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Parental Education and Skill Indicators of Children: An Intergenerational Mobility Study

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PARENTAL EDUCATION AND SKILL INDICATORS OF CHILDREN: AN INTERGENERATIONAL MOBILITY STUDY

SARA OLOOMI

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1 Executive Summary

This study aims to explore the extent of intergenerational social mobility in the United States for the population as a whole, as well as differentiated by gender and race/ethnicity. Study of intergenerational social mobility is important because it shows whether individuals can prosper in a society regardless of their socioeconomic background, as long as they work hard. There are two types of intergenerational mobility: (1) absolute mobility and (2) relative mobility. Absolute mobility refers to the extent to which people do better than their parents, whereas relative mobility studies the extent to which an individual's chances depend on his/her parents' status, such as education and income (Chetty et al., 2014; Miller, 1960). In a society with low relative mobility, children from low socioeconomic status tend to stay in the cycle of disadvantage and fall considerably behind in learning outcomes (OECD, 2010).

Three main indicators of socioeconomic status are parental income, parental education, and parental occupation (Gottfried, 1985; Hauser, 1994; Mueller & Parcel, 1981). The Program for the International Assessment of Adult Competencies (PIAAC) dataset provides information regarding parental education. Therefore, this study uses parental education as a proxy for socioeconomic background. This study examines the correlation between parental education and a variety of outcomes of their children, including highest level of education, cognitive skills (literacy, numeracy, and problem-solving scores), employment status, occupation skill classification, and earnings, as well as likelihood of having a STEM-related area of study in the highest education level achieved.

More specifically, the following research questions are studied in this research:

1. The extent of the association between parental education and outcomes of children (intergenerational mobility) in the United States:

   1.1. What are the ranges of absolute upward mobility in the United States using summary statistics?

1.2. What is the extent of relative mobility in education, employment status, occupational skill classification, earnings, and cognitive skills (literacy, numeracy, and problem-solving scores) in the United States using summary statistics and inferential statistics?[1]

1.3. Does relative mobility mentioned in research question 1.2 vary across different segments of the population in the United States, including racial/ethnic and gender groups?

2. Relationship between parental education and propensity to study in the Science, Technology, Engineering, and Mathematics (STEM) fields:

   2.1. Is parental education associated with the propensity to study in the Science, Technology, Engineering, and Mathematics (STEM) fields?

   2.2. To what extent is parental education associated with the gender gap in studying in the STEM fields?

   2.3. Does the association between parental education and propensity to study in STEM fields vary by race/ethnicity?

   2.4. Does the relationship between parental education and the gender gap in the propensity to study in the STEM fields vary across different racial/ethnic groups?[2]

[1] Absolute upward mobility estimates the percentage of children that have higher rank outcomes than their parents. However, relative mobility compares the probability of attaining different levels of outcome variables for children with different parental education. Summary statistics are used in the investigation of the absolute mobility. Relative mobility is investigated using both inferential (regression analysis) and summary statistics.

[2] Due to the limited number of observations, gender gap analysis is solely performed for Whites.

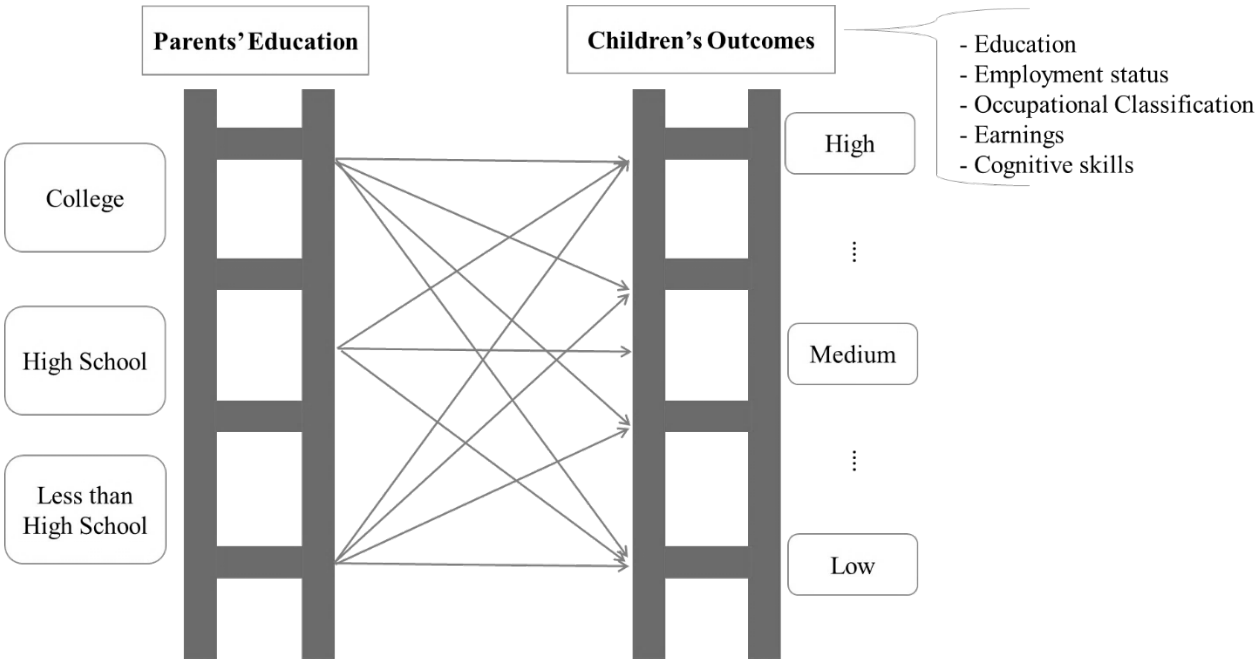


Figure 1: Ladder for intergenerational mobility analysis in this study

Intergenerational mobility refers to the changes in social status between generations (parents and children). This study examines intergenerational mobility through the investigation of the association between parental education and likelihood of children acquiring different levels of education as well as other outcome variables, including employment status, earnings, occupational skill classification, cognitive skills, and STEM-Study.

In a society with low relative mobility, it is expected to see a high association between parental education and outcomes of the children. In other words, in an immobile society, an individual's wages, education, and occupation tend to be strongly related to those of his/her parents. Reducing the impact of family background on individuals' life chances is a major challenge and helps break the cycle of transition of disadvantages (or advantages) from one generation to the next (OECD, 2010). Effective educational and redistributive policies are among the main contributing factors that increase relative mobility and reduce the importance of the family background as the main determinant of children's achievements (Hilger, 2016). In the case of high relative mobility, it is expected to see a low association between parental education and outcomes of the children.

Using parental education as a proxy for socioeconomic background, this study finds that parents' socioeconomic status is able to predict educational and economic outcomes of their children. Children with highly-educated parents are more likely to have higher cognitive skills, achieve college degrees, be employed, engage in skilled occupations, and receive higher quartiles of earnings than children with less parental education. Females in families with college-educated parents are more likely to achieve a college degree compared to males. Results also show that parental education is not a significant explanatory factor affecting propensity to study STEM. Results also indicate that at different levels of parental education (less than high school, high school, and college), males are more likely than females to study STEM. Findings indicate that as parental education increases (from high school to college) the odds of studying STEM are not significantly different for females compared to males. In other words, an increase in parental education is not a significant factor in reducing the gender gap in STEM. There are gender gaps in skilled occupations, earnings, and employment status; however, the gender gaps in earnings and skilled occupations tend to decrease among children with higher parental education.

The existence of high association between parental education and outcomes of their children calls for two types of policies. First, policies that promote better education for parents, which will help parents to improve their welfare and the outcomes of their children. Second, policies that help parents to overcome their inadequate parental education or financial ability. Redistributive policies and early life interventions are examples of such policies. More explanations are provided in the following paragraphs.

Policies promoting better education: Not only will such policies improve the welfare of the parents, but they will also improve a variety of outcomes for the next generation. Results of this study show that children with higher parental education tend to have higher cognitive skills, and better education and labor market outcomes. Furthermore, the gender gaps in earnings and skilled occupations are reduced among children with college-educated parents.

Policies reducing the impact of low socioeconomic background on individual's life chances: Redistributive policies with the purpose of shaping equal opportunities for all children help talented and hardworking children to climb up the ladder of success, regardless of their socioeconomic backgrounds (Corack, 2013). Furthermore, policies promoting early life interventions to improve health and educational opportunities of children help to overcome inadequate parenting skills or/and financial abilities. Literature shows that early life qualities (e.g., education and health) are important predictors of outcomes during childhood and adulthood (e.g., Black et al., 2007; Figlio et al., 2014). Therefore, such policies help to break the cycle of transition of disadvantages from one generation to another. In addition, policies ensuring high standards in learning, classroom size, and student-teacher ratio across all classrooms, regardless of neighborhoods, help to reduce the racial gap in education (Chetty et al. 2018).

Literature Review

Intergenerational social mobility refers to the relationship between the socioeconomic status of parents and the status their children will attain as adults, and it can be measured in terms of education, occupational status, and earnings (OECD 2010). In an immobile society, an individual's wages, education, and occupation tend to be strongly related to those of his/her parents. For example, children with highly-educated parents are more likely to achieve college degrees and receive higher earnings than children with less parental education. Effective educational and redistributive policies reduce the importance of the family background as the main determinant of children's achievements and help break the cycle of transition of disadvantages (or advantages) from one generation to the next (Hilger, 2016; OECD, 2010).[3] The following paragraphs review current literature on intergenerational mobility.

The literature on intergenerational mobility trends based on income distribution provides mixed results for the United States. Some studies find declining trend (Aaronson & Mazumder, 2008; Putnam, Frederick, & Snellman, 2012) and some find no trend (Hertz, 2007; Lee & Solon, 2009; Hauser, 2010). Trend analysis refers to the investigation of intergeneration mobility through time. Declining trend means that intergenerational mobility has decreased through time and no trend means that the direction of the trend is not significant. Hilger (2016) finds that intergenerational mobility in terms of education increased dramatically after WWII from 1940 to 1980, before stabilizing in the 1960-1980 period in the United States. He shows that the increase in intergenerational mobility is due to policy reforms in education and the subsequent increase in high school enrollments. This trend is mainly documented for minorities such as Black adults, and is much larger in the South.

Chetty et al. (2016) provide evidence that there are geographical disparities in opportunities in the United States. They study more than seven million families who move across commuting zones and counties in the United States and find that the neighborhoods in which children grow up shape their earnings, college

[3] The Executive Summary section and the Summary and Policy Recommendations section review recommended policies.

attendance rates, fertility, and marriage patterns. They conclude that neighborhoods affect intergenerational mobility primarily through childhood exposure. They controlled for parents' marital status, parents' age at child birth, gender, region fixed effect, fraction of females with teen births, number of children, and whether children attain college degrees. [4] In another study, Chetty et al. (2018) study the intergenerational persistence of disparities across racial groups. They find that Hispanic Americans have high rates of intergenerational income mobility and therefore are moving up significantly in the income distribution across generations. In contrast, Black Americans have large income disparities that persist across generations, which is substantially due to lower rates of upward mobility than Whites. They also find that the Black-White income gap is relatively smaller in low-poverty neighborhoods. In their study, they control for different family-level factors such as parental marital status, parental education, and wealth. In order to isolate the impact of parental education on the outcomes of their children, this study also controls for region fixed effects, race, gender, and children's education (for outcome variables of occupational skill classification, earnings, and cognitive skills).

Svoboda et al. (2016) find that low SES students are less likely to take STEM courses in high school and college. They use years of parental education as a proxy for SES and find that this relationship is partially mediated through motivational beliefs of parents and students concerning mathematics and science. Maker and Kim (2014), using national freshman survey data, examine the predictor variables of STEM major choice. They find that students are more likely to choose STEM majors if they have strong confidence in mathematics and had parents with STEM occupations. Houtenville and Conway (2008), using data from the National Education Longitudinal Study (NELS), find that parental effort has a strong positive effect on students' achievement relative to the effect of school resources. Parental effort is measured by the degree to which parents attend school meetings, discuss activities, and study with their children and is not captured by family background variables including parental education and earnings.

[4] Based on the findings of Chetty et al. (2016), in the model proposed in this study, we include regional fixed effects to partly control for the geographic dispersion of the respondents.

Parental background is also a driving force of social status in OECD countries. Intergenerational persistence of earnings is 38% in OECD countries, which means that if one father has twice the earnings of another father, then the son of the former will on average earn 38% more than the son of the latter (OECD, 2017). A cross-national comparison shows more upward mobility in Denmark, Norway, Sweden, and the United States in comparison to other countries, due to the high attainment of college education in previous generations (OECD, 2016).[5] Children of parents with a college degree are more likely to achieve a higher level of education and to receive income in the highest quintile (monthly earnings) compared to children whose parents achieved a high school diploma or some college with no degree, in a cross-country analysis (OECD, 2015 & 2016). These studies have used individual control variables, including urbanization of the area of residence, marital status, and migration background. Sherman and Meakin (2015), using the PIAAC OECD countries dataset, find that children of parents with a higher level of education on average have higher literacy scores. Main control variables in their study are age, gender, and country controls.

Hout (1988) finds that the influence of social origins on children's occupational classification is strong among those with lower levels of schooling. However, this effect fully disappeared among college graduates. In other words, having a college degree erases the advantages of social origin in the competition for economic success. Using the PIAAC dataset, Ford and Umbricht (2016) show that first-generation college graduates have lower numeracy skills but the same labor market outcomes compared to second-generation college graduates. They controlled for background variables, including race/ethnicity (Asian, Black, Hispanic, and White), age (25-29, 30-34, 35-39, 40-44, 45-49, 50-54), gender, and immigration status. Following the studies of Sherman and Meakin (2015) and Ford and Umbricht (2016), this study also controls for race, age, and gender of the respondents in the examination of the effect of parental education on educational and labor market outcomes of their children.

[5] Causa et al. (2009), in an analysis for European OECD countries, find high intergenerational wage persistence in southern European countries and in the United Kingdom, and high intergenerational persistence in education in southern European countries, Luxembourg, and Ireland. However, Nordic countries show lower persistence in both wage and education.

This study contributes to the literature by providing a comprehensive analysis of intergenerational mobility in terms of cognitive skills, education, employment, earnings, and occupation skill classification using the PIAAC dataset. The link between parental education and the propensity to study in STEM fields and its relative gender gap is also investigated in this study.

2 Approach

2.1 Data

This study uses the U.S. PIAAC 2012/2014 Public Use Data Files dataset. This dataset provides survey data from a representative sample of adults (8,670 individuals) and their basic skills and competencies. The PIAAC measures of adult cognitive skills (literacy, numeracy, and problem-solving scores), education, occupation, and earnings combined with a variety of measures of demographic characteristics, as well as educational attainment of parents, offer a unique opportunity to explore our research questions. Table 1 presents a list of variables of interest from the PIAAC dataset that are used in this study:

Table 1: List of Variables

Category of variables	Variables	Original PIAAC variable	Note
A. Outcome variables			
Cognitive skill	Numeracy	pvnum1 - pvnum10	Continuous variables.
	Literacy	pvlit1-pvlit10	Continuous variables.
	Problem solving	pvpsl1-pvosl10	Continuous variables.
	Education	b_q01aus_c	Categorical variable; gets values of 1, 2, & 3 for less than high school, high school plus some college, and college degree or higher, respectively.[6]
Occupation	Employment	C_D05	Categorical variable; gets values of 1, 2, & 3 for employed*, unemployed, & out of the labor force, respectively.
	Earnings	earnmthpppus_c	Derived categorical (quartile) variable getting values of 1, 2, 3, and 4 for first (lowest), second, third, and forth (highest) quartiles, respectively.
	Occupation-skill	iscoskil4	Categorical variable; gets values of 1, 2, 3, & 4 for skilled, semi-skilled-white collar, semi-skilled-blue collar, and elementary occupations, respectively.
STEM	STEM-Study	uscip_h_c	Derived dummy variable getting values of 0 & 1 for non-STEM and STEM field of study, respectively.

[6] Reference group is identified with *. Reference groups are selected in the way that makes the interpretation of the results more informative. Usually the normative category will be used as the reference group. For example, White category will be used as the reference group because it is helpful to investigate the intergenerational mobility for Black, Hispanic, and Other races in comparison to White. Education, Earnings, and Occupational Skills are analyzed with ordinal logistic regressions; therefore, reference groups are not selected, since comparisons are made for each adjacent pair of outcomes. More explanations are included in the methodology section.

Explanatory variable			
Parental Education	Highest education of Parents	pared	Categorical variable; highest level of mother's or father's education and gets values of 1, 2, & 3 if highest parental education is less than high school diploma, high school diploma/some college but no degree*, & college degree or higher, respectively.
Control Variables			
Control Variables	Age	ageg5lfsext	Categorical variable for 5 years age band. Age 20-24 is used as the reference category.
	Gender	gender_r	Dummy variable; gets values of 0 & 1 for male* & female, respectively.
	English-language	language	Categorical variable; gets values of 1, 2, & 3 for English as the first language*, learned at age 15 or younger, & learned at age 16 or older, respectively.
	Region	region_us	Categorical variable; gets values of 1, 2, 3, & 4 for Northeast*, Midwest, South, and West, respectively.
	Race	racethn_5cat	Derived categorical variable getting values of 1, 2, 3, & 4 for Hispanic, White*, Black, and Other races, respectively.
	Urbanicity	urban_4cat	Categorical variable; gets values of 1, 2, 3, & 4 for City*, Suburban, Town, and Rural areas, respectively.

Note: * refers to the reference group

STEM-Study is generated from the PIAAC variable "uscip_h_c" and takes a value of one if the discipline of study is STEM related (Science, Technology, Engineering, and Mathematics). The PIAAC dataset provides detailed information on area of study for the highest education level attained (for those with more than high school education), using four-digit 2010 Classification of Instructional Programs (CIP) codes from the National Center for Education Statistics (NCES). The Department of Homeland Security (DHS) provides the CIP codes for the STEM designated degree programs. Using the CIP codes in the PIAAC dataset and matching with the CIP codes of STEM designated programs from DHS, I derived a dummy variable "STEM-Study," which takes a value of one if the area of study of the highest level of education attained is STEM and zero otherwise. The list of STEM designated programs is exhaustive (please refer to DHS STEM Designated Degree Program). However, Table 2 provides a sample of STEM programs used in the construction of STEM-Study.

Table 2: List of fields in STEM-Study extracted from PIAAC variables

STEM	Majors/ fields
Study	**Computer and information sciences:** Computer and Information Sciences; Computer Programming/Programmer, General; Computer Programming, Data Processing and Data Processing Technology/Technician; Information Science/Studies; Computer Systems Analysis/Analyst; Computer Science; Web Page, Digital/Multimedia and Information Resources Design; Computer Graphics; Computer Systems Networking and Telecommunications, etc.
	Engineering and engineering technologies: Engineering, General; Aerospace, Aeronautical and Astronautical Engineering; Agricultural/Biological Engineering and Bioengineering; Architectural Engineering; Biomedical/Medical Engineering; Ceramic Sciences and Engineering; Chemical Engineering; Civil Engineering, General; Computer Engineering; Electrical, Electronics and Communications Engineering; Engineering Mechanics; Engineering Physics, etc.
	Biological and biomedical sciences: Biology/Biological Sciences, General; Biochemistry; Botany/Plant Biology; Cell/Cellular Biology and Histology; Microbiology, General; Zoology/Animal Biology; Genetics; Physiology; Pharmacology; Biometry/Biometrics; Ecology, etc.
	Mathematics and statistics: Mathematics; Applied Mathematics; Statistic; Mathematical Statistics and Probability; Actuarial Science; Algebra and Number Theory; Analysis and Functional Analysis; etc.
	Physical sciences: Physical Sciences; Astronomy; Atmospheric Sciences and Meteorology; Chemistry; Geology/Earth Science; Physics, General, etc.
	Sciences technologies: Military Technologies; Industrial Radiologic Technology/Technician; Chemical Technology/Technician; Medical Scientist (MS, PhD), etc.

Source: PIAAC 2012/2014 dataset and the Department of Homeland Security (DHS)

2.2 Methodology

Research Question 1: The first research question intends to study the absolute upward mobility in education and the relative mobility in education, cognitive skills (literacy, numeracy, and problem solving), employment, occupation-skill, and earnings.

Research question 1.1 studies absolute upward mobility, which refers to the extent to which people do better than their parents. Education is the only information for the parents provided by the PIAAC dataset. Therefore, this study investigates absolute upward mobility only in education. Summary statistics are used to study absolute upward mobility and it is measured as the percentage of children that acquire higher educational outcomes than their parents.

Research question 1.2 studies relative mobility. Relative mobility examines the association between parental education and the different outcomes of children. Both summary statistics and inferential statistics are used to study relative mobility. Relative mobility using summary statistics is measured as the proportion of different parental education (less than high school, high school plus some college, college or higher) for each level of respondents' outcomes. For example, what percentage of children who have attained college degrees have parents with college, high school, or less than high school education. This investigation helps to understand the association between parents' and children's educational level. Relative mobility using inferential statistics is examined using regression analysis, looking at the extent to which children's achievement in education, employment, occupational skill, earnings, and cognitive skills (literacy, numeracy, and problem-solving scores) depends on their socioeconomic background.

This study uses parental education as a proxy for children's socioeconomic background. For the categorical variables, including education, occupational skill classification, earnings, and employment status, a logistic model (ordinal logistic model for education, occupational skill classification, and earnings; multinomial logistic regression for employment status) is used and is presented in equation (1). Table 3 shows the appropriate model for different outcome variables.

Table 3: List of models used in this study

Outcome variable	Model
Employment	Multinomial logistic regression
Education, occupational skill, earnings	Ordinal logistic regression
STEM-Study	Binary logistic regression
Literacy, numeracy, problem solving	Linear regression

$EducCollege_{parent_i}$ and $EducLessHighSchool_{parent_i}$ are two dummy variables regarding parental education (college and less than high school, respectively). Parents with high school degrees are used as the reference group. β_1 and β_2 are the coefficients of interest and measure the extent to which parental education is associated with outcomes of their children. $\boldsymbol{X_{child_i}}$ is a vector that controls for demographic characteristics of respondents such as gender, race, age, urbanicity, region, and English as the first language, consistent with the literature (Ford & Umbricht, 2016). A complete list of control variables ($\boldsymbol{X_{child_i}}$) is included in Table A.2.[7]

ln

$$ln\left(\frac{P\left(Outcome_{child_i}\right)}{P\left(OutcomeRef_{child_i}\right)}\right) = \beta_0 + \beta_1 EducCollege_{parent_i} + \beta_2 EducLessHighSchool_{parent_i} + \beta_{child}\boldsymbol{X_{child_i}} \quad (1)$$

[7] In the model proposed in this study, we include regional fixed effects to control for the geographic dispersion of the respondents. There are 4 different regions: Northeast, Midwest, South, and West. Using Northeast as the reference group, three dummies for Midwest, South, and West are included in the estimations. Inclusion of these dummies helps to control for geographic dispersion (Chetty 2016). One might argue that northern states on average have a higher density of colleges and universities compared to southern states, which might change the share of college-educated people disproportionately. Including region fixed effects helps to control for unobserved heterogeneities due to geographical dispersion across regions and consequently helps in reducing standard errors and increasing the precision of the estimates.

In the multinomial logistic regression, the effect of the independent variables on the odds ratio of one outcome variable value compared to the base outcome are measured. For example, employment takes the values of 1, 2, and 3 for employed, unemployed, and out of labor force, respectively. Considering the base outcome of employed, we will estimate the effect of parental education on the relative odds of the child being unemployed vs. employed, and out of labor force vs. employed ($Ln(\frac{P(unemployed)}{P(employed)})$ and $Ln(\frac{P(out\ of\ labor\ force)}{P(employed)})$). Then, predicted marginal proportions of each value of the categorical outcome variable (education, employment status, earnings, and occupation-skill) are calculated.[8] In the ordinal logistic regression used for education, occupational skill, and earnings, the odds ratio of achieving higher levels of outcomes are calculated. In the ordinal model, the odds are for two adjacent levels; the denominator is the lower group, while the numerator is the next higher group. The odds ratios are constrained to be equal across comparisons of different adjacent levels in the outcome. For example, in the ordinal regression for education, we are interested in the odds of achieving a college degree or higher vs. high school $Ln(\frac{P(college\ or\ higher)}{P(high\ school)})$ or high school vs. less than high school $Ln\left(\frac{P(high\ school)}{P(less\ than\ high\ school)}\right)$. A separate intercept is estimated for each comparison.

For the continuous variables of numeracy, literacy, and problem solving, linear regression is used. See equation (2) using Ordinary Least Square (OLS):

$$Outcome_{child_i} = \beta_0 + \beta_1 EducCollege_{parent_i} + \beta_2 EducLessHighSchool_{parent_i} + \beta_{child}\boldsymbol{X}_{\boldsymbol{child_i}} + \varepsilon_i \qquad (2)$$

[8] Predicted marginal proportions are calculated using the post-estimation command of margins in Stata. Similarly, in ordinal logistic regression of earning, we are interested to see the impact of parental education on the relative odds of children achieving the highest quantile of earning. Also, using the post-estimation command of margins, we estimate the probability of children with different parental education acquiring the highest, mid-highest, mid-lowest, and lowest 25 percentiles of the outcome of interest.

$Outcome_{child_i}$ measures different outcome variables for the respondent i, including numeracy, literacy, problem-solving scores. Literacy, numeracy, and problem solving each include 10 plausible values. Macro command repest in Stata is used to examine the impact of parental education on cognitive skills.[9]

Research question 1.3 examines the heterogeneity impact of relative mobility by race/ethnicity and gender using interaction terms, represented in equation (3):

$$
\begin{aligned}
ln\left(\frac{P(Outcome_{child_i})}{P(OutcomeRef_{child_i})}\right)
&= \beta_0 + \beta_1 EducCollege_{parent_i} + \beta_2 EducLessHighSchool_{parent_i} \\
&+ \beta_3 EducCollege_{parent_i} \times popcharacter_{child_i} \\
&+ \beta_4 EduLessHighSchool_{parent_i} \times popcharacter_{child_i} \\
&+ \beta_{child} \boldsymbol{X_{child_i}} \qquad (3)
\end{aligned}
$$

$popcharacter_{child_i}$ is an additional term representing the heterogeneity, with gender (female vs. male) in one regression and racial groups (Hispanic vs. White, Black vs. White, and Other vs. White) in another regression.[10] The interaction of $popcharacter_{child_i}$ with parental education help in identifying the effect of parental education on the outcome of interest for subgroup populations (gender and racial groups).

Research Question 2.1 studies the association between parental education and the propensity to study in Science, Technology, Engineering, and Mathematics (STEM). A logistic model is used to estimate the impact of parental education on the propensity to study/work in STEM.

[9] repest estimates statistics using replicate weights (balanced repeated replication or brr weights, jackknife replicate weights, …), thus accounting for complex survey designs in the estimation of sampling variances. It is specially designed to be used with the PISA, PIAAC, and TALIS datasets produced by the OECD. It also allows for analyses with multiply imputed variables (plausible values); where plausible values are used, the average estimator across plausible values is reported and the imputation error is added to the variance estimator (Francesco Avvisati & François Keslair, 2014).

[10] For subgroup analysis by race, considering White as the reference group, three interaction terms are included in the regression: Black vs. White, Hispanic vs. White, and Other races (including Asian) vs. White.

$$ln\left(\frac{P(STEM_{child_i})}{P(NoSTEM_{child_i})}\right) = \beta_0 + \beta_1 EducCollege_{parent_i} + \beta_2 EducLessHighSchool_{parent_i} + \beta_{child}\boldsymbol{X_{child_i}} \quad (4)$$

$STEM_{child_i}$ is the binary outcome variable and takes a value of one if child i studies STEM and zero otherwise. Post-estimation command of margins is used to measure the impact of parental education on the probabilities of a child studying STEM.

Research question 2.2 examines the impact of parental education on the gender gap in STEM-Study, using interaction terms as follows:

$$\begin{aligned} ln\left(\frac{P(STEM_{child_i})}{P(NoSTEM_{child_i})}\right) &= \beta_0 + \beta_1 EducCollege_{parent_i} + \beta_2 EducLessHighSchool_{parent_i} \\ &+ \beta_3 EducCollege_{parent_i} \times Female_{child_i} \\ &+ \beta_4 EducLessHighSchool_{parent_i} \times Female_{child_i} + \beta_5 Female_{child_i} \\ &+ \beta_{child}\boldsymbol{X_{child_i}} \qquad (5) \end{aligned}$$

$EducCollege_{parent_i} \times Female_{child_i}$ and $EducLessHighSchool_{parent_i} \times Female_{child_i}$ are the interaction terms between parental education and gender. β_3 and β_4 are the coefficients of interest in this specification and show whether the impact of parental education on STEM-Study varies by gender (female vs. male).

Research question 2.3 estimates whether the relationship between parental education and the propensity to study in STEM varies across racial groups. To study this research question, regression similar to equation (5) is used. However, instead of interaction terms with gender (female), interaction term with respect to racial groups are used (Hispanic vs. White, Black vs. White, and Other races (including Asian) vs. White).

Research question 2.4 estimates the effect of parental education on the gender gap in studying STEM for different racial/ethnic groups, using a similar regression to equation (5). Sample sizes of Hispanic, Black, and Other races (including Asian) in the study of STEM by gender gap are small. Therefore, gender gap in

STEM is only investigated for White adults. To study this research question, the sample is restricted to White and, similar to equation (5), interaction terms for gender and parental education are included.

Sample of the study: Individuals responding "not stated or inferred" are controlled for by creating a dummy variable with a value of one if an individual responded "not stated or inferred" and zero otherwise.[11] The number of individuals responding "do not know" or "refused" is less than 10 in each outcome variable and those cases are dropped from the sample.

A different regression is used for each outcome variable. The control variables mentioned in Table 1 are included in each analysis. Appropriate outcome variables are also included as the control variables. The main purpose of this study is to identify the impact of parental education on the outcomes of their children. It is more likely that higher-educated children are engaged in skilled occupations. Therefore, to identify the impact of parental education on occupation-skill, we need to control for respondents' educational level. PIAAC has also revealed the importance of educational attainment as a control variable in the identification of gender variation in numeracy proficiency (OECD 2013a, p. 28). Therefore, in the estimation of the impact of parental education on cognitive skills, the highest educational level of children is included. In the estimation of the impact of parental education on earnings, education and occupational skill classification of children are also included as the control variables.

The sample of the study contains 7,714 respondents aged 20 and older; however, sample sizes in different analyses vary depending on the outcome variable of interest. In the analysis of the association between parental education and employment status, earnings, and occupation-skill, the sample is limited to non-student respondents.

[11] Sample size varies depending on the outcome variable of interest.

3 Results

Research question 1: Summary statistics are used to study absolute and relative mobility in education and other outcomes of interest, including employment status, occupational skill classification, earnings, and cognitive skills (literacy, numeracy, and problem-solving scores). However, relative mobility is further examined using inferential statistics (regression analysis) in research questions 1.2 and 1.3. Figure 1 shows the percentages of parents with different educational levels in the sample of study. It shows that 38% percent of parents have attained at least a college degree, 44% have a high school education, and 18% have less than a high school education. The left graph in Figure 2 studies absolute upward mobility in education. More specifically, it indicates that 48% of children have similar educational attainment as their parents, while only 26% of children achieved higher education than their parents and 26% achieved less education than their parents.

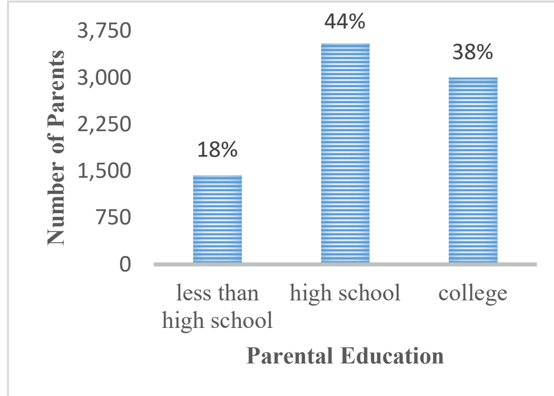


Figure 1: Parental educational levels

The right graph in Figure 2 studies absolute upward mobility more closely by breaking down the levels of educational attainment of children with different parental education. It indicates that 48% of children with college-educated parents have college degrees, while only 29% of children with high school-educated parents have achieved a higher degree than their parents (college degree) and 16% of children of parents with less than a high school education achieved a college degree. Fifty-seven percent of children with high school-educated parents have similar education as their parents.

Figure 2 shows that children in families with college- and high school-educated parents tend to achieve similar educational attainment to their parents. Forty-eight percent of children with college-educated parents attain a college degree and 57% of children with high school-educated parents attain high school education. However, among children of parents with less than a high school education, 29% of them have less than a high school education. The right-hand graph in Figure 2 indicates high absolute mobility among children of parents with less than a high school education, since 71% of children of parents with less than a high school education achieved higher education than their parents (55% high school and 16% college). Higher absolute mobility among children with parents with less than a high school education could be due to policy reforms in education, including compulsory education acts, which increased high school enrollment and the probability of attaining higher education and reduced school dropout (Hilger 2016; Cabus, & Kristof De Witte, 2011).

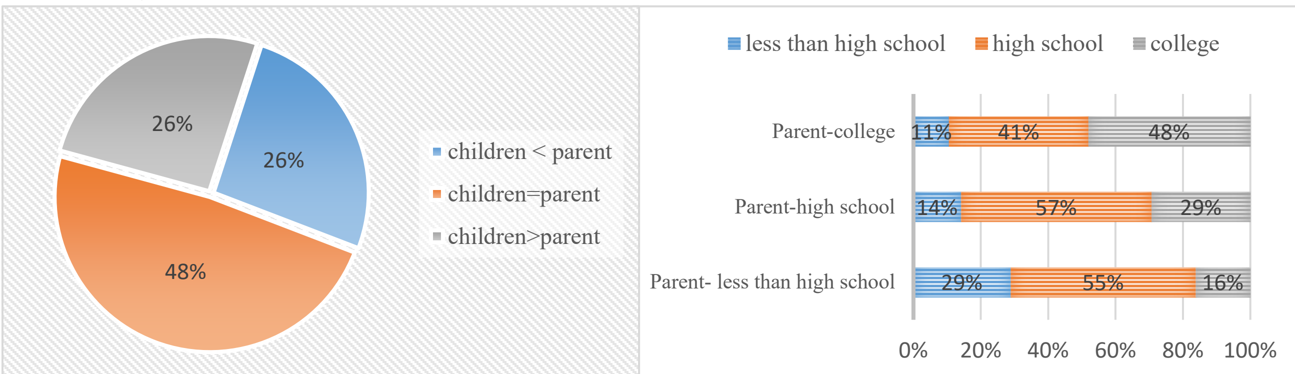


Figure 2: Relationship between educational levels of parents and children (absolute mobility)

Figure 3 presents the relative mobility and examines the probability of attaining different levels of outcomes for children with different parental education. Figure 3 shows the results for cognitive skills, including literacy, numeracy, and problem-solving scores.[12] As we move from the lower quartiles to the higher quartiles in literacy, numeracy, and problem solving, the percentages of children with college-educated parents increase and the percentages of children with less than high school education decrease. As shown in Figure 3, the higher quartiles of scores are achieved by children with college-educated parents (59%, 58%, and 66% in literacy, numeracy, and problem solving, respectively).

Figure 4 illustrates the relative mobility in other outcome variables, including education, employment, occupational skill classification, and earnings. Those who have achieved a college degree, are employed, are engaged in skilled occupations, and earn the highest quartile of earnings are more likely to have higher-

[12] Macro command repest in Stata is used to calculate quartiles as well as run regression analysis in equation (2) in the analysis of plausible values, literacy, numeracy, and problem-solving scores. Repest is especially designed for complex survey designs, accommodating final weights and using replicate weights for the sampling variance. It also accepts plausible values and incorporates imputation variance in the computation of total variance (Francesco Avvisati & François Keslair, 2014).

educated parents. These findings highlight the importance of adults' education in the education, cognitive skills, employment status, and earnings of the next generation (children).

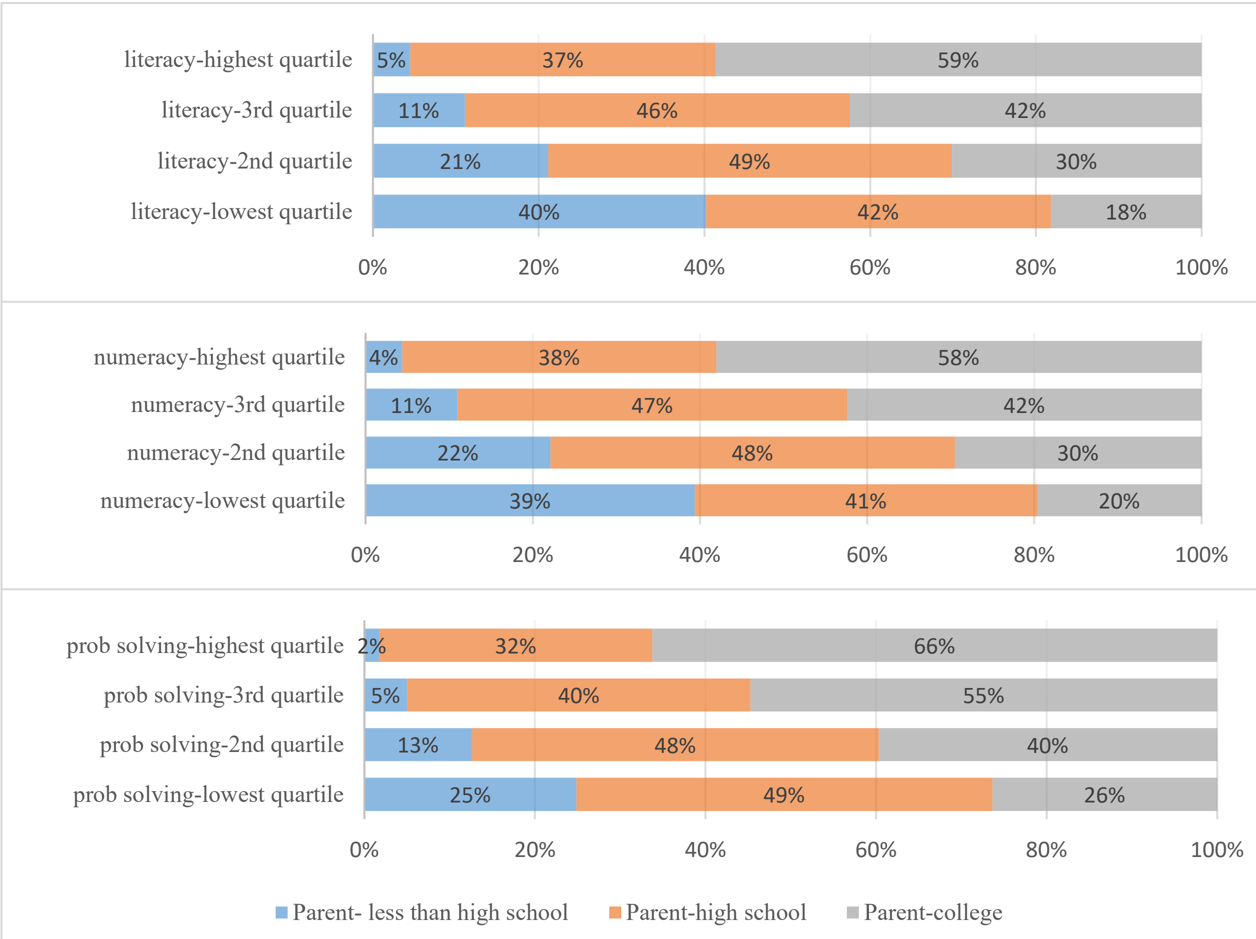


Figure 3: Relationship between parental education and cognitive skills of children (relative mobility)

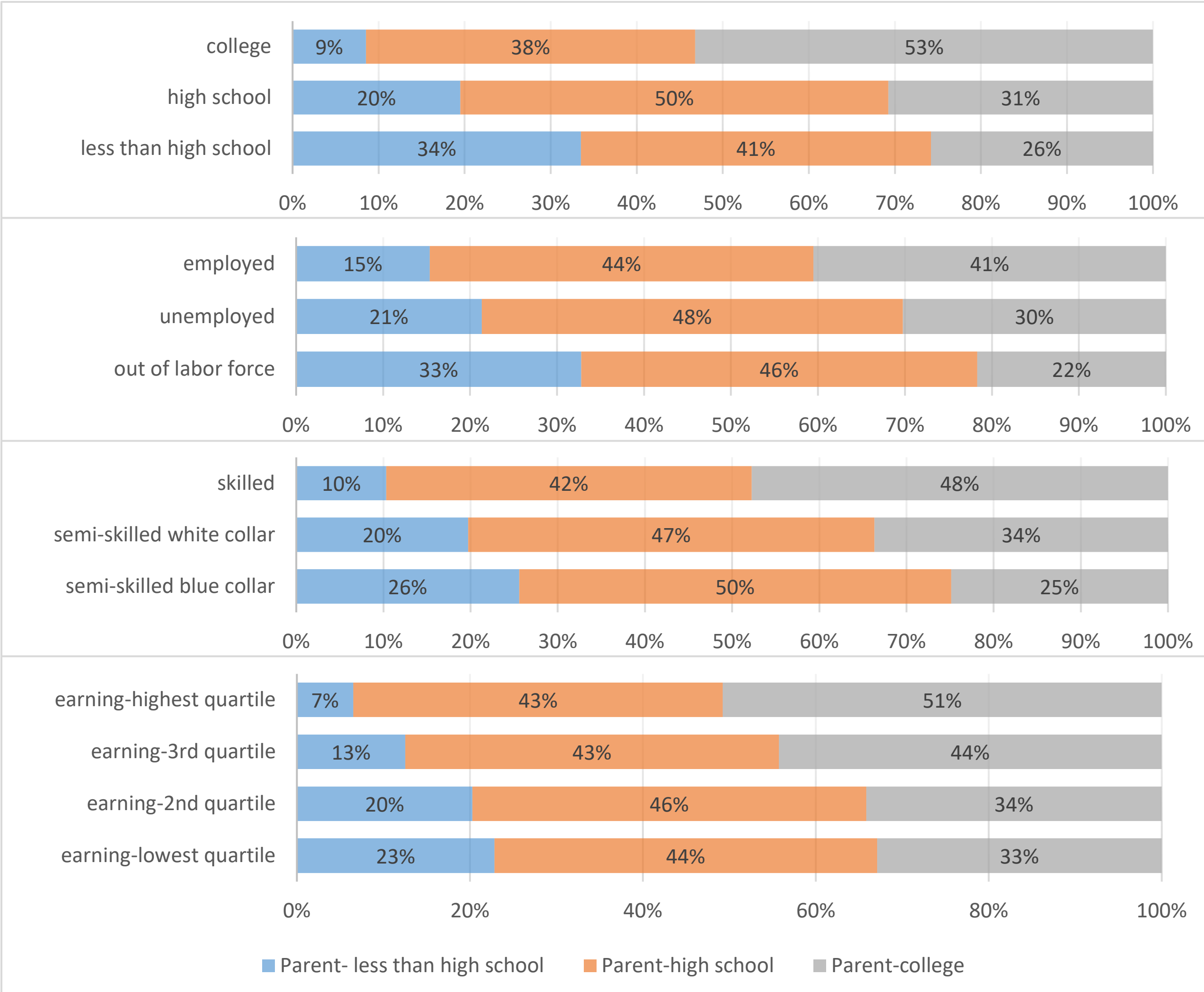


Figure 4: Relationship between parental education and outcomes of their children, including education, employment, occupation-skill, and earnings (relative mobility)

Research questions 1.2 and 1.3 study relative mobility using inferential statistics. More specifically, they examine the impact of parental education on outcomes of interest for population (children) as a whole and differentiated by gender and race/ethnicity.[13] Table 4 shows relative mobility in literacy, numeracy, and problem solving. Results show that children with college-educated parents have significantly higher scores compared to children with high school-educated parents.

[13] It should be noted that repest command in Stata has been used in estimations in Table 4. Interaction terms have been used in the analysis of the subgroup population.

It should be noted that the coefficients presented in Table 4 are unstandardized and therefore they are not comparable across domains of cognitive skills for magnitude of effects (i.e., one should not compare the impact of parental education across domains of literacy, numeracy, and problem solving and, for example, conclude that the relationship between parental education and cognitive skills is stronger for literacy than for numeracy and problem solving). Coefficients are interpreted based on their sign and significance level and not magnitudes.

Table 4 shows a positive correlation between college-educated parents and the cognitive skills of their children when investigating the population as a whole and differentiated by gender and race. These results once again highlight the importance of parental education on the skill indicators of the next generation. Results refer to low relative mobility because children with higher-educated parents have statistically better cognitive skills and children with less parental education have statistically lower cognitive skills. We would expect high relative intergenerational mobility if children, regardless of parental education, could achieve higher outcomes. However, results support the importance and significant role of parental education in determining the outcomes of their children and reflect low relative intergenerational mobility.[14] Table 4 panel B shows that females are not statistically different than males in cognitive skills. Panel C also shows that there are no significant differences in cognitive skills across racial groups.

[14] Low and high intergenerational mobility are defined based on the results and whether they are significant or not. If there is no relationship between parental education and the outcomes of children, it is concluded that intergenerational mobility is low. For example, intergenerational mobility is low if the odds ratio of children with high school-educated parents attaining higher education is not significantly different from that of children with less high school-educated parents and if the odds ratio of children with college-educated parents is not significantly different from that of children with high school-educated parents. These results indicate low intergenerational mobility. In this case, there is no relationship between parental education and outcomes of children, based on the definition of intergenerational mobility explained in the executive summary and methodology. However, it is concluded that there is high intergenerational mobility if there is high association between parental education and outcomes of children. For example, if the odds ratio of children with less than high school-educated parents attaining higher education is less than that of children with high school-educated parents and if the odds ratio of children with college-educated parents attaining higher education is higher than that of children with high school-educated parents. Then, it is concluded that there is high association between parental education and children’s attainments, which indicates high intergeneration mobility.

Table 4: Impact of parental education on Literacy, Numeracy, and Problem Solving – coefficients are unstandardized

Panel A.	**Literacy**	**Numeracy**	**Problem Solving**
Parent-less than high school	-10.84038***	-14.4570***	-11.40733***
	(1.716135)	(2.2977)	(2.316653)
Parent-college	10.0508***	9.6632***	6.8792***
	(1.673141)	(1.8039)	(1.594603)
Panel B. by gender			
Parent-less than high school*Female	3.07748	2.6107	4.808575
	(3.700361)	(3.8596)	(4.982917)
Parent-college*Female	0.8878967	0.0161	-0.2146238
	(2.736646)	(2.5595)	(2.546328)
Panel C. by race			
Parent-less than high school*Hispanic	4.0613	3.1369	3.0846
	(5.2417)	(5.5787)	(5.8227)
Parent-less than high school*Black	0.2863	4.8280	0.8460
	(6.5913)	(6.4882)	(5.7697)
Parent-less than high school*Other	6.6289	7.4778	5.1679
	(8.5727)	(10.1833)	(9.5313)
Parent-college*Hispanic	-3.6515	-1.3121	-1.3305
	(5.9818)	(6.9308)	(6.5210)
Parent-college*Black	-4.3454	-1.5597	-2.2098
	(4.3756)	(4.2965)	(4.1160)
Parent-college*Other	3.9214	4.3362	6.2672
	(5.9582)	(6.8951)	(5.9883)
Controls	Yes	Yes	Yes

Note: All estimates controlled form age groups, gender, language, racial groups, urban city, region, and highest level of education achieved. Literacy, numeracy, and problem solving each include 10 plausible values. Estimates are performed using repest command in Stata. The number of observations for literacy, numeracy, and problem solving are, respectively, 6982, 6982, and 5743. Interaction terms have been used in the analysis of the subgroup population. Further information on the variables and reference groups for control variables can be found in Table 1. Regressions with the full list of the control variables are provided in the appendix tables A.2, A.3, and A.4. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$.

Table 5 studies the association between parental education and the education, occupation-skill, and earnings of children for the population as a whole and differentiated by gender and race using odds ratio. Odds ratios are compared to 1. An odds ratio of 1 means that both groups/categories have the same odds. An odds ratio of less than 1, for example 0.50, means that the odds of one group are 50% less than those of the other group. An odds ratio of 1.50 means that the odds of one group are 50% more than those of the other group.

Outcome variables in Table 5 are ordinal and therefore the appropriate model used in the estimation is ordinal logistic regression.

Odds ratios for outcomes of occupation-skill and earnings are 1.16 and 1.1, respectively. This means that the odds of achieving skilled occupations and higher quartiles of earnings are 16% and 10% more, respectively, for children with college-educated parents than for children with high school-educated parents.[15] Table 5 shows a high odds ratio of 2.48 for attaining higher education for children with college-educated parents compared to children with high school-educated parents. These results support low relative mobility, as children of higher-educated parents have higher odds of attaining higher education, engaging in skilled occupations, and receiving higher quartiles of earnings than children of high school-educated parents. Furthermore, children of less than high school-educated parents have lower odds of achieving higher outcomes than children of high school-educated parents.

Table 5: Association between parental education and children's outcomes using ordinal logistic regression - coefficients are in odds ratio

Panel A.	**Outcome 1 Education**	**Outcome 2 Occupation-Skill**	**Outcome 3 Earnings**
Parent-less than high school	0.3426^{***}	0.7739^{**}	0.6945^{***}
	(0.0539)	(0.0789)	(0.0864)
Parent-college	2.4845^{***}	1.1636	1.1064^{**}
	(0.3304)	(0.1212)	(0.0489)
Panel B. by gender			
Parent-less than high school*Female	0.8392	1.3644	0.7699
	(0.1002)	(0.2777)	(0.1295)
Parent-college*Female	1.2234^{***}	0.8586	1.5103^{***}
	(0.0430)	(0.1080)	(0.0656)
Panel C. by race			
Parent-less than high school*Hispanic	1.3790	1.1832	1.5774^{***}
	(0.2788)	(0.3042)	(0.2486)
Parent-less than high school*Black	1.4812^{***}	1.0831	1.1642
	(0.1529)	(0.1437)	(0.4387)

[15] Comparing children with college-educated parents and those with high school-educated parents, the odds of achieving second quartile earnings are 10% more than those of getting first quartile earnings; the odds of achieving third quartile earnings are 10% more than those of getting second quartile earnings. Similarly, the odds of achieving skilled occupations are 16% more than those of getting semi-skilled white collar occupations; the odds of achieving semi-skilled white collar occupations are 16% more than those of getting semi-skilled blue collar occupations.

Parent-less than high school*Other	1.8152	1.3938	1.3177
	(0.6706)	(0.4875)	(0.7083)
Parent-college*Hispanic	0.7752	0.7972**	1.1667
	(0.2709)	(0.0853)	(0.4037)
Parent-college*Black	0.7737	1.1516*	0.9921
	(0.2440)	(0.0840)	(0.2087)
Parent-college*Other	0.8644	0.9685	1.0185
	(0.1534)	(0.2499)	(0.3536)
Controls	Yes	Yes	Yes

Note: Students are dropped from all the estimations in this table.[16] All estimates controlled form age groups, gender, language, racial groups, urbanicity, and region. In the estimation of the occupation-skill, the additional control of educational level is included. In the estimation of earnings, additional controls of education and occupation-skill are included. In both estimations of column 2 and 3, the sample is limited to non-students and employed individuals. However, to save space, coefficients of interest are included in the main tables throughout this study. The numbers of observations are 7972, 4178, and 3215 in the estimation of education, occupation-skill, and earnings, respectively. For each outcome variable, comparisons of each two adjacent levels produce a different intercept. For example, for the outcome variable of education, ordinal logistic regression will produce one set of coefficients for parental education with two intercepts: one for the odds of achieving college degree vs. high school and one for the odds of achieving high school vs. less than high school. For simplicity, intercepts are not reported in this table. A full list of coefficients of the control variables is provided in the appendix Table A.5.
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$.

In Panel B in Table 5, interaction terms between parental education and gender are added. [17] Results show that the effect of an increase in parental education (from high school to college) on the odds ratios of attaining higher education and quartiles of earnings is significantly higher for females than males (22% and 51%, respectively). However, changes in the outcomes of children (education, occupation-skill, and earnings) are not significantly different for females vs. males when parental education changes from high school to less than high school. This result highlights the importance of parental education in reducing potential gender gaps because females have significantly better outcomes (education and earnings) than males in families with higher-educated parents.

[16] Variable “empstat” in the PIAAC dataset is used to identify students. This variable takes a value of one if the respondent is a student (part-time, employed, unemployed, or out of labor force).
[17] Each coefficient presented in panels B and C is the interaction between parental education and the subgroup population (gender and racial groups). The reference group for parental education is high school. Therefore, the coefficient of, for example, 1.22 in panel B indicates that the effect of an increase in parental education from high school to college on the odds ratio of attaining higher education is 22% higher for females than males (Stock and Watson, 2014).

In panel C in Table 5, interaction terms between parental education and race/ethnicity groups are added. Results show that the effect of change in parental education from high school to less than high school is not statistically different for Hispanic vs. Whites and Other races (including Asian) vs. Whites. However, Blacks have higher odds of attaining higher education than Whites when parental education changes from high school to less than high school. The effect of increase in parental education from high school to college on the odds ratio of attaining higher education and quartiles of earnings is not statistically different for children of Other races vs. Whites. This result highlights the importance of parental education in reducing racial gaps in education and earnings.

These results indicate low relative mobility. The results show that children of less-educated parents have higher odds of staying less educated and children with higher-educated parents have higher odds of attaining college degrees. There are similar effects for occupation-skill and earnings, but with less intensity. Females in families with high-educated parents have significantly higher odds of attaining higher education and higher quartiles of earnings than men. There are no racial differences in the odds of higher education and earnings in families with college-educated parents. This result indicates that racial gaps tend to weaken among children with high-parental education. The main control variables in all the tables are age groups, gender, language, racial groups, urbanicity, and region. However, in the estimation of occupation-skill and earnings, the additional control variable of education is included. Further information on the variables is provided in Table 1. A full list of all the coefficients for control variables is provided in Table A.2.

The predicted probabilities of children with different parental education attaining college degrees, skilled occupations, and 3rd quartile of earnings, differentiated by gender and racial groups, are illustrated in Figure 5. The graphs illustrate the predicted probability of each level of parental education (less than high school, high school and some college, college), holding control variables at their means. It is important to note that the results in Figure 5 are the predicated probabilities for the specific levels of the outcome variables (college degrees, skilled occupations, and 3rd quartile of earnings).[18] All individual estimates are statistically

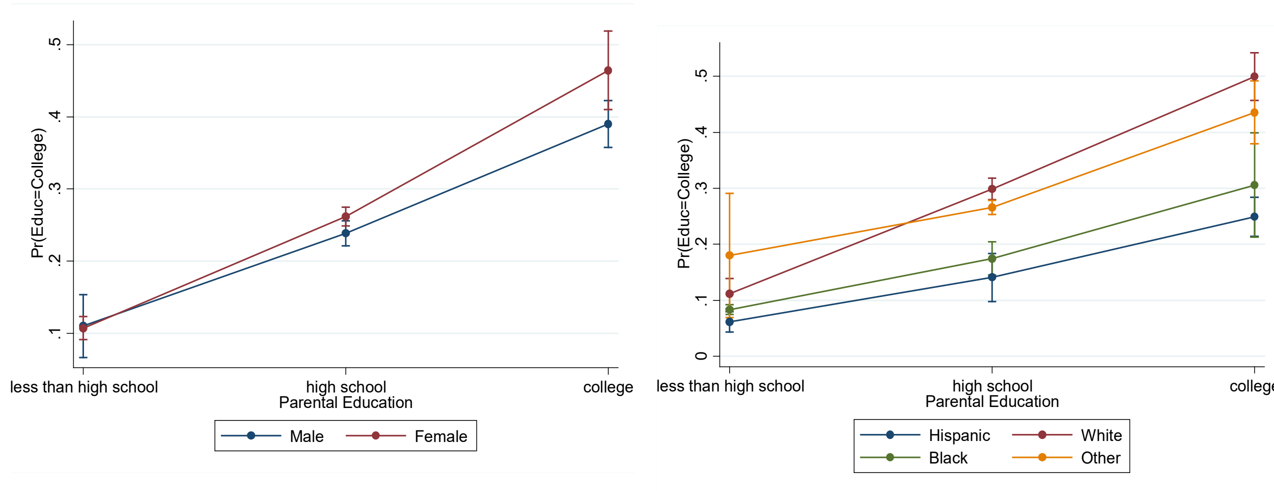
[18] However, outcome variables in Table 5 are ordinal and the impact of parental education is estimated using odds ratio in achieving higher levels of education, occupation-skill, and earnings.

significant. Figure 5 shows that as parental education increases, the probabilities of children acquiring college degrees, receiving higher earnings, and engaging in high-skilled occupations also increase. The predicted probabilities of each level of parental education are also examined for gender gap in the 4^{th} quartile of earnings (see Appendix, Figure A.1). Results also show a lower gender gap in the 4^{th} quartile; however, the reduction in gender gap is higher in the 3^{rd} quartile of earnings.

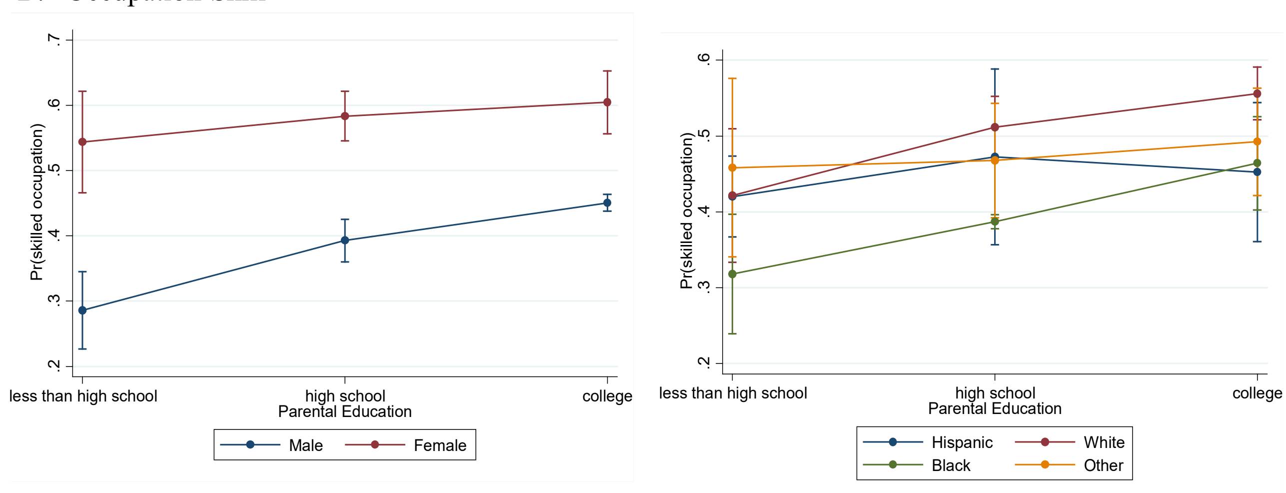
Results reveal that females with higher-educated parents are more likely than men to receive higher education. Females also are more likely than males to be engaged in skilled and semi-skilled white collar occupations. However, compared to males, females are less likely to receive high earnings. Analysis by gender shows that gender gaps in occupation-skill and earnings (3^{rd} quartile) tend to decrease among children with higher parental education. Interestingly, females in families with college-educated parents have a significantly higher likelihood of attaining a college degree. This result is consistent with the analysis in Table 5. Males tend to receive higher earnings than females for all levels of parental education. However, as parental education increases (from high school to college) the odds of females receiving higher earnings and engaging in skilled occupations increase, which helps to reduce the gender gaps in earnings and skilled occupations among children with higher parental education.

Figure 5 also shows that as parental education increases from less than high school to high school and college, the predicted probabilities of children acquiring college degrees increase for all racial groups. However, Black and Hispanic adults have a lower probability of acquiring college degrees for all levels of parental education, compared to White adults and other races. As parental education increases from high school to college, the slope of increase in the probability of children engaged in skilled occupations is steeper for Blacks vs. Whites and less steep for Hispanics vs. Whites. This result indicates that the probability of children engaging in skilled occupations is higher for Blacks compared to Whites when parental education increases from high school to college. It also shows that the probability of children engaging in skilled occupations is lower for Hispanics compared to Whites when parental education increases from high school to college.

A. Education



B. Occupation-Skill



C. Earnings

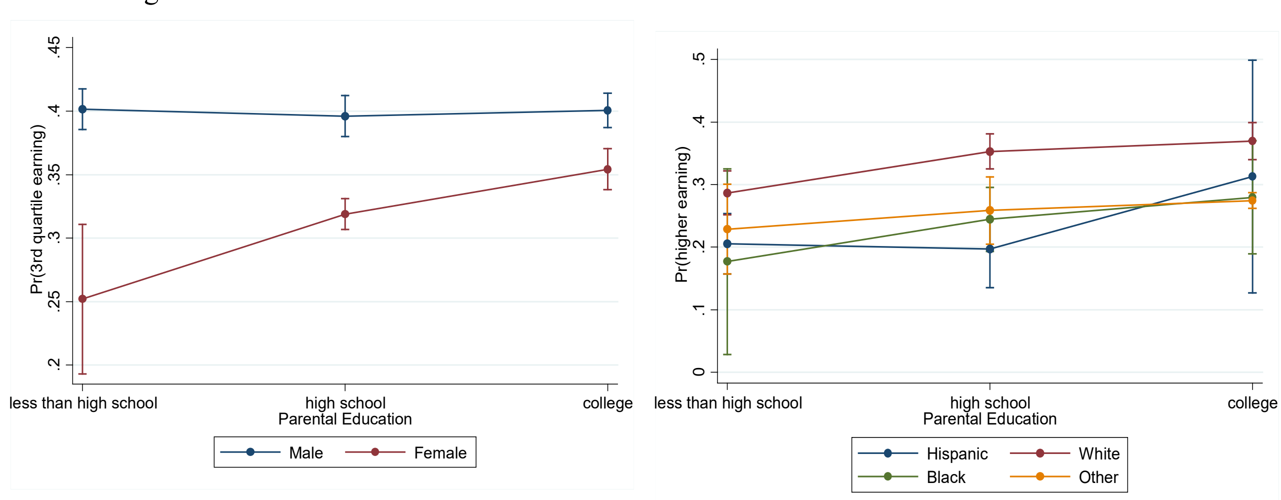


Figure 5: Predicted probability of each level of parental education for college, skilled occupations, and 3rd highest quartile of earnings by gender and racial groups

Table 6 investigates the association between parental education and labor market outcomes $\frac{P(unemployed)}{P(employed)}$ and $\frac{P(out\ of\ labor\ force)}{P(employed)}$ using multinomial logistic regression. Results show that children of college-educated parents have lower odds of being unemployed or out of labor force compared to children with high school-educated parents. Children with less than high school-educated parents have higher odds of being out of labor force than children with high school-educated parents.

Females with college-educated parents are not statistically different from males in the odds of being unemployed or out of labor force compared to those of high school-educated parents. There are no racial differences among children of college-educated parents in the odds of being unemployed or out of labor force. However, among children with less than high school-educated parents, Hispanics and Blacks tend to have lower odds of being unemployed than Whites. Hispanics with less than high school-educated parents also have lower odds of being out of labor force than Whites.[19]

It should be noted that the sample is restricted to non-student respondents and in addition, to control the variables illustrated in Table 1, education is also included in the estimation in Table 6. Figure 6 illustrates the predicted probability of each level of parental education on the probability of being employed, differentiated by gender and racial groups.[20] Results shows that as parental education increases, the probability of being employed increases for both females and males. However, there is a persistent gender gap in the probability of being employed, regardless of parental education.[21] As parental education increases, the probability of children being employed increases for all racial groups. However, in comparison, Blacks have a lower probability of being employed than the other race categories for all levels of parental education.

[19] Reference group for parental education throughout the paper is high school education.
[20] To avoid including an excessive number of tables, the results of predicted probabilities are illustrated using graphs. All individual estimates are statistically significant.
[21] Table 6 also shows that as parental education increases from high school to college, the odds ratios of females being unemployed or out of labor force are not statistically different from those of males.

Table 6: Association between parental education and labor market outcomes using multinomial logistic regression - coefficients are in odds ratio

Panel A.	**Unemployed**	**Out of labor force**
Parent-less than high school	1.0987	1.2491***
	(0.1253)	(0.0743)
Parent-college	0.8071*	0.7518***
	(0.0933)	(0.0164)
Panel B. by gender		
Parent-less than high school*Female	1.1315	0.7694
	(0.2139)	(0.1521)
Parent-college*Female	1.0651	0.9839
	(0.1471)	(0.0851)
Panel C. by race		
Parent-less than high school*Hispanic	0.5315**	0.4834***
	(0.1481)	(0.1144)
Parent-less than high school*Black	0.6904**	0.8567
	(0.1229)	(0.1687)
Parent-less than high school*Other	0.6891	0.7328
	(0.3224)	(0.2758)
Parent-college*Hispanic	1.0626	1.0792
	(0.1714)	(0.3315)
Parent-college*Black	0.9165	0.9089
	(0.2971)	(0.3358)
Parent-college*Other	0.8930	1.2744
	(0.3182)	(0.4555)
Controls	Yes	Yes

Note: Multinomial logistic model is used in this table since the outcome variable is categorical but not ordinal. All estimates controlled form age groups, gender, language, racial groups, urbanicity, and region. The sample is limited to non-student individuals. The number of observations is 6601. A full list of coefficients of the control variables is provided in appendix Table A.6. * p < 0.10, ** p < 0.05, *** p < .01.

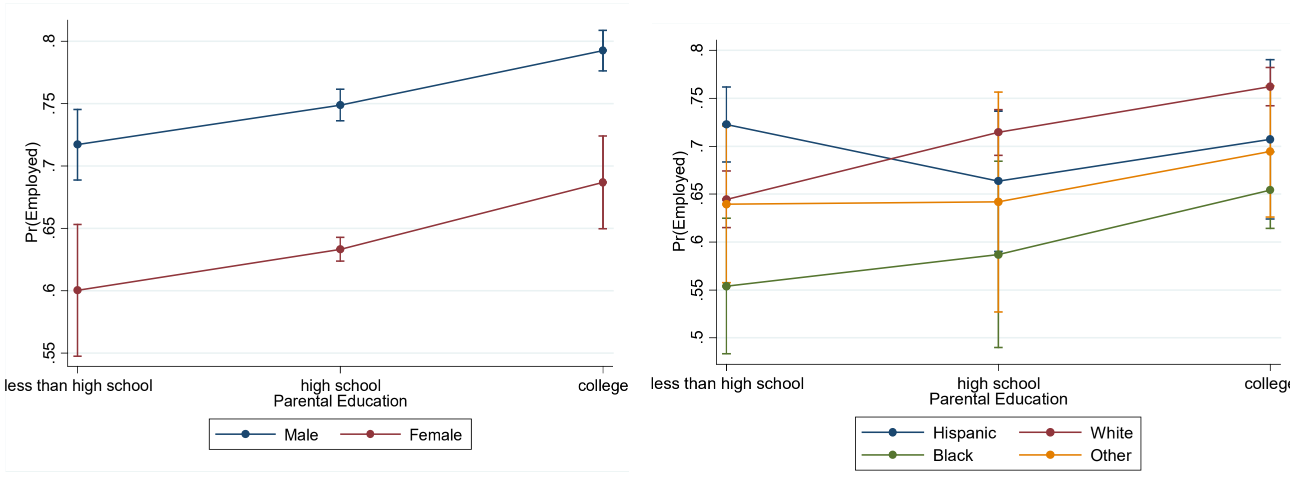


Figure 6: Predicted probability of each level of parental education of being employed by gender and racial groups.

Research question 2: Table 7 shows the association between parental education and the odds of STEM-Study using logistic regression, since the outcome variable is binary. In order to create the variable of interest “STEM-Study”, the PIAAC dataset is merged with STEM designated majors from the National Center for Education Statistics (NCES) using four-digit 2010 Classification of Instructional Programs (CIP) codes provided in both datasets. A dummy variable “STEM-Study” is generated, with a value of one if the area of the study is STEM and zero otherwise. The list of STEM designated programs is exhaustive; however, Table 2 provides a sample of STEM programs used in the construction of STEM-Study. Table 7 shows that children of college-educated parents are about 12% less likely ((1 - 0.88)*100) to study STEM majors compared to children with high school-educated parents. Children with parents with less than a high school education are not statistically different from those with high school-educated parents in terms of STEM-Study. Results also show that females are not significantly different from males in their odds of STEM when parental education changes either from high school to less than high school or from high school to college. Also, there are no racial differences (Black vs. White, Hispanic vs. White, Other vs. White) in the odds of studying STEM when parental education decreases from high school to less than high school or increases from high school to college. Results do not support a significant association between parental education and the odds of STEM-Study by gender and race.

Table 7: Association between parental education and STEM-Study coefficients are in odds ratio

Panel A.	**STEM**
Parent-less than high school	0.8259
	(0.2125)
Parent-college	0.8794***
	(0.0335)
Panel B. by gender	
Parent-less than high school*Female	0.7686
	(0.3050)
Parent-college*Female	1.1285
	(0.2519)
Panel C. by race	
Parent-less than high school*Hispanic	0.6184
	(0.2213)
Parent-less than high school*Black	0.6495
	(0.3349)
Parent-less than high school*Other	1.3123
	(0.6507)
Parent-college*Hispanic	1.2793
	(0.2804)
Parent-college*Black	0.9042
	(0.3461)
Parent-college*Other	1.0929
	(0.5628)
Controls	Yes

Note: A logistic model is used in this table since the outcome variable is binary. The number of observations is 4282. A full list of coefficients of the control variables is provided in appendix Table A.6. * p < 0.10, ** p < 0.05, *** p < .01.

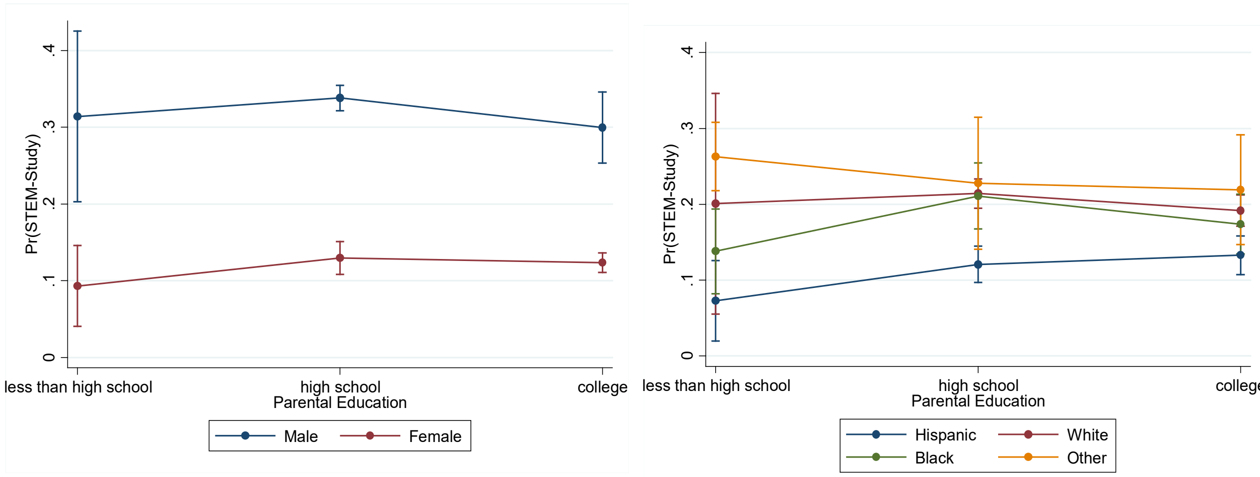


Figure 7: Predicted probabilities of each level of parental education in STEM-Study by gender and racial groups.

Figure 7 shows the predicted probabilities for children with different parental education of studying STEM in their highest level of education attained. Figure 7 shows that, holding all the control variables at their mean, the probabilities of studying STEM for females with less than high school-, high school-, and college-educated parents are respectively 0.09, 0.129, and 0.123. However, the same probabilities for males are respectively 0.31, 0.33, and 0.29. All individual coefficients presented in Figure 7 are significant and presented in Table A.1.[22] Figure 7 shows that at different levels of parental education (less than high school, high school, and college), males are more likely than females to study STEM. Table 7 shows that the effect of changes in parental education from high school to college on the odds ratio of studying STEM is not significantly different for males compared to females. Therefore, these findings show that changes in parental education (from high school to college) do not significantly change the gender gap in STEM. From Figure 7, the gender gap seems to be decreasing among children with college-educated parents. However, results in Table 7 confirm that this reduction in gender gap is not statistically significant.

An investigation by racial categories shows that Other (including Asian) racial groups have a higher likelihood of studying STEM. However, the likelihood of studying STEM does not necessarily increase as

[22] Figure 7 is depicted based on 4282 observations. Keeping all the control variables at their means and looking into the proportion of children studying STEM by gender, the analysis shows that among families with parental education less than high school, 31% of males vs. 9% of females study STEM. Results show a higher confidence interval for male vs. female, which is due to a lower number of observations for males (191) compare to females (285) when looking at eligible respondents to STEM-Study in families with less than high school-educated parents.

parental education increases.[23] Figure 8 illustrates the predicted probabilities for each level of parental education by gender on studying STEM for Whites. It shows that at each level of education, males have a higher likelihood of studying STEM majors. The likelihood of studying STEM for females tends to increase slightly as parental education increases. The gender gap tends to decrease among college-educated parents; however, the results in Table 8 show that this decrease is not significant.

Figure 8: Gender gap in STEM-Study for Whites

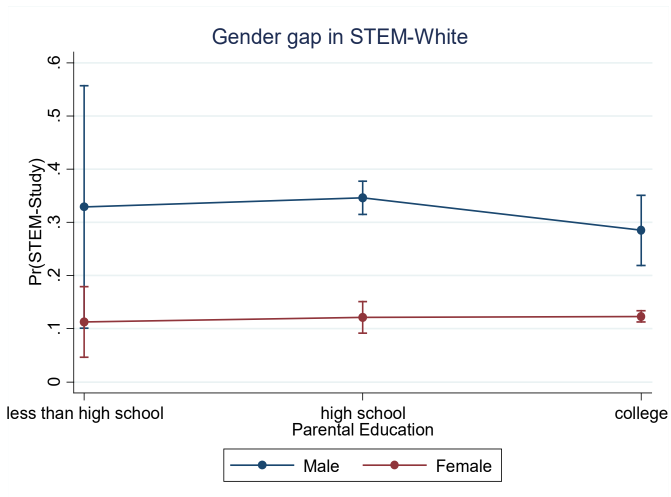


Table 8: Association between parental education and STEM-Study for Whites coefficients are in odds ratio

Panel A.	**Stem**
Parent-less than high school	0.8981
	(0.4455)
Parent-college	0.7447
	(0.1698)
Panel B. by gender	
Parent-less than high school*Female	1.0350
	(0.3052)
Parent-college*Female	1.3783
	(0.3940)

[23] It should be noted that the results presented in the tables are the odds ratios and the results depicted in the graphs are the predicted probabilities for each level of the outcome variables. The interpretation of odds ratio is different than that of predicted probability. For example, the predicted probability of, say, 0.1 for females with less than high school parental education in Figure 7 means that when keeping control variables at their means, 10% of the females with less than high school-educated parents study STEM compared to males. The individual coefficients related to Figure 7 are significant as presented in appendix Table A.1. However, the coefficient of 0.7686 in Table 7 for females interacted with parental education less than high school (when using parents with high school education as the reference group) shows that females are 23% less likely to study STEM than males when parental education decreases from high school to less than high school. However, this effect is not significant, and therefore the effect of the change in parental education on the odds ratio of studying STEM is not significantly different for females than for males.

4 Limitations of the Study

The PIAAC dataset only provides information on parental education. Hence, this study measures mobility as the association between a child's outcomes and parental education. Collecting extra information such as occupation and income of parents would help to increase the depth of analysis. This research did not study the trends of intergenerational mobility across time since the PIAAC dataset is a cross-sectional dataset and not a time series dataset.

The sample is limited to adults over the age of 20. In the analysis of the association between parental educations and employment status, earnings, and occupation-skill, the sample is limited to non-student respondents. The variable "empstat" in the PIAAC dataset is used to identify students. This variable takes a value of one if the respondent is a student. Reducing the sample to non-student respondents for these variables consequently reduces the sample size of study for these outcome variables. In the analysis of employment and skilled occupation (as the outcome variable), individuals who responded "not stated or inferred" are dropped from the analysis. The frequency of such respondents is 2.5% and 3.1% (218 and 275 observations) of the population, respectively. In the estimation of the impact of parental education on skilled occupations, based on the data collection design, the sample is limited to respondents with more than 5 years' work experience. Parental education is the main explanatory variable. In all the regression analyses, individuals who responded "do not know," "not stated or inferred," or "refused" to the parental education question are dropped from the analysis.

This paper studies different outcome variables including education, earnings, employment status, cognitive skills, occupation-skill, and STEM-Study. Investigating intergenerational mobility on various outcome variables adds complexity to the paper in terms of using various econometric models, depending on the outcome variable of interest. For example, for cognitive skills (literacy, numeracy, and problem solving), linear regression is used. For ordinal categorical variables, including occupation-skill, education, and earnings, ordinal logistic regressions are used. For non-ordinal categorical variables like employment, multinomial logistic regression is used. Finally, logistic regression is used for STEM-Study since this variable is binary.

This study uses a different regression for each outcome variable. The control variables mentioned in Table 1 are included in each analysis. Other than the control variables mentioned in Table 1, appropriate outcome variables are also included as the control variables in some of the analyses. For example, in the estimation of occupation-skill, the additional control of educational level is included.

The PIAAC dataset provides 2-digit level occupational classification, which is a very broad classification and does not allow the researcher to clearly extract STEM-related fields using available classification codes, such as the Standard Occupational Classification (SOC) provided by the Bureau of Labor Statistics (BLS). Therefore, we only examine STEM study and not STEM occupation.

The variable “uscip_h_c,” which shows the field of study in the highest education attained, has a considerable number of missing observations. Although missing observations are not at random, since the respondents needed to have attained a certain level of education to be asked about the area of study, dropping the missing cases reduces the sample of study in the investigation of STEM-Study.

The age of respondents when their parents attained their highest level of education could be an important contributing factor in their own education and labor outcomes. For example, parents who received their postsecondary education before or while their children were in their early schooling years could have a stronger impact than parents who received their postsecondary education when their children were older. However, the PIAAC dataset does not provide additional information in this regard.

5 Summary and Policy Recommendations

This study uses the Public Use Data Files from the U.S. 2012/2014 Program for the International Assessment of Adult Competencies (PIAAC) dataset. The PIAAC dataset provides survey data from a nationally representative sample of adults and their basic skills and competencies, as well as the educational attainment of their parents. Therefore, this dataset offers a unique opportunity to explore intergenerational mobility in terms of the association between parental education and different outcomes of their children, including education, cognitive skills (literacy, numeracy, and problem solving), employment status, earnings, skilled occupation, and STEM-Study.

Overall, the results of this study show that family socioeconomic background can explain children's achievements. This study uses parental education as a proxy for socioeconomic background. Parental education is an important driving factor in most of the outcome variables of interest in this study, which supports low relative mobility. In a society with low relative mobility, an individual's wage, education, and occupation tend to be strongly related to those of his/her parents. Low relative mobility strengthens the cycle of disadvantages (or advantages). Results show that children with college-educated parents have higher cognitive skills (literacy, numeracy, and problem solving) and are more likely to achieve college degrees, engage in skilled occupations, be employed, and receive higher earnings.

One of the main challenges for societies is breaking the cycle of the transition of disadvantages from one generation to another. Reducing the impact of low socioeconomic background on an individual's life chances can be best mitigated at early ages. Policies promoting early interventions to improve health and educational opportunities help with overcoming inadequate parenting skills and/or their financial abilities. Literature shows that early life qualities (e.g., education and health) are important predictors of outcomes during childhood and adulthood (e.g., Black et al., 2007; Figlio et al., 2014). Therefore, early interventions increase the life chances for children with low socioeconomic backgrounds of succeeding and attaining higher education, earnings, and labor market outcomes.

Furthermore, effective social assistance programs (e.g., Head Start) buffer the impact of parental disadvantage and help provide more equal opportunities for all children (Blank, 2000).[24] In addition, ensuring high standards in learning, classroom size, and student-teacher ratio across all classrooms, regardless of neighborhoods, helps in reducing the racial gap in education.

The findings of this study highlight the importance of parental education for the education and labor market achievements of the next generation. Policies promoting higher education will improve the welfare of adults, as well as improve a variety of outcomes for the next generation, including education, cognitive skills, and labor market outcomes. Results show that females with college-educated parents have significantly higher odds ratios of attaining skilled occupations and earnings than males. Therefore, higher parental education helps with reducing the gender gaps in occupation-skill and earnings. Policies supporting adult literacy have economic advantages through improving the outcomes of the next generation, as well as reducing gender gaps (Chetty et al., 2018).

This study did not find any association between parental education and the probability studying STEM or the gender gap in STEM. Literature shows that male-dominated STEM fields are more associated with masculinity (Francis et al., 2017). In response to lower grades, women are less likely to persist in STEM fields than males, especially in majors strongly associated with masculinity (Francis et al., 2017). Overcoming stereotypes related to STEM fields of study (Kugler et al., 2017) as well as equal pay for equal work initiatives (Blau and Kahn, 2006; Kugler et al., 2017) have been documented as policies that help with reducing the gender gap in STEM.

This study finds strong associations between parental education and a variety of outcomes for their children. Children with higher-educated parents are more likely to attain college degrees, be employed, engage in

[24] The Head Start program is intended to provide comprehensive early childhood education, nutrition, and health, as well as parent involvement services, to low-income children and their families. This program provides a variety of programs, including: (1) Early learning: Children progress in social skills and emotional well-being, along with language and literacy learning and concept development; (2) Health: Programs connect families with medical, dental, and mental health services to ensure that children are receiving the services they need; and (3) Family well-being: Programs support and strengthen parent-child relationships and engage families around children's learning and development (Head Start Act, 2012).

skilled occupations, and receive higher quartiles of earnings. The results of this study highlight the importance of parental education and of policies improving adult literacy. In addition, redistributive policies with the purpose of shaping equal opportunities for all children help talented and hardworking children to climb up the ladder of success, regardless of their socioeconomic backgrounds (Corack, 2013). Effective educational and redistributive policies provide equal opportunities that help increase relative mobility and reduce the importance of the family background as the main determinant of children's achievements (Hilger, 2016).

6 Direction for Future Studies

To better understand the scope of intergenerational mobility, future research should investigate the relationship between parental education and other PIAAC variables, such as skill use at home and at work, as well as the relationship between parental education and health status and the ways in which their children seek health information. The results of this study suggest that children of highly educated parents are more likely to have higher literacy, numeracy, and problem-solving scores. It would be interesting to examine if highly educated parents also have healthier children. If so, this investigation would further highlight the importance of adult education in improving the outcomes of the next generation.

Some of the variables provided by PIAAC on skill use at work include frequency of influencing people, negotiating with people, working physically for long periods of time, not being challenged, solving complex problems, performing analytics, etc. Looking into these variables can shed light on more detailed impacts of parental education on the aspects of their children's jobs. For example, are children with higher parental education better influencers, negotiators, or sellers? Do they perform more analytical jobs, tend to read more, or use the internet and computers more often?

PIAAC also provides detailed information on skill use in everyday life, which highlights the degree of using cognitive skills in literacy, numeracy, and problem solving at home and in everyday life. It is interesting to see if children with higher parental education tend to read more, use calculators and advanced math or statistics more often, etc. Furthermore, variables related to "about yourself" highlight some qualities of children's characters. This set of variables provides information on learning strategies, cultural engagement, political efficacy, social trust, and health. They can add insight to investigations of whether children with higher parental education are significantly different from children with lower parental education in terms of cultural engagement, social trust, and political efficacy.

Another plan for future study could be exploring the association between parental education and children's achievements, differentiated by mothers' and fathers' educational achievement. This can help researchers and policy makers to better understand whether mothers' levels of education play a more important role than fathers' on children's achievements. To this end, testing the hypothesis of whether gender differences in the outcomes of interest discussed in this study (in particular numeracy and gender gaps in STEM-study) are lower/higher among children with higher maternal education could be considered. In addition, studying the association between parents' field of study in terms of STEM vs. non-STEM and that of their children could add insights regarding the importance of parental influence on children's decision to study STEM majors. However, the PIAAC dataset does not contain any information regarding field of study of parents.

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8 Appendix:

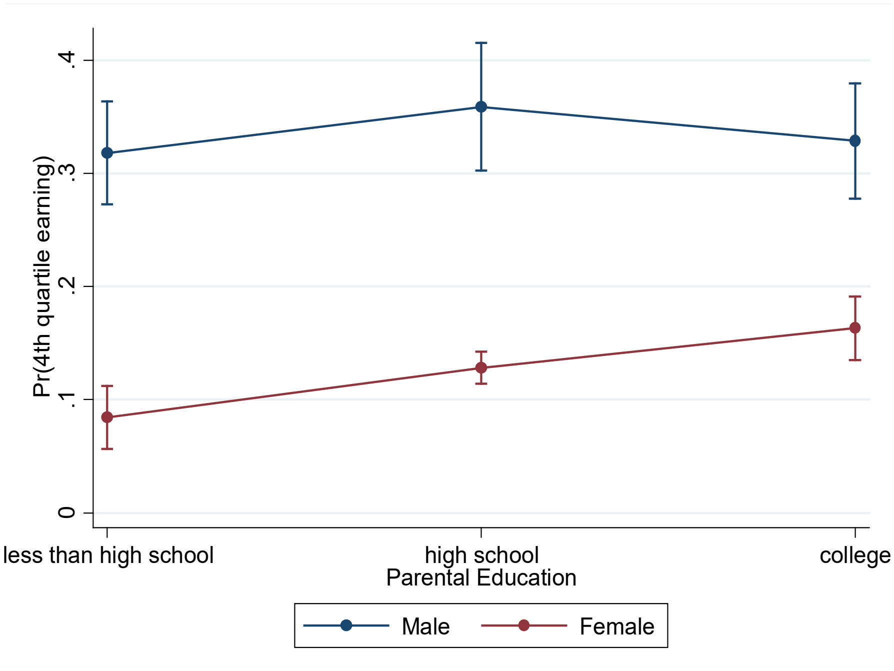

Figure A.1: Gender gap in 4^{th} quartiles of earnings

Table A.1: Predicted probabilities of parental education on likelihood of STEM-Study

	(1) Margin	(2) s.e.	(3) P-value
Parent-less than high school	0.1725	(0.0353)	<0.001
Parent-high school	0.2046	(0.0038)	<0.001
Parent-college	0.1845	(0.0046)	<0.001
Parent-less than high school * Male	0.3142	(0.0567)	<0.001
Parent-less than high school * Female	0.0931	(0.0269)	0.001
Parent-high school * Male	0.3382	(0.0084)	<0.001
Parent-high school * Female	0.1297	(0.0110)	<0.001
Parent-college * Male	0.2997	(0.0237)	<0.001
Parent-college * Female	0.1235	(0.0066)	<0.001
Parent-less than high school * Hispanic	0.0727	(0.0270)	0.007
Parent-less than high school * White	0.2007	(0.0742)	0.007
Parent-less than high school * Black	0.1380	(0.0285)	<0.001
Parent-less than high school * Other	0.2629	(0.0230)	<0.001
Parent- high school * Hispanic	0.1209	(0.0121)	<0.001
Parent- high school * White	0.2141	(0.0098)	<0.001
Parent- high school * Black	0.2110	(0.0223)	<0.001
Parent- high school * Other	0.2277	(0.0444)	<0.001
Parent-college * Hispanic	0.1328	(0.0129)	<0.001
Parent-college * White	0.1917	(0.0104)	<0.001
Parent-college * Black	0.1738	(0.0201)	<0.001
Parent-college * Other	0.2191	(0.0369)	<0.001
Control variables	yes	yes	yes

Note: All estimates controlled form age groups, gender, language, racial groups, urbanicity, and region. The number of observations is 4282. Further information on the variables and reference groups for control variables is indicated in Table 1.

Table A.2: Association between parental education and literacy

– Coefficients are in odds ratio

Literacy	**Std.**	**Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
Parent-LHS	-10.84038	1.716135	-6.32	0	-14.20395	-7.476821
Parent-college	10.0508	1.673141	6.01	0	6.771509	13.3301
25-29	-0.4245673	2.908105	-0.15	0.884	-6.124349	5.275214
30-34	-1.743654	2.285318	-0.76	0.445	-6.222795	2.735487
35-39	-2.509142	3.164604	-0.79	0.428	-8.711651	3.693367
40-44	-4.601096	3.135147	-1.47	0.142	-10.74587	1.543679
45-49	-11.77689	3.175793	-3.71	0	-18.00133	-5.552455
50-54	-6.42593	3.418021	-1.88	0.06	-13.12513	0.2732678
>55	-17.5967	2.330541	-7.55	0	-22.16448	-13.02893
Female	-1.273858	1.309455	-0.97	0.331	-3.840343	1.292627
Learned English age <15	-8.219312	3.037324	-2.71	0.007	-14.17236	-2.266267
Learned English age >=16	-36.42428	3.686873	-9.88	0	-43.65042	-29.19814
Hispanic	-18.84037	2.575634	-7.31	0	-23.88852	-13.79222
Black	-29.26541	2.225065	-13.15	0	-33.62645	-24.90436
Other	-16.36259	3.123145	-5.24	0	-22.48384	-10.24134
Suburban	0.6137217	1.822123	0.34	0.736	-2.957573	4.185016
Town	-4.680919	2.552578	-1.83	0.067	-9.68388	0.3220418
Rural	-4.747291	2.32709	-2.04	0.041	-9.308302	-0.186279
Midwest	-1.046915	2.557286	-0.41	0.682	-6.059103	3.965274
South	0.4232771	2.073862	0.2	0.838	-3.641417	4.487972
West	4.290614	2.912597	1.47	0.141	-1.417971	9.999199
Education-LHS	-31.77352	3.090183	-10.28	0	-37.83017	-25.71687
Education-college	28.42522	1.629012	17.45	0	25.23241	31.61802
Constant	281.6518	2.945816	95.61	0	275.8781	287.4255

Note: Further information on the variables and reference groups for control variables is indicated in Table 1.

Table A.3: Association between parental education and numeracy
– Coefficients are in odds ratio

Numeracy	Std.	Err.	z	P>z	[95% Conf. Interval]	
Parent-LHS	-14.45701	2.297671	-6.29	0	-18.96036	-9.953654
Parent-college	9.663177	1.803889	5.36	0	6.127618	13.19874
25-29	2.795105	2.987648	0.94	0.35	-3.060577	8.650786
30-34	1.971247	2.721448	0.72	0.469	-3.362693	7.305187
35-39	0.7370503	3.166964	0.23	0.816	-5.470085	6.944186
40-44	-2.906989	3.187456	-0.91	0.362	-9.154287	3.340309
45-49	-9.927246	3.57233	-2.78	0.005	-16.92889	-2.925608
50-54	-1.844644	3.987578	-0.46	0.644	-9.660154	5.970865
>55	-11.81245	2.760943	-4.28	0	-17.2238	-6.401101
Female	-15.07912	1.193628	-12.63	0	-17.41859	-12.73966
Learned English age <15	-3.944965	3.194054	-1.24	0.217	-10.20519	2.315266
Learned English age >=16	-17.16856	4.36533	-3.93	0	-25.72445	-8.612672
Hispanic	-21.56596	2.973577	-7.25	0	-27.39406	-15.73785
Black	-43.9051	2.732073	-16.07	0	-49.25987	-38.55034
Other	-16.11651	3.428227	-4.7	0	-22.83571	-9.397304
Suburban	0.5237723	2.041108	0.26	0.797	-3.476725	4.52427
Town	-4.890882	2.574847	-1.9	0.058	-9.937489	0.1557246
Rural	-4.384558	2.504948	-1.75	0.08	-9.294166	0.5250494
Midwest	-0.8027121	3.055506	-0.26	0.793	-6.791394	5.18597
South	1.314005	2.451472	0.54	0.592	-3.490793	6.118802
West	4.626497	3.166917	1.46	0.144	-1.580547	10.83354
Education-LHS	-34.76136	2.824565	-12.31	0	-40.29741	-29.22531
Education-college	32.58148	1.608528	20.26	0	29.42883	35.73414
Constant	270.799	3.561475	76.04	0	263.8186	277.7794

Note: Further information on the variables and reference groups for control variables is indicated in Table 1.

Table A.4: Association between parental education and problem solving

– Coefficients are in odds ratio

Problem Solving	**Std.**	**Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
Parent-LHS	-11.40733	2.316653	-4.92	0	-15.94789	-6.866774
Parent-college	6.8792	1.594603	4.31	0	3.753836	10.00456
25-29	-4.799635	2.971621	-1.62	0.106	-10.62391	1.024635
30-34	-5.583791	2.381319	-2.34	0.019	-10.25109	-0.9164919
35-39	-9.799833	2.869991	-3.41	0.001	-15.42491	-4.174755
40-44	-16.99592	3.05578	-5.56	0	-22.98514	-11.0067
45-49	-20.24265	2.669931	-7.58	0	-25.47562	-15.00969
50-54	-23.82172	2.954424	-8.06	0	-29.61228	-18.03116
>55	-32.04499	2.679986	-11.96	0	-37.29767	-26.79232
Female	-2.200936	1.507882	-1.46	0.144	-5.15633	0.7544578
Learned English age <15	-10.96155	3.203755	-3.42	0.001	-17.24079	-4.682302
Learned English age >=16	-37.08335	5.347297	-6.93	0	-47.56386	-26.60284
Hispanic	-12.37624	2.689308	-4.6	0	-17.64718	-7.105289
Black	-30.79149	2.542823	-12.11	0	-35.77533	-25.80765
Other	-15.43434	3.123668	-4.94	0	-21.55661	-9.312061
Suburban	0.6390103	2.014895	0.32	0.751	-3.310111	4.588132
Town	-3.925019	3.048467	-1.29	0.198	-9.899906	2.049867
Rural	-5.265002	2.329031	-2.26	0.024	-9.829819	-0.7001844
Midwest	-0.0121161	2.861739	0	0.997	-5.621022	5.596789
South	1.692478	2.026089	0.84	0.404	-2.278583	5.663539
West	5.19295	2.683522	1.94	0.053	-0.0666559	10.45256
Education-LHS	-22.31985	3.4669	-6.44	0	-29.11484	-15.52485
Education-college	23.10256	1.461798	15.8	0	20.23749	25.96763
Constant	286.5701	3.226624	88.81	0	280.2461	292.8942

Note: Further information on the variables and reference groups for control variables is indicated in Table 1.

Table A.5: Association between parental education and education, occupation-skills, and earnings - coefficients are in odds ratio

	(1) Education	(2) Occupation-skill	(3) Earnings
Parent-LHS	0.3426***	0.7739**	0.6945***
	(0.0539)	(0.0789)	(0.0864)
Parent-college	2.4845***	1.1636	1.1064**
	(0.3304)	(0.1212)	(0.0489)
25-29	2.2737***	1.3755***	2.3012***
	(0.1323)	(0.0647)	(0.1832)
30-34	2.4310***	1.6621***	4.0017***
	(0.1914)	(0.1910)	(0.5311)
35-39	2.6406***	1.3233*	5.5610***
	(0.2689)	(0.1907)	(0.8115)
40-44	2.4263***	1.6143***	5.2430***
	(0.1423)	(0.2740)	(1.5067)
45-49	2.8676***	1.6675***	7.2721***
	(0.1879)	(0.1711)	(1.8315)
50-54	2.4853***	2.1705***	6.6952***
	(0.1669)	(0.2838)	(1.6090)
>55	3.1843***	2.0468***	6.4552***
	(0.3302)	(0.2578)	(1.3050)
Female	1.1971**	2.1303***	0.3013***
	(0.0973)	(0.1976)	(0.0551)
Learned English age <15	2.0259***	1.0191	1.2448
	(0.2344)	(0.1449)	(0.2020)
Learned English age >=16	0.7520	0.4329***	0.6723**
	(0.1338)	(0.0778)	(0.1254)
Hispanic	0.3743***	0.8002	0.6001**
	(0.0500)	(0.2215)	(0.1346)
Black	0.4786***	0.6372***	0.6306***
	(0.0333)	(0.0559)	(0.0855)
Other	0.9277	0.8293	0.7028***
	(0.0830)	(0.1021)	(0.0430)
Suburban	0.9640	0.9568	1.2179
	(0.1313)	(0.0820)	(0.1682)
Town	0.4643***	0.7533**	0.6745***
	(0.0555)	(0.1057)	(0.0556)
Rural	0.5228***	0.4656***	0.7501***
	(0.0235)	(0.0625)	(0.0718)

Midwest	0.7491***	0.7632***	0.8227***
	(0.0140)	(0.0168)	(0.0390)
South	0.7714***	0.9009***	0.7816***
	(0.0216)	(0.0079)	(0.0185)
West	0.7991***	0.9387**	0.9330***
	(0.0104)	(0.0269)	(0.0148)
Education-LHS		0.4958***	0.5612***
		(0.0662)	(0.1019)
Education-college		6.7708***	2.4471***
		(1.0079)	(0.3225)
Occupation-skill			2.1162***
			(0.0946)

Note: Further information on the variables and reference groups for control variables is indicated in Table 1. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$.

Table A.6: Association between parental education and STEM-Study and employment status – coefficients are in odds ratio

	(1) Unemployed	(2) Out of labor force	(3) STEM-Study
Parent-LHS	1.0987	1.2491***	0.8259
	(0.1253)	(0.0743)	(0.2125)
Parent-college	0.8071*	0.7518***	0.8794***
	(0.0933)	(0.0164)	(0.0335)
25-29	0.6976***	0.7252	1.0920
	(0.0296)	(0.1587)	(0.1080)
30-34	0.5732***	1.0423	0.8780**
	(0.0590)	(0.1177)	(0.0469)
35-39	0.9431	1.1599	1.2189
	(0.0484)	(0.2239)	(0.2423)
40-44	0.7427*	1.2855	0.7943**
	(0.1331)	(0.2046)	(0.0776)
45-49	0.7238***	1.1689	0.6416***
	(0.0714)	(0.2857)	(0.0862)
50-54	0.7496***	1.2587	0.6020***
	(0.0291)	(0.2388)	(0.0484)
>55	0.5785***	6.3224***	0.6931***
	(0.0806)	(1.0185)	(0.0673)
Female	1.3015***	1.9175***	0.2998***
	(0.1013)	(0.0890)	(0.0264)
Learned English age <15	0.8891	1.2353	1.6744***
	(0.0994)	(0.2526)	(0.2158)
Learned English age >=16	0.7046	1.3462	1.9337***
	(0.2879)	(0.5280)	(0.4805)
Hispanic	1.5045	0.7457**	0.4987***
	(0.5239)	(0.0975)	(0.0867)
Black	2.7081***	1.0227	0.9446
	(0.5431)	(0.1092)	(0.0718)
Other	1.6593***	1.0991	1.2044*
	(0.0815)	(0.1873)	(0.1317)
Suburban	0.8478	0.8564	1.0490
	(0.1656)	(0.1427)	(0.0877)
Town	1.0479	1.2734	1.0095
	(0.2771)	(0.2445)	(0.1089)
Rural	0.7864	1.2367*	1.0092
	(0.1185)	(0.1406)	(0.0680)

Midwest	1.0150	0.8764***	0.8627***
	(0.0607)	(0.0256)	(0.0418)
South	0.8673***	1.1428***	0.7929***
	(0.0314)	(0.0113)	(0.0288)
West	1.2731***	0.9909	0.9069***
	(0.0552)	(0.0338)	(0.0145)
Education-LHS	0.6141***	0.4420***	—
	(0.0569)	(0.0442)	
Education-college	0.2674***	0.2431***	1.4259***
	(0.0383)	(0.0355)	(0.0296)

Note: In the estimation of the impact of parental education on STEM-Study, control variables for the educational level of the respondents are included. Respondents have either a high school education or a college degree. College degree is used as the reference group. Further information on the variables and reference groups for control variables is indicated in Table 1. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$.