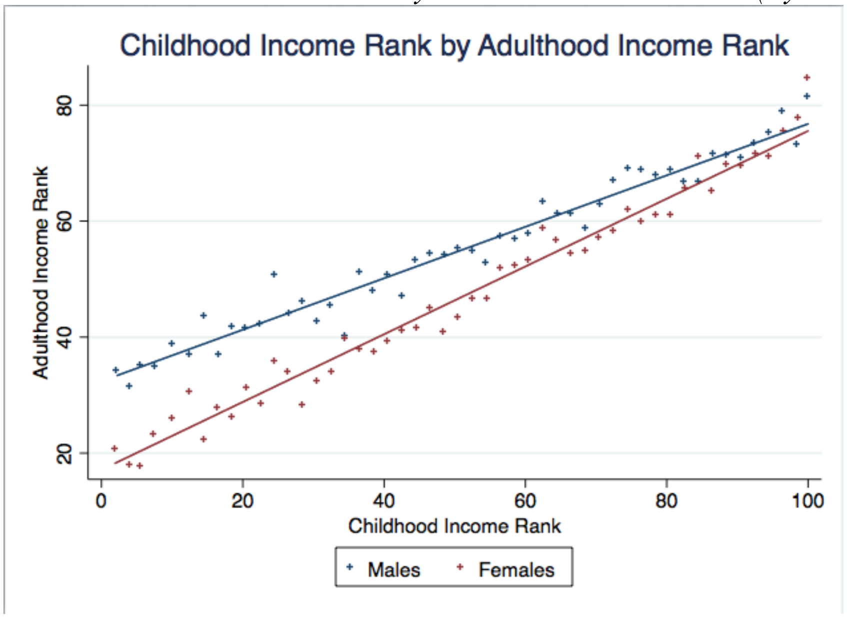
Appendix A: Mobility Binned Scatter Plots

Figure 1a: Childhood Income by Adulthood Income, 100 Bin Scatter



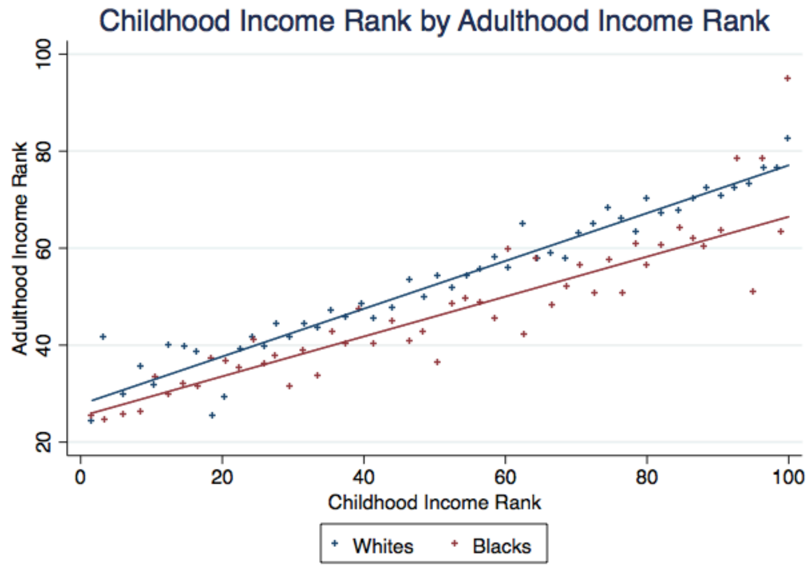
This 100 bin scatter plot illustrates the same concavity that the 25 bin scatter plot exhibits in Part 1 of the analysis. An extra dollar of childhood income increases adulthood income more for those at the bottom of the childhood income distribution compared to those at the top of the income distribution.

Figure 2a: Childhood Income Rank By Adulthood Income Rank (By Gender)



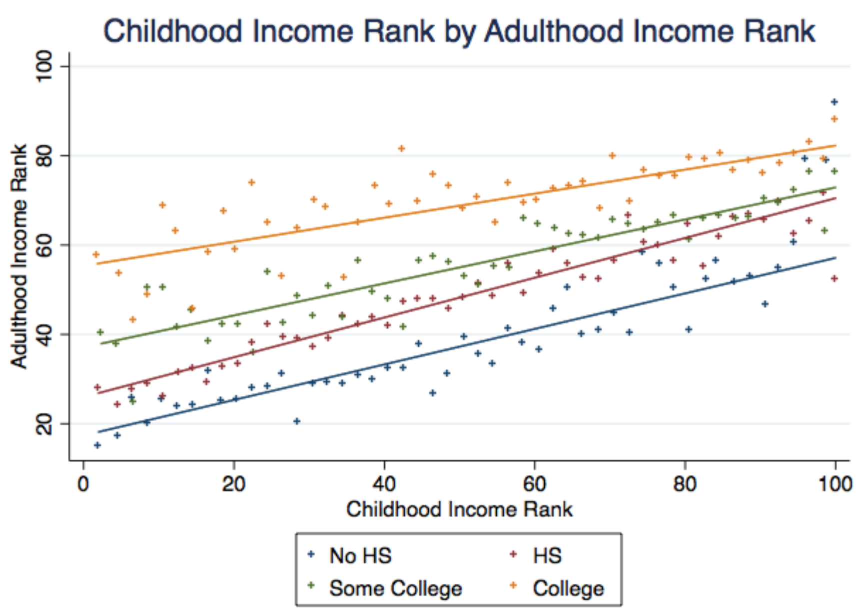
This is a binned scatter plot with 25 bins. The slope of the IRA for females is 0.574 and the slope of the IRA for males is 0.436. The intercept for females is 17.44 and the intercept for males is 32.94.

Figure 3a: Childhood Income Rank By Adulthood Income Rank (By Race)



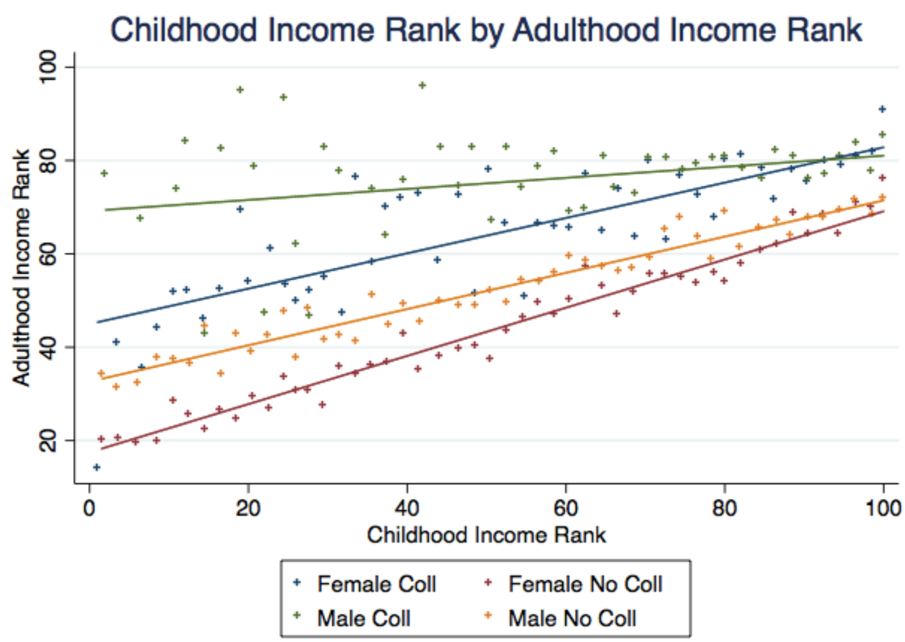
This is a binned scatter plot with 25 bins. The slope of the IRA for blacks is 0.403 and the slope of the IRA for males is 0.483. The slopes are not statistically significantly different from each other. The intercept for blacks is 25.33 and the intercept for whites is 28.39. The intercepts are statistically significantly different from each other.

Figure 4a: Childhood Income Rank By Adulthood Income Rank (By Education)



This is a binned scatter plot with 25 bins. The slope for people who have graduated from college is 0.259, and the intercept is 55.97. The slope for people who attended some college is 0.36, and the intercept is 36.94. The slope for people who graduate high school is 0.436 and the intercept is 26.48. The slope for people who did not graduate high school is 0.40 and the intercept is 17.07.

Figure 5a: Childhood Income Rank By Adulthood Income Rank (By Gender and Education)



This is a binned scatter plot with 25 bins. The slope for females with college education is 0.378 and the intercept is 44.98. The slope for females with not college education is 0.516 and the intercept is 17.49. The slope for males with college education is 0.12 and the intercept is 69.18. The slope for males without college education is 0.39 and the intercept is 32.65.

Appendix B: Transition Matrices

For all matrices, childhood income quintiles are listed from poorest to wealthiest in rows and adulthood income quintiles are listed from poorest to wealthiest in columns.

Table 1b: Transition Matrix - Female

	1	2	3	4	5
1	57.35	22.77	11.82	5.48	2.59
2	34.33	28.96	19.4	12.99	4.33
3	21.55	23.57	24.5	18.45	11.94
4	9.53	18.39	22.41	25.25	24.41
5	3.83	10	16.33	24.33	45.5

Table 2b: Transition Matrix – Male

	1	2	3	4	5
1	32.95	25.95	20.08	14.02	7.01
2	19.32	26.83	24.51	18.43	10.91
3	10.54	21.77	24.49	25.85	17.35
4	5.26	14.04	19.78	28.07	32.85
5	2.26	9.35	16.44	27	44.95

Table 3b: Transition Matrix – Black

	1	2	3	4	5
1	48.48	23.64	14.04	9.14	4.71
2	32.75	26.47	19.45	14.3	7.03
3	25.1	25.31	19.55	17.9	12.14
4	12.97	22.18	19.67	22.18	23.01
5	11.9	16.67	21.43	17.86	32.14

Table 4b: Transition Matrix – White

	1	2	3	4	5
1	33.81	28.06	25.9	9.35	2.88
2	17.82	30.79	25.93	17.59	7.87
3	10.58	21.02	27.71	24.63	16.06
4	5.98	14.71	21.4	27.79	30.12
5	17.82	30.79	25.93	17.59	7.87

Table 5b: Transition Matrix – College Educated

	1	2	3	4	5
1	12.73	18.18	21.82	29.09	18.18
2	6.06	12.12	21.21	34.85	25.76
3	2.11	7.04	19.01	34.51	37.32
4	1.55	6.2	15.89	25.97	50.39
5	0.95	5.48	8.88	24.01	60.68

Table 6b: Transition Matrix – Non College Educated

	1	2	3	4	5
1	48.41	24.42	15.08	8.23	3.86
2	28.72	28.89	21.75	14.36	6.28
3	18.15	24.75	25.21	20.35	11.55
4	8.89	18.82	22.44	26.89	22.96
5	4.5	12.67	21.8	26.98	34.06

Appendix C: Split Regressions by College Education

	Black	White	Non College	College
	(1)	(2)	(3)	(4)
VARIABLES	$Log(Y_a)$	$Log(Y_a)$	$Log(Y_a)$	$Log(Y_a)$
$Log(Y_c)$	0.302***	0.339***	0.294***	0.222***
	(0.0475)	(0.0275)	(0.0272)	(0.0518)
College	2.339**	1.490***		
	(0.921)	(0.387)		
Female	-2.690***	-1.141***	-1.826***	-1.167*
	(0.581)	(0.327)	(0.310)	(0.596)
$Coll*Log(Y_c)$	-0.207**	-0.121***		
	(0.103)	(0.0406)		
$Fem*Log(Y_c)$	0.279***	0.111***	0.183***	0.113*
	(0.0674)	(0.0346)	(0.0337)	(0.0618)
Black			-0.934**	0.526
			(0.374)	(0.941)
$Black*Log(Y_c)$			0.0778*	-0.0831
			(0.0425)	(0.106)
Constant	6.072***	5.848***	6.349***	7.179***
	(0.445)	(0.266)	(0.258)	(0.506)
Observations	2,586	3,341	4,904	1,023
R-squared	0.293	0.281	0.267	0.180

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, *
p<0.1

Model 1 and Model 2 split and run the regressions by race. Model 3 and Model 4 split and run the regressions by college education. Using a z-test, I find that there is not a significant difference in female coefficients or black coefficients between non-college and college group, which is consistent with the non significant 3 way interaction terms between race, childhood income and adulthood income and gender, childhood income, and adulthood income. This model includes control variables and sampling weights.

Appendix D: Fixed Effects Models

All of the regressions included control variables that are not listed.

Table 1d: Linear Regression Models with Childhood State Fixed Effects

VARIABLES	(1) Log(Y_a)	(2) $Rank_a$	(3) Log(Y_a)	(4) $Rank_a$	(5) Log(Y_a)	(6) $Rank_a$
Log(Y_c)	0.308***		0.312***		0.265***	
	(0.0154)		(0.0339)		(0.0270)	
Fem*Log(Y_c)			0.235***		0.214***	
			(0.0224)		(0.0268)	
Black* Log(Y_c)			0.00518		0.0239	
			(0.0304)		(0.0329)	
Coll* Log(Y_c)			-0.262***		-0.120*	
			(0.0418)		(0.0619)	
Hs* Log(Y_c)			-0.119***			
			(0.0321)			
Sc* Log(Y_c)			-0.202***			
			(0.0360)			
Female	-0.239***	-7.904***	-2.353***	-16.74***	-2.153***	-16.03***
	(0.0170)	(0.586)	(0.202)	(1.172)	(0.238)	(1.239)
Black	-0.264***	-7.787***	-0.307	-5.991***	-0.476	-7.113***
	(0.0226)	(0.785)	(0.271)	(1.464)	(0.292)	(1.522)
College	0.724***	27.51***	3.080***	37.88***	1.438**	31.94***
	(0.0414)	(1.428)	(0.380)	(2.518)	(0.591)	(4.652)
High School	0.294***	9.422***	1.325***	10.25***		9.514***
	(0.0224)	(0.772)	(0.280)	(1.392)		(0.767)
Some college	0.465***	15.69***	2.252***	20.54***		15.66***
	(0.0256)	(0.883)	(0.320)	(1.740)		(0.881)
$Rank_c$		0.301***		0.287***		0.244***
		(0.0139)		(0.0298)		(0.0227)
Fem*$Rank_c$				0.172***		0.157***
				(0.0200)		(0.0230)
Black*$Rank_c$				-0.0356		-0.0311
				(0.0270)		(0.0284)
Coll*$Rank_c$				-0.184***		-0.113*
				(0.0383)		(0.0593)
Hs*$Rank_c$				-0.0236		
				(0.0289)		
Sc*$Rank_c$				-0.100***		
				(0.0320)		
Black*Female					0.722	9.665*

					(0.864)	(4.964)
Female*College					-0.0357	-6.311
					(0.652)	(4.683)
Female*College *Log(Y_c)					0.00618	
					(0.0688)	
College*Black*Log(Y_c)					-0.0508	
					(0.0962)	
Coll*Fem*Log(Y_c)						0.0995
						(0.0628)
Coll*Black*Log(Y_c)						-0.0210
						(0.0837)
Constant	6.020***	12.52***	6.006***	13.04***	6.618***	15.81***
	(0.151)	(2.324)	(0.304)	(2.543)	(0.250)	(2.262)
Observations	5,990	5,990	5,990	5,990	5,990	5,990
R-squared	0.345	0.360	0.363	0.371	0.323	0.372
Number of state_a	57	57	57	57	57	57

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 1d: Linear Regression Models with Adulthood State Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	lnavinc_a	rank_adult	lnavinc_a	rank_adult	lnavinc_a	rank_adult
Log(Y_c)	0.296***		0.301***		0.254***	
	(0.0156)		(0.0340)		(0.0272)	
Female*Log(Y_c)			0.229***		0.210***	
			(0.0224)		(0.0268)	
Black* Log(Y_c)			0.0201		0.0378	
			(0.0309)		(0.0333)	
Coll* Log(Y_c)			-0.275***		-0.118*	
			(0.0419)		(0.0622)	
Hs* Log(Y_c)			-0.121***			
			(0.0320)			
Sc* Log(Y_c)			-0.212***			
			(0.0359)			
Female	-0.242***	-8.081***	-2.297***	-16.71***	-2.118***	-16.15***
	(0.0170)	(0.584)	(0.202)	(1.168)	(0.238)	(1.234)
Black	-0.288***	-8.582***	-0.465*	-7.503***	-0.622**	-8.556***
	(0.0238)	(0.825)	(0.276)	(1.509)	(0.296)	(1.562)
College	0.727***	27.70***	3.198***	38.76***	1.412**	32.46***
	(0.0416)	(1.429)	(0.381)	(2.523)	(0.594)	(4.665)

High School	0.303***	9.831***	1.350***	10.65***		9.920***
	(0.0224)	(0.770)	(0.280)	(1.387)		(0.765)
Some College	0.474***	16.12***	2.347***	21.28***		16.09***
	(0.0256)	(0.882)	(0.319)	(1.734)		(0.880)
$Rank_c$		0.289***		0.273***		0.227***
		(0.0141)		(0.0298)		(0.0228)
Fem*$Rank_c$				0.168***		0.157***
				(0.0200)		(0.0229)
Black* $Rank_c$				-0.0208		-0.0174
				(0.0273)		(0.0286)
College* $Rank_c$				-0.197***		-0.118**
				(0.0383)		(0.0595)
Hs* $Rank_c$				-0.0241		
				(0.0287)		
Sc* $Rank_c$				-0.107***		
				(0.0318)		
Black*Coll					0.603	8.622*
					(0.876)	(4.984)
Female*Col					0.201	-5.076
					(0.652)	(4.670)
Fem*Coll* $\log(Y_c)$					-0.0188	
					(0.0688)	
Black*Coll* $\log(Y_c)$					-0.0379	
					(0.0976)	
Female*Coll* $Rank_c$						0.0801
						(0.0627)
Black*Coll* $Rank_c$						-0.00165
						(0.0842)
Constant	6.168***	14.76***	6.140***	15.39***	6.765***	18.10***
	(0.154)	(2.324)	(0.305)	(2.551)	(0.252)	(2.265)
Observations	5,992	5,992	5,992	5,992	5,992	5,992
R-squared	0.327	0.342	0.346	0.354	0.303	0.354
Number of state_c	47	47	47	47	47	47

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

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