Master Thesis

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Expectations, aspirations and labor market outcomes: evidence from the U.S.

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Abstract

Do children from wealthier families have bolder professional aspirations? We answer this question in the context of intergenerational mobility in the U.S. in the last decade. Using data from PSID and its supplements, we analyze a relationship between parental well-being - measured by total family income - and teenagers's beliefs about their future careers at the age of 30. We rank occupations by mean remuneration it has in the U.S. and subsequently map desired and expected jobs onto earnings space. We find that teenagers coming from more economically advantaged backgrounds aspire to better-paying jobs: a 1 pp increase in parent income rank is associated with a 0.15 pp increase in the rank of desired occupation. The coefficient is stable across specifications with controls on confounders - components of personal endowment (personal perceptions, family values, college education of parents, family structure).

Introduction

Do child's chances to succeed in future depend on the family background? This is a seminal question that has received a notable amount of attention in both theoretical (Becker et al. 1979) and empirical (Solon, 1999) literature. Current consensus is that economic well-being tend to persist across generations. It has been also widely documented that many factors (sometimes referred to as *personal endowment of a child*) underline the differences in intergenerational mobility. In reality children's endowment is a «black box» encompassing such factors as genetics, family connections and reputation, skills and knowledge of family members, and goals set by parents. However, establishing causality has been proven to be formidable (Mogstad and Torsvik, 2021).

This study is attempt to explore why the family may matter. Specifically, we investigate empirically whether parental wealth is associated with bolder ambitions about future careers and professional self-realization among American teenagers. Ambition is an umbrella term spanning wide range of concepts (Ray, 2016). We narrow it down by looking at *aspirations* - specific outcomes in professional domains individual covets the most. Is it true that children from relatively affluent families desire to have a job that is more rewarding? Our project thus aims at answering this question, at least on a correlational level.

If the answer is affirmative, one may want to conclude that disproportionate family resources affect children on early stages of their development and alter their ambitions. Studies from anthropology and culture (Appadurai, 2004) argue that if poorer lack means and abilities to learn about their potential. This could in turn mean that children born into hardships and difficult circumstances endogenously select into areas where their talents remain severe underdeveloped.

We also look into the relationship between teenagers' career expectations and family background. Put in economic terms, expectations are defined as first moments of beliefs about future careers. They are essentially different from aspirations, since the former -

when elicited in an interview - might pertain to abstract desires and longings in future. Self-earnings beliefs pertain to capability of achieving certain professional outcomes.

Attributing variation in aspirations to differences in parental income ranks would be belying and hence inconclusive, since any component of children's endowment could be a confounder. We limit out attention to the following factors - **family perceptions** (e.g. cultural norms and perceptions fostered by parents), **family background** (e.g. parental education and family structure) and **personal perceptions** towards success (self-efficacy).

We test our hypotheses using 10 - years data on American teenagers. Our core sample comprises information on demographics and characteristics of the environment in which a teenager grows up. The key advantage of our data is that we observe self-reported beliefs and aspirations related to individual careers at the age of 30. The panel is sufficiently long and thus enables us to track individuals to that age. We collect information on jobs people wind up landing and remuneration they get, which allows us to asses accuracy of predictions.

We then quantify career aspirations and expectations by mapping them onto mean remuneration within an occupation on a national level. For this approach to be valid, we make certain assumptions about first moments of individual beliefs. We leverage data on earnings across occupations in the United States which comes from the Bureau of Labor Statistics annual databases. We also use the Census Current Population Survey (2019) to estimate mean wages accruing to certain age groups across all occupations.

Our main finding is that a positive relationship exists: children from wealthier families aspire to careers that pay better. A one-point increase in parental family income rank is associated with 0.14 points increase in the desired job rank. Similar conclusion holds for career expectations. The result is robust to controlling on components of personal endowment that should correlate with parental income. We do not find a relationship between self-efficacy and «boldness» of aspirations, in contrast to some empirical studies (e.g. Krishnan et al. 2013).

We also document that over the span of 10 years, young people from more affluent families are less accurate in their predictions about career outcomes. Ceteris paribus, an individual with a family that ranks 1 point higher errs to the extent of almost 0.2 points in the occupation earning's ranking. Also, females from the least advantaged backgrounds are prone to significant overstatement: on average, the job they end up having at the age of 30 ranks 40 points less than what was expected when they were around 20.

The rest of the paper is organized as follows. Section I describes various sources of our data and reports core sample statistics. Section II elaborates on the empirical strategy and presents the main results. Section III contains several robustness checks, and section IV concludes the project.

I Data

This section highlights key aspects of the sample this paper is dealing with. We provide a detailed account of how we construct our analysis sample starting from the raw data in Appendix A. Descriptions of the key variables are likewise available in Appendix B.

I.A Overview

Data on various sources of family-level income, wealth, individual earnings and demographics come from the Panel Study of Individual Dynamics (PSID) administered by the Institute for Social Research (ISR) at the University of Michigan. PSID is a representative longitudinal survey of the US population that has been tracking over 18000 individuals from 5000 American families since 1968 when the first batch of interviews was conducted. These individuals and their descendants (individuals born to or adopted by the former) are then followed by the study and are therefore interviewed in the subsequent waves.

Data on aspirations and beliefs regarding labor market outcomes originate from the TAS supplement, which is an extension of the main PSID study. Respondents are directly asked about jobs they *would like to have the most* when they reach the age of 30. Consequently, they are then reporting which job *they expect to be having* when they are 30. Appendix B delineates relevant questions of the survey and provides information on variable construction.

When quantifying aspirations, we map occupational data on mean remuneration (wages and salaries) a job pays in the U.S. in a given year. Moments of the empirical distribution of occupational earnings come from the Bureau of Labor Statistics Databases, which span the universe of all occupations contained in the Standard Occupational Classification. A comprehensive account of our methodology is available in Appendix B.

In order to gauge components of personal endowment, we use data on family background and perceptions from the Child Development Supplement. This database contains information on values fostered by the parents and cultural norms of the household.

We also estimate average wages and salaries across occupations in broad age groups using the Current Populations Survey (CPS). It is a monthly household survey which aims at measuring labor force participation and employment. Since labor income is measured in 2018 and 2019, we rely on the 2019 wave of the Survey and employ if for wage computations. In 2019, 50-60,000 households per month were queried.

We utilize extracts of individual data to aggregate data into five broad age groups. Following the Census methodology, we compute an empirical moment for each of the following strata defined by age: 16-24; 25-34; 35-44; 45-54; 55-64; 65-87.

To link kids with parents, we employ the family relationship matrix provided by ISR. A parent is defined as a person who claims the child to be their dependent. PSID data collects information on biological parents as well as on the head and his spouse of the family unit a child belongs too. Unlike (Chetty et al. 2014), our procedure incorporates changes in parental marital status or dependent claiming: we are unable to use individual income data for parents and hence have to rely on the family – level data for a given wave. By construction, 100 % of the individuals in the main dataset are linked to the families of their parents.

I.B Sample Statistics

The dataset consists of young individuals who:

- were born between 1987 and 1991;
- participated in the 2009 wave of TAS interview and hence were part of a PSID family unit;
- were not heads of the family unit they belonged to during the interview and who were

claimed to be a «dependent child»;

- whose families were part of a PSID longitudinal studies in earlier wave of 2007;
- whose parents reported strictly positive total family income when filing 2009 tax returns.

Our core sample comprises 730 young individuals who have already graduated from high school by the year of 2009 and reside with parents. 52% are female; mean age of respondents is 20.26 years. Forty percent of individuals self-identify as Black, which is an over-representation as compared to the population. Appendix A provides a comprehensive account of sample construction and discusses its key features. Sample characteristics are shown in Table 1.

Table 1: Summary Statistics for Core Sample

	Mean	**Median**	**SD**	**Min**	**Max**	**N**
Par. Income	117368.12	84783.22	148773.60	1953.99	2478835.80	730
Female	0.52	1.00	0.50	0	1	730
Black	0.39	0.00	0.49	0	1	730
Age	20.26	20.00	1.66	17	23	730
Child Income	69305.60	54813.19	54317.32	0.00	421205.94	730
Self-Efficacy	3.14	3.00	0.61	1.00	4.00	730
Good N-hood	0.86	1.00	0.35	0	1	730
Mover	0.53	1.00	0.50	0	1	730
College, Mother	0.52	1.00	0.50	0	1	730

II Empirical Analysis

II.A Intergenerational Mobility in PSID Sample

We begin our empirical analysis with documenting patterns of intergenerational mobility in our core sample. We do so to ensure that our data is representative of the U.S. population in terms of demographic composition, income and mobility trends. The reference study encompassing the U.S. population is (Chetty et al, 2014).

We first outline some of the methodological aspects of measuring intergenerational mobility in the US. We then compare our results with those for the population.

Measuring Intergenerational Mobility

Following (Chetty et al. 2014), we explore intergenerational persistence in earnings and wealth. We characterize the joint distribution of a child's lifetime pre-tax family income Y, and her parents' lifetime pre-tax total family income X.

As shown in (Mazumder, 2016), when establishing a link between incomes across generations, one should use data with multiple years of earning for both kids and parents, preferably measured around the middle of their careers. As described earlier in the data section, our analysis exploits family income averaged over four years from 2006 to 2009, while adult income for individuals is averaged over two years - 2018 and 2019. Data is no longer available for years after 2019, so we have to confine our analysis to early years of careers.

We discard negative and zero family income values. This could either overstate or understate true degree of intergenerational mobility. As demonstrated by (Chetty et al. 2014), recoding zero incomes as $1 raises the IGE in log-log specification almost twofold. Appendix D presents the estimates of IGE in our sample; the slope coefficient is also in accordance with the population-level estimate of (Chetty et al. 2014).

Rank - Rank Approach

We begin our analysis with an estimate of intergenerational mobility based on percentile ranks. Specifically, we compute empirical ranks R_c for children in the core sample using average total family income. We do the same for their parents, assigning each family a rank R_p. We then estimate the following model:

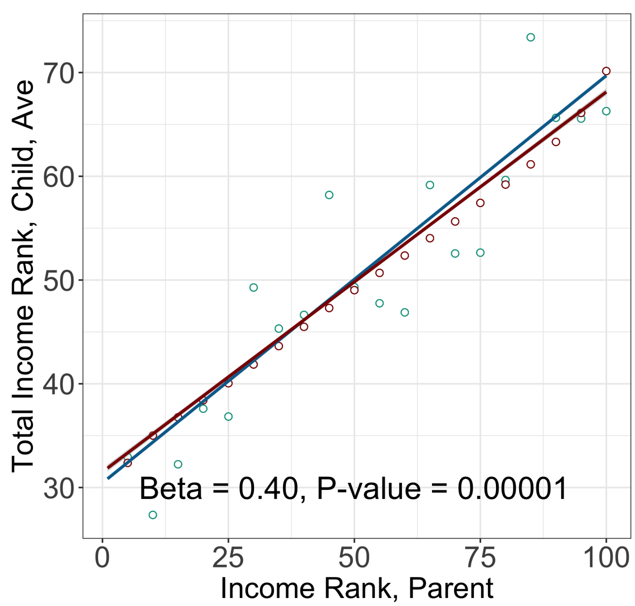
$$R_c = \alpha + \beta \cdot R_p + \epsilon \tag{1}$$

and relate to β as relative mobility.

Note that: $\beta = \frac{cov\,(R_c, R_p)}{var\,(R_p)} = corr\,(R_c, R_p)$ since both ranks follow a $Uni(0, 1)$ distribution in population by construction (by quantile transform theorem).

Results are presented in a figure 1 below. We divide the horizontal axis into 20 equal-sized bins (vingtiles) and plot mean child income vs. mean parent income in each bin.

Figure 1: Rank-Rank Specification, Core Sample (Red Line: Population)



The estimate we obtain here ($\beta = 0.40$) is compatible to the ones of (Chetty et al. 2014) whose estimates lie in the range between 0.344 and 0.360 (see right panel of Figure 1).

II.B Personal Endowment, Aspirations and Expectations

We now turn attention to the core part of this study which explores the relationship between child's personal background and her aspirations alongside beliefs about future career. We use family income rank as a strong predictor of our endowment measures, as discussed in previous subsection). However, the composition of family's relative well-being in terms of other observables - components of kid's personal endowment - may be a confounder. We therefore extend our analysis and include additional controls that ought to partly explain the relationship.

II.B.1 Aspirations, Expectations and Parental Income

We begin with establishing a link between family income and aspiration of a child. As described in introduction, our database is silent about respondents' beliefs with respect to self-earnings across occupations. Nor does it elicit beliefs about average remuneration at occupational level in the US. We make the following assumption:

Assumption 1:

At the occupational level, first moments of self-earnings beliefs are equal to the corresponding first moments of population earnings beliefs.

Assumption 2:

At the occupational level, first moments of population earnings beliefs are equal to the corresponding first moments of true distribution of earnings.

Specifically, we:

- map each occupation from Census Occupational Classification to mean remuneration it had in the U.S. in 2009 (wage and salary);
- assign a percentile rank to each occupation R_{asp}, using empirical distribution of hourly

wages (salaries);

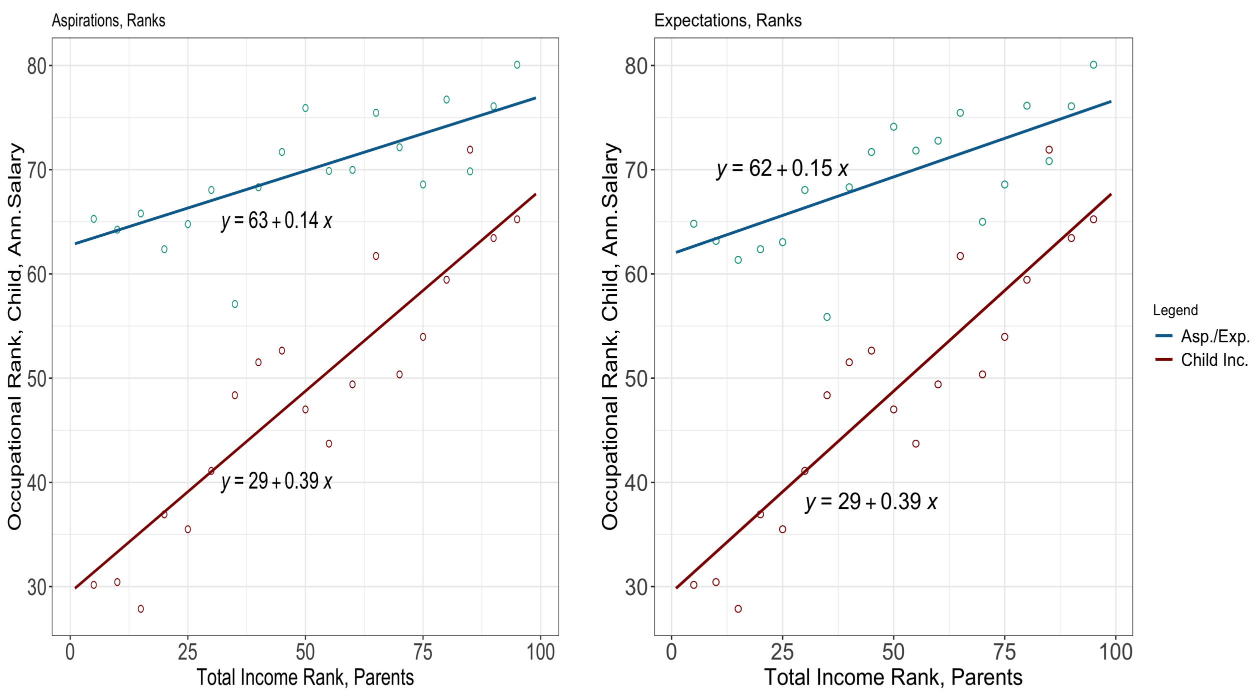
- estimate the following equation [1]:

$$R_{asp} = \alpha_{asp} + \beta_{asp} \cdot R_p + \epsilon \tag{2}$$

Appendices A and B elaborate on calculation of average wages and salaries across occupations. They also provides details on the mapping procedure.

Results of the estimation are presented graphically below in Figure 2 (see Appendix D for tables with coefficients with standard errors).

Figure 2: Parental Family Rank, Aspirations and Expectations



[1] By construction, mean rank for aspirations does not need to be equal to 0.5 in the core sample so there are effectively «two degrees of freedom» in estimated equation.

Our estimation suggests that parental Income has a positive statistically significant at 1% level association with labor market aspirations: $\hat{\beta}_{asp} = 0.14$. It means that, on average, a child from a household that ranks 1 percentile higher in the family income distribution desires to have a job that ranks 0.14 points higher. However, transmission of parental income to aspirations is less pronounced as compared to integenerational transmission of incomes (at least at a correlational level). Estimated slope in rank-rank specification for incomes is more than two times larger than that in regression (5).

In that same vein, conclusions hold for the relationship between parental income rank and expected occupational rank, except for the fact that $\hat{\beta}_{exp} = 0.15 > \hat{\beta}_{asp} = 0.14$. Our conjecture is that aspiration should have a more quixotic and idealistic nature as compared to expectation, meaning that when describing a job, people report what they truly desire - which, at least in theory, should be less affected by family well-being.

At each level of $R_{par} : \hat{R}_{asp} > \hat{R}_{inc}$ which coupled with slope estimates implies that while all individuals make mistakes, the ones coming from relatively more affluent families err to a lesser extent. This pattern, however, should not be take at face value. We explore this in a greater detail in subsection (II.C).

II.B.2 Other Components of Personal Endowment

Overview

Estimates of equation (5) obtained in Section III may be masking many potential mechanisms at play. While not being able to establish causal mechanism behind the relationship, we explore factors that can explain observed variation in job aspirations.

Our *family background* measures comprises race and self-assessed neighborhood quality Recent empirical studies suggest that rates of absolute upward mobility are lower for African Americans as compared to other races (Chetty et al. 2019). The gap persists intergenerationally - conditional on parental income, black boys reach worse outcomes in adulthood relative to their white peers. The phenomenon holds even for boys who grow up in the same neighborhood. Since information on home address ZIP codes is not available, we have to rely on self-reported evaluation of the neighborhood family resides in, which is clearly far from true quality, gauged by (potentially) observed characteristics of the neighborhood. Controlling on it is still essential, since kids in more affluent areas interact with other advantaged children, who in turn exert peer pressure. As argued in (Ray, 2016), peers may serve as role models and induce behavioral changes, since they alter aspirations and goals set by people around them.

We also control on *parental education* - namely, on whether child's primary caregiver (usually mother) has a college education (see Appendix B for details). Even though college education is correlated with income rank (on the core sample it is equal to), college-educated parents are, on average, more knowledgeable about labor markets and educational opportunities. The effect operates via multiple channels. First, insights from parents mitigate informational frictions adolescents face when they think about future career and make relevant choices (Zafar et al. 2020). Next, better educated parents have access to information that allows them to make more efficient investment. It has been shown (e.g. Doepke and Zilibotti, 2017) that if the return to skills is steep, then in countries with higher levels of income inequality rich parents mold educational choices of their children and skills the latter acquire.

Individual Perceptions: Self-Efficacy

We think that beliefs in one's own ability to complete tasks and reach goals should be affecting individual's aspirations when it comes to possible future achievements at a workplace. This perception a person holds regarding his or her power to affect positively situations is known in psychology literature as self-efficacy. It has been shown in number of studies (Seligman et al. 1984; Dweck et al. 1978; Guiso et al. 2016) that it might be handed down for generations. Transmission patterns differ because of dissimilarities of the present environment, historical events, socialization and education. We thus conjecture that self-efficacy should be affecting aspirations and aspirational gap. While not being able to test causally, we include it as a control in our main specification (5).

Following (Guiso et al. 2016) we construct self-efficacy scale using respondents' assessments of their personal control over aspects of their lives (see Appendix B for details). Table 1 shows summary statistics of the overall score.

II.B.3 Empirical Analysis

We first explore pairwise associations between aspirations (and expectations) and components of personal endowment:

$$R_{asp} = \alpha_{asp} + \beta_{asp} \cdot R_p + \gamma_{asp} \cdot X + \epsilon \tag{3}$$

$$R_{exp} = \alpha_{exp} + \beta_{exp} \cdot R_p + \gamma_{exp} \cdot X + \epsilon \tag{4}$$

where X is a single component of personal endowment $\mathbf{X}$ described below.

Estimation results are presented below in Table 2 for aspirations and in Table 3 for expectations. Even though components of personal endowment should not be interpreted as casual determinants of aspirations and expectations, a few factors described above are statically significant.

As expected, college education of mother is associated with a 6 pp increase in rank level of the job a child desires to have. Also, on average, an African American respondent aspires to a job that ranks 3.5 lower relative to her white or Asian peer. One should be cautious about the last statement since our sample is representative of the U.S. population by construction, and race is strongly correlated with relative position of the family in income distribution. While being positive, self-efficacy remains insignificant at any admissible level.

Table 2: Aspirations and Components of Personal Endowment (one by one)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	71.343***	65.451***	71.154***	69.806***	66.809***	63.271***
	(1.100)	(2.839)	(1.286)	(4.818)	(1.408)	(1.978)
Black	-3.521+					
	(1.948)					
Good Nhood		5.207+				
		(2.999)				
Mover			-2.252			
			(1.836)			
Self-Efficacy				0.046		
				(1.514)		
College Mom					6.013**	
					(1.842)	
Par.Inc Rank						0.134***
						(0.031)
Num.Obs.	670	670	670	670	670	670
R2	0.005	0.006	0.002	0.000	0.016	0.027

Core Sample; see variables description in Appendix B

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Expectations and Components of Personal Endowment (one by one)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	70.460***	62.944***	69.997***	66.875***	65.752***	61.329***
	(1.145)	(2.994)	(1.347)	(5.129)	(1.450)	(2.071)
Black	-3.825+					
	(2.031)					
Good Nhood		6.943*				
		(3.158)				
Mover			-1.971			
			(1.916)			
Self-Efficacy				0.659		
				(1.603)		
College Mom					6.141**	
					(1.918)	
Par.Inc Rank						0.152***
						(0.033)
Num.Obs.	665	665	665	665	665	665
R2	0.006	0.009	0.002	0.000	0.015	0.032

Core Sample; see variables description in Appendix B

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We then explore the relationship between aspirations (and expectations) and components of personal endowment, adding one at a time at each step k:

$$R_{asp} = \alpha_{asp} + \beta_{asp} \cdot R_p + X_k \cdot \gamma_{asp} + \epsilon \tag{5}$$

$$R_{exp} = \alpha_{exp} + \beta_{exp} \cdot R_p + X_k \cdot \gamma_{exp} + \epsilon \tag{6}$$

where X_k is a matrix with components at step k.

Estimation results are presented below in Table 4 for aspirations and in Table 5 for expectations. Controlling for components of personal endowment, we document a positive significant relationship between family income rank of parents and job ranking that child wants to have (Table 4) or expects to have (Table 5) upon reaching the age 30. The slope coefficient is stable across models: (residualized) relative position of total parental income is associated with higher occupational aspirations and expectations. As specification (5) from Table 4 suggests, ceteris paribus, a child coming from a household that ranks 1 pp higher in income distribution is eager to have a job whose average compensation ranks 0.1 pp higher.

Table 4: Aspirations and Personal Endowment

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Constant	62.886***	60.950***	61.750***	63.496***	64.196***
	(2.511)	(3.427)	(3.639)	(5.727)	(5.782)
Par.Inc Rank	0.138***	0.131***	0.129***	0.131***	0.106**
	(0.035)	(0.036)	(0.036)	(0.036)	(0.039)
Black	Yes	Yes	Yes	Yes	Yes
N-hood Quality		Yes	Yes	Yes	Yes
Mover			Yes	Yes	Yes
Self Efficacy				Yes	Yes
College (Mother)					Yes
Num.Obs.	670	670	670	670	670
R2	0.027	0.028	0.029	0.029	0.033

Core Sample; see variables description in Appendix B
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 5: Expectations and of Personal Endowment

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Constant	60.655***	57.693***	58.203***	58.382***	58.983***
	(2.631)	(3.566)	(3.751)	(5.881)	(5.936)
Par.Inc Rank	0.159***	0.149***	0.147***	0.147***	0.127**
	(0.037)	(0.038)	(0.038)	(0.038)	(0.042)
Black	Yes	Yes	Yes	Yes	Yes
N-hood Quality		Yes	Yes	Yes	Yes
Mover			Yes	Yes	Yes
Self Efficacy				Yes	Yes
College (Mother)					Yes
Num.Obs.	665	665	665	665	665
R2	0.032	0.035	0.035	0.035	0.038

Core Sample; see variables description in Appendix B
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

II.C Expectational Errors

To this end, our empirical analysis suggests that there is a positive association between parent income ranks and child income ranks; the former is also positively related to offsprings' expectations about their future careers in the medium-term horizon. In this section we examine whether children from more affluent families make more accurate predictions about their future careers.

Specifically, we test for a link between parental income and expectational error, defined as a difference between expected labor income earnings and realized ones. We adopt the following definition:

Definition 1: Expectational Error in Ranks

$$\Delta(x, t, G) := \mathbf{R}\left(x_{30}\right) - \mathbf{R}\left(\mathbb{E}_G\left[x_{30} \,|\, \mathfrak{F}_t\right]\right)$$

where R is the rank assigned to earnings x, G is a (conditional) probability measure, and t is time period associated with information set $\mathfrak{F}_t$.

Following a logic similar to (Ray, 2016), we introduce a concept of *aspirational gap*, which gauges discrepancy between aspiration and expectations (both in ranks):

Definition 2: Aspirational Gap

$$Gap\,(x, t, G) := \mathbf{R}_{asp}\,(x_{30},\, t) - \mathbf{R}\,(\mathbb{E}_G\,[x_{30}\,|\,\mathfrak{F}_t])$$

In our sample $t = 2009$. Under the assumptions 1 - 2 of Section 3, at the occupational level, the expectation of self-earnings is equal to the expectation of true empirical distribution of earnings. Our empirical strategy may be described parsimoniously via following equation:

$$\Delta(x,\, 2009) = const + \theta \cdot R_p + \eta \cdot Gap\,(x,\, 2009) + u \tag{7}$$

We estimate equation (10) using labor income averaged over two years (see Appendix B) for earnings measure x. Estimation results are presented in Table 6:

Table 6: Expectational Errors and Parental Income, Full Sample

	Exp. Error, Ranks
Constant	-30.531***
	(4.210)
Par, Income, Rk	0.194**
	(0.064)
Aspirational Gap, Rk	0.801***
	(0.212)
Num.Obs.	640
R2	0.060

Conditional on zero aspirational gap (that is observed for 91% of sample), our analysis suggests that children whose parents rank higher are less accurate: ceteris paribus, an $1\,pp$ increase in family income rank is associated with a $0.152\,pp$ increase in the magnitude of error.

Note that we do not interpret the constant since our dependent variable - *expectational error* - incorporates adult family income rank. Assignment of latter implies that there is essentially one «degree of freedom» in income rank - income rank regressions (see Section 3), so intercept is known conditional on slope estimate.

Estimation results indicate that aspiratinal gap is negatively linked with accuracy of expectations: a unit increase in the former is associated with errors that are on average larger by $0.8\,pp$. Using the argot of (Ray, 2016), we conjecture this is in line with «pushing to one's limit» story, when positive aspirational gap triggers realization of better outcomes as compared to initial beliefs. One would require panel with higher frequency of observations to delve into learning and updating patterns.

We then estimate equation (9) on subsamples within the core sample:

$$\Delta(x,\, 2009) = const + \theta \cdot R_p + u \tag{8}$$

By construction, mean rank in subsample does need to be equal to 0.5; this enables us to draw conclusions from both estimates of the linear equation (9). Results are presented in Table 7.

Table 7: Expectational Errors and Parental Income (Labor Income Ranks)

	Males Only	Females Only	Black
Constant	-16.840***	-39.228***	-33.439***
	(3.788)	(5.080)	(5.042)
Par. Income,	0.083	0.268***	0.118
Ranks	(0.093)	(0.077)	(0.126)
Num.Obs.	insert	insert	insert
R2	0.005	0.05	0.005

From, our analysis suggests that females from the lower tail of parental income distribution err the most.

III Robustness Checks

In this section, we relax assumptions (1-2) stated in Section II . These assumptions validate our main rank imputation procedure, when we quantify aspirations and expectations by assigning a percentile rank to average remuneration a job has in the U.S.

Using earnings estimates within an occupation at the national level may overstate expected labor earnings, and can thus introduce a bias in estimates. If a person faces a steep earnings profile, then job performed at the age of 30 might be lying at the beginning of career ladder (e.g. assistant position as a part of long-term career in investment banking). If the occupation is furthermore coded as «financial executive», then it will be overstating labor earnings from IB work, since the national average would be capturing more senior positions, given the typical contractual structure in IB.

We therefore alter the ranking imputation procedure we adhered to throughout the paper. Specifically, using the CPS, we calculate mean earnings (hourly wages) occupation pays within an age group. We still average labor income over a period when respondents are 30 to 33 years old.

Table 8: Aspirations and Personal Endowment, Both Ranking Procedures

	(1)	**(1')**	**(2)**	**(2')**	**(3)**	**(3')**	**(4)**	**(4')**	**(5)**	**(5')**
Constant	62.886***	58.025***	60.944***	55.902***	61.740***	57.707***	63.515***	53.173***	64.193***	53.009***
	(2.491)	(3.056)	(3.417)	(4.047)	(3.628)	(4.278)	(5.722)	(6.776)	(5.775)	(6.842)
Par.Inc Rk	0.140***	0.129**	0.133***	0.122**	0.131***	0.117**	0.133***	0.114**	0.108**	0.119*
	(0.035)	(0.042)	(0.036)	(0.043)	(0.036)	(0.043)	(0.036)	(0.044)	(0.039)	(0.048)
Num.Obs.	586	586	586	586	586	586	586	586	586	586
R2	0.027	0.020	0.029	0.021	0.029	0.024	0.030	0.025	0.034	0.026

Core Sample. Specifications marked with a prime use age-specific ranks computed on CPS data. See Appendices B-D.
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 9: Expectations and Personal Endowment, Both Ranking Procedures

	(1)	(1')	(2)	(2')	(3)	(3')	(4)	(4')	(5)	(5')
Constant	61.635***	56.038***	58.964***	52.677***	59.500***	54.432***	59.200***	48.650***	59.602***	48.421***
	(2.906)	(3.193)	(3.851)	(4.161)	(4.057)	(4.411)	(6.497)	(6.928)	(6.531)	(6.992)
Par.Inc Rk	0.166***	0.149***	0.158***	0.137**	0.157***	0.132**	0.156***	0.128**	0.137**	0.136**
	(0.040)	(0.044)	(0.041)	(0.045)	(0.041)	(0.045)	(0.041)	(0.046)	(0.045)	(0.050)
Num.Obs.	584	584	584	584	584	584	584	584	584	584
R2	0.034	0.025	0.036	0.028	0.036	0.031	0.036	0.033	0.039	0.033

Core Sample. Specifications marked with a prime use age-specific ranks computed on CPS data. See Appendices B-D.
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Both Table 8 and Table 9 suggest that across all specifications using age-specific ranks slightly reduces the intercept estimate which, nonetheless, is still of the same order of magnitude. The slople estimate in our main specifications (5) - where all components of personal endowment are included in the estimated specification - are almost identical.

IV Conclusion

This paper investigates whether parental economic well-being is associated with bolder aspirations about future careers and higher expectations in labor earnings. Parental wealth is widely known to be positively related to future outcomes of kids; this persistence in outcomes might be masking many mechanisms at play, from biological (genetic constraints to abilities to acquire skills) to environmental (wealthier parents choose better places to live and select peers for their off-springs). Our study looks at a particular aspect - career aspirations and beliefs of adolescents about their professional self-realization in future.

We leverage data on young individuals from the U.S. born in 1986-1991 who have not yet formed a separate household by 2009. We conclude that more advantaged parental background is associated with aspirations to have a job that pays more. We further control on various components of child's personal endowment like parental education, family perceptions and self-efficacy, and find that parental income ranks is still a significant and positive predictor of teenager's self-earnings beliefs and aspirations. In a multivariable regression, the five key factors described above generally remain statistically significant predictors of career aspirations. However, we emphasize that these factors should not be interpreted as causal determinants because all of these variables are endogenously determined and our analysis does not control for numerous other unobservables.

Appendix A: Data

In this part of the appendix, we describe the data sources in greater detail and discuss caveats we faced when constructing the core sample. We briefly outline key definitions variables of empirical analysis presented in the main part.

PSID Family File

Panel Study for Income Dynamics (PSID henceforth) and its supplements are freely available data provided by ISR. The 1968 sample described in the main part is being constantly replenished: since as members of 1968 families grow up and move out, they form their own independent households and are hence interviewed separately.

In 1997, the main PSID sample was updated to reflect changes in the population. A representative sample of recent immigrants who migrated to the USA after the original PSID sample selection in 1968 and who were not married to persons legally residing in the USA in 1968.

Before 2017, one member of a family unit would receive "head" status; the definition was changed in 2017 when the concept of "reference person" was introduced. Therefore, a family-level interview collects information on the head/reference person and separately on spouse/reference person.

Children Development Supplement

Children Development Supplement (CDS) is an extensive study on children from PSID families that began in 1997. It spans topics related to social, psychological, and economic aspects of childhood - psychological and social wellbeing, health status, health-related behaviors, family environment, schooling, sibling relationships, caregiver social and psychological resources. Families in the CDS study either descended from 1967 sample or are coming directly from the immigrant refresher sample of 1997. Each interview is conducted on primary caregiver level (usually mother) and then separately with a child.

Most importantly, CDS contains information on the family background of young individuals, including parental education and family structure. It also covers rearing values and cultural norms on the family level (e.g., gender equality, acceptance of patriarchy in decision-making). Unlike the main PSID database which does not provide any information on the geospatial aspects of the data, CDS does report information about neighborhood quality and family perceptions of the area they reside in.

Data used in this project comes from the first two waves of CDS – namely, CDS-I (1997) and CDS-II (2002). The 1997 study collected data from 2,394 PSID families with 3,586 children aged twelve and under. In 2002, CDS reinterviewed families from the 1997 study who remained active in the PSID panel as of 2001. That resulted into 2019 family interviews (92% of 1997 sample) who provided data on 2907 children and adolescents.

Transition into Adulthood Supplement

Transition into Adulthood Supplement (TAS henceforth) is our main source of data on young individuals who have already finished high school. It is an extension of CDS study that bridges the gap between CDS database and PSID study. Since the former garners information on the years between birth and 18 years, and the latter covers the years after the economic independence is established, TAS survey features young individuals aged 18 to 28 years old.

My main TAS sample of young individuals is a sub-sample of TAS-09 sample (N=1599), which in turn is a part of longitudinal study of young individuals (2005-2017).

To be eligible for TAS-09 sample, an individual:

- Should be 18 years or older in 2009;
- Should no longer be attending high school;
- Should have participated in CDS baseline interviews of 1997 and 2002;
- Their family should have participated in the main PSID study of 2009 wave.

Family Relationship Supplement of PSID

Family Relationship Matrix is another PSID supplement that synthesizes the relationship data between individuals within a Family Unit for a given year, and across years. It enables us to identify legal parents of young individuals in both PSID and CDS data. PSID study collects information on both the legal parent – whoever was claiming the child as a dependent in the year of interview – and biological parents, who might differ from the legal ones. This matching procedure allows to construct parental level variables for the relevant family of a young individual in the core sample.

PSID Individual File Data

PSID is a family study and hence does not allow to identify individuals within PSID family units and retrieve relevant data for them. Individual data is coming from a cross-year individual database which contains one record for each individual present in an interviewed family in any survey year. The PSID unique identifier allows to link individual observations across years. It also enables us to match individuals with their families which in turns makes it possible to link family-level files relating to different periods of time, including the ones that span childhood and early adolescence years of young individuals from TAS sample (see below).

BLS data on wages and salaries

Data on mean and median wages and salaries originate from the Occupational Employment and Wage Statistics program (OEWS) run by the U.S. Bureau of Labor Statistics.

It is based on a semiannual survey and provides estimates of earning in specific occupations and industries on a national level. Note that data from self-employed persons are not collected and are not included in the estimates. Employment and wage statistics are available for around 800 occupations with the occupational classification based on Standard Occupational Classification system (SOC henceforth).

The occupational classification systems used by BLS in OEWS data varied from year to year since SOC itself underwent major revisions in 2000, 2002, 2010 and eventually in 2018. While first two editions differed in number of digits a particular occupation code has, the 2010 revision altered the entire occupational structure by including new occupational areas and modifying the existing once.

To circumvent the issue of varying classification systems, we use a crosswalk between 2000 and 2010 SOC systems which is provided directly by BLS. This crosswalk from the 2000 system to the 2010 SOC matches every detailed occupation from the 2000 SOC with the corresponding new 2010 SOC code(s) and title. This matching is not bijective since an occupation from 2000 system may have multiple matches in the 2010 counterpart. Detailed delineation of the issue is provided in the "Sample Construction" subsection of this section.

Current Population Survey

We also used the Current Population Survey (CPS) data to construct estimates of hourly wages in specific occupation across different age groups. CPS is a monthly household survey continuously run by BLS. Around 60000 households are queried every month, and weight samples are supplied to make the sample representative of the U.S. population aged 16 and older. Age-level estimates that we provide are based upon Information from a separate Merged Outgoing Rotation Groups (MORG) file. which spans labor-related domains like detailed occupation and industry codes of the job, typical hours worked, weekly and hourly earnings

MORG data is available for each year of our sample time span from 2009 to 2019.

GDP Deflator

To measure everything in 2017 dollars, we used the annual consumer price index (CPI, non-adjusted for seasonality) provided by the Federal Reserve Bank of St. Louis.

Appendix B: Variable Definitions

This section outlines the key variables used in our empirical analysis.

Demographics

Race: for waves prior to 2015, the main PSID study keeps track of a coarsely defined racial group an individual identifies herself with (White, African/African American, Asian, Native American or of Alaskan Origin, Pacific Islander). The study also specifies whether an individual belongs to a group of Hispanic/Spanish descent and if she does, which ethnicity the origin is associated with (Cuban, Mexican, Spanish, Chicano, Puerto Rican or other).

Age: information on age comes from two sources – PSID individual data and TAS. The former contains the date of birth which we use to calculate the age of an individual. The latter reports a respondent's age in full years as of the date of the interview. We relate to this measure as imputed age, and it may naturally differ from the actual one by one year.

Date of birth is missing for 1% of individuals in the core sample. For them, imputed age is used in the analysis instead of the actual one.

Family Background

Parental college education: using data on actual years of education from the TAS database, we construct a group of indicator variables reflecting whether primary caregiver (mother in most cases) received a college education (any completed education beyond high school, a community college degree).

Neighborhood Quality: this variable gauges the extent to which parents agree with the following question "The neighborhood is a good place to raise children". We are unable to identify the zip code of the neighborhood due to privacy restrictions of the PSID study. We recode this categorical variable as an indicator that represents parental perception of the area.

Change of Neighborhood: using CDS data on children upbringing, we construct an indicator variable for parents who moved to a different area specifically to ameliorate living conditions and prospects for kids.

Parental Income: I follow (Solon, 2009) and (Chetty,2014) and define total family income as the total pre-tax income at the family level. It is a sum of seven components: 1) taxable income of head and wife, which itself is comprised of labor, business and capital income; 2) head and wife transfer income; 3) taxable income of other family unit members (OFUMs henceforth); 4) transfer income of OFUMS; 5) social security income of head (including unemployment and disability benefits); 6) social security income of wife; 7) social security of OFUMS

Negative values indicate a net loss which typically occur because of business or farm losses. PSID estimates are constructed via tax returns submitted in the preceding year by the head of the family unit. Therefore, if parents have no tax return and no information returns, family income is coded as zero.

Average family income: simple average of family incomes over four years from 2006 to 2009. It is a proxy for lifetime income that should reflect the economic resources of parents while their kids are growing up.

Adult family income: variable is constructed analogously to that of parents. Individual's adult family income is measured in last years available in the main dataset – 2017 to 2019 provided that she is not a member of the parental household anymore.

Average adult family income: accordingly, is a simple average of adult family income over two years – 2018 and 2019.

Labor Market Perceptions

Most desired job: in each wave of TAS, a teenager is asked to describe a job that she would like to have the most when she reaches the age of thirty. She is asked to provide a detailed account of responsibilities that job would entail. The description is then linked to the occupation that matches the interview answer most closely. The 2009 study uses three-digit 2000 Census Occupational Classification.

Expected job by the age of 30: same as most desired job. The interview asserts that individual distinguishes between expectation and preferred job.

Labor market Outcomes

Main Occupation: relates to the main job for the employed and the most recent main job for the unemployed actively seeking for job. A code for the occupation is assigned by an interviewer upon obtaining a description of main tasks and responsibilities the job entails. In case of multiple jobs, the one with the highest remuneration is classified as "main". For waves prior to 2017, 2000 Census Occupational Classification System is used; 2017 and 2019 waves utilize 2010 Census Occupational Classification System (see later).

Adult Labor Income: estimate of remuneration received at the main job, self-employment and part-time work at the age of 29 to 32. Includes income from bonuses, overtime, tips and commissions. This variable utilizes the Family File: labor income data was first retrieved for heads/references persons and then for the wives/spouses (including partners cohabitating for a period over 12 months).

Adult Average Labor Income: we average labor income over two consecutive years. Earnings from labor activity in year immediately preceding the year of the interview is obtained analogously to the current labor income with the use of the Family File.

Hourly Wage: hourly wages are measured in the CPS MORG data which reports weekly earnings and numbers of hours worked per typical week. We divide reported weekly remuneration by weekly hours. The hourly wage is coded as missing for those with zero hours worked.

Appendix C: Estimates of Wages and Salaries

This subsection outlines our methodology for computing mean wages and salaries across occupations in each year of the sample. We first delineate our procedure for obtaining estimates at the U.S. level irrespective of grouping on age.

Occupational classification systems employed in our dataset differ both intertemporally for a given database type and across databases. While the BLS data on average remuneration is based on the Standard Occupational Classification (SOC), it uses the older SOC – 2000 system for years prior to 2011. The PSID always uses the Census system, but last two waves switched to the 2010 version of the Census classification of occupations (namely, 2017 and 2019 waves, which we use to retrieve data on labor market outcomes).

To obtain estimates at the national level:

- We use the SOC crosswalk to link SOC-2010 codes to SOC-2000 codes in the BLS data. Mapping between these two classification systems is not bijective, meaning that a SOC-2010 code may correspond to multiple SOC-2000 codes, and vice versa. For cases when a SOC-2000 code is mapped to two or more SOC-2010 codes, we add both to the dataset.
- For each occupation defined by a SOC-2000 code we compute a simple average across wages/salaries across SOC-2010 codes:
- We match each occupation defined by a SOC - 2000 code with a Census – 2000 code of that occupation. This is implemented with the use of a crosswalk from SOC-2000 to Census-2000 which is provided directly by the BLS.
- Each occupation defined by a Census-2000 is assigned a percentile rank which is computed across all occupations on a country level.
- To this end, we can link each expected and mostly desired occupation to its percentile rank, and to the mean remuneration that occupation is associated with in the U.S.
- Using a crosswalk between the Census – 2010 and SOC-2010 systems, we map actual jobs to their mean wages and salaries and assign percentile ranks for each of the Census-2010 jobs.

To produce estimates on national level within age groups, we:

1. Define “age group – occupation” cells using Census-2010 occupations and thresholds for age groups as defined above
2. With the use of CPS MORG sample weights, we estimate mean earnings in each cell defined above

Appendix D: Other Tables

Intergenerational Income Elasticity

Another commonly computed measure of relative mobility is the elasticity of child (family) income with respect to parent (family) income, typically known as intergenerational income elasticity (IGE):

$$IGE = \frac{d\,\mathbb{E}[log(Y_i) \mid X_i = x]}{d\,log(x)} \tag{9}$$

Under the log-normality it follows that:

$$IGE = corr\,[log(Y_i), log(X_i)] \cdot \frac{SD\,[log(Y_i)]}{SD\,[log(X_i)} \tag{10}$$

The expression demonstrates that the magnitude of IGE is directly affected by both the structure of dependence between outcomes (intergenerational mobility component) and marginal distributions (income inequality in the generation).

Estimation results are presented in Table 10:

Table 10: Intergenerational Elasticity, Core Sample

	Parent Family Income, Log
Constant	7.219***
	(0.454)
Parent F. Income, Log	0.322***
	(0.040)
Num.Obs.	435
R2	0.120

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