AN ESSAY ON THE FACTORS OF INCOME

By

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Declaration

It is hereby declared that

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2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
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1) This material is the authors' own original work, which has not been previously published elsewhere.

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Abstract/ Executive Summary

This paper examines the effect of different factors on the composition of individuals earning by using the Panel Study of Income Dynamics (PSID) data. This paper also exhibits the contribution of individual's non-cognitive skills and first occupation on yearly real earning. The contribution towards the literature of this paper is few ways; finding real change in income due to different factors; using different categories of occupation to estimate the result; developing ability index to measure the non-cognitive skill. The result finds a strong effect of education on individuals' earnings. The result also shows other factor's importance on individual earnings and finds evidence of the contribution of first occupation and non-cognitive ability on real earnings.

Keywords: *Income; education; experience; mincer equation; non-cognitive ability*

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Chapter 1: Introduction

1.1 Background:

The composition of individual's earning is one of the major core interest areas in labor economics. Over time, the factors that affect income vary across different groups. Numerous papers use Mincer's earnings function to analyze the factors affecting income (1962). Mincer (1962) and Becker (1962) are considered the pioneers of the concept of rates of return in labor economics. They anticipated the shift in the American labor market that began in the 1970s, and Mincer (1974) proposed a model that is regarded as a significant development in the area. Mincer (1974) focused on only the wage-earning function and considered education as an investment, and analyzed the impact of education on several aspects of labor force income. Their empirical analysis emphasized on finding the rate of return to human capital, the impact of human capital investment on employment, and the trends in the structure and composition of labor force earnings. However, the role of education in wage determination changed over time. In the first half of 1980's, the returns to education increased rapidly, and which forced the economists to introduce cognitive and non-cognitive ability into the literature (Cawley et al. 1998; Angrist and Kruger, 1991; Ashenfelter and Krueger, 1994). People with the same levels of education can have different work income and career opportunities, demonstrating that non-cognitive ability is a vital component of human capital and that knowledge and skill are only one element of an individual's capabilities (Zhou, 2022). Heckman (1999) also argued that a serious bias can be created if we exclude non-cognitive skills in evaluating accumulated human capital.

Since then, many studies have been conducted to find the trends in factors that contribute to an individual's income across cohorts (Ashworth et al., 2020). More recent literature focuses on the effect of demographic characteristics, paternal attributes, cognitive and non-cognitive skill attainment on the composition of an individual's income over time. Though non-cognitive ability has significant contribution in an individual's earning, very few paper includes non-cognitive ability due to data limitation (Heckman, Lochner and Todd, 2006; Ashworth et al., 2020). Also, there is no fixed measure for non-cognitive ability. This paper takes various non-cognitive traits of the individuals from PSID dataset to construct an ability variable, while the paper cannot measure the cognitive ability directly. Moreover, this paper accounts for the individual endowments (education, experience); social endowments (parental education, parental occupation); and demographic endowments (race, gender) to find the contribution of these factors on income. The other contribution of this study to the literature is that this study estimates the change in real income. Moreover, this paper addresses the issue of endogeneity in the Mincer equation and tries to resolve this issue by examining different factors' contributions to real income. This study uses the Panel Study of Income Dynamics (PSID) data from 1968 to 2017.

1.2 Research Question:

1.2.1 How does an individual’s level of education effect the returns to education and experience (Sheepskin effect)?

1.2.2 Does individual’s first occupation influence his annual real income?

1.2.3 At what level, an individual’s annual real income is affected by his non-cognitive ability.

Chapter 2: Literature review

2.1 Changes in wage equation:

The work of Mincer (1974) has a great influence on the theoretical as well as empirical labor economics. He developed a wage equation and focused more on the effect of skills on an individual's earnings. In the Mincerian model, experience is a significant factor besides education. Besides, Mincer (1974) used different models to estimate the specific factor's contribution to an individual's earnings. In Mincer's schooling model, the role of age was not presented. However, age is an inherent reason for the depreciation of human capital. The earning structure represents the effect of age more precisely as the working life earning profile graph is concave and the degree of concavity depends on how rapidly investments decline over time (Mincer, 1974). The findings demonstrate that more educated and experienced individuals earn more money per year than their less-skilled counterparts for two reasons: their hourly wage rates are higher, and they spend more time working throughout the year (Mincer, 1974). However, in recent times, Mincer's primary human capital earning model fails to estimate the features of earning function. The data availability increased over time, and it creates the scope to address the endogeneity problem in Mincer earning function (Heckman, 2006). Heckman (2006) tried to estimate the distribution of schooling and experience as well as introduced instrumental variables to mitigate the endogeneity problem. Also, Heckman (2006) ran a more comprehensive analysis using more features (e.g., log earning-experience profile, over the life cycle the pattern of the variance of log earnings) of earnings function than the Mincer (1974) paper. The returns to education for different races across different level of schooling was also computed. The endogeneity of schooling, missing wages, and psychic costs of schooling made the Mincer model misleading. Heckman's study also controlled for different levels of education to find non-linearity in returns to schooling and sequential resolution of uncertainty.

Ashworth et al. (2020), also tried to find the change in the composition of wage across different cohorts. They used longitudinal data to accurately measure the schooling and experience and similar measures of earnings, cognitive skill, family background characteristic, personal characteristics, local labor market, and higher-education conditions for conducting their study. The NLSY79 and NLSY97, two panels of the National Longitudinal Survey of Youth (NLSY) were used to conduct this study. Their paper had three objectives – measuring returns to wage, returns to experience, and changes in the effect of cognitive and non-cognitive ability across cohorts. They found that there is a significant change in different cohorts for parents' education as recent cohort's parents are more educated than previous. However, they found the effect of family income to be insignificant. They used AFQT to measure the cognitive ability and observed that there is an increase in cognitive skill in recent cohort. Moreover, they used six subject tests from the ASVAB (Arithmetic Reasoning, Coding Speed, Mathematics Knowledge, Numerical Operations, Paragraph Comprehension, and Word Knowledge) to measure the unobserved cognitive ability. However, due to the data limitation, they were unable to include comparable measures of noncognitive ability from their cohort and only observed the panel nature of the data. Furthermore, they estimated the sheepskin effect and returns to schooling and experience across different specifications.

2.2 Non-cognitive skill's influence on wage:

A significant change in the pattern of educational attainment has been seen in the previous studies. Over time the college attendance has increased as well the professional work during the college education has also increased. This represents the increase in on-the-job (OJT) training and skills over the time (Altonji et al. (2012); Bacolod and Hotz (2006); Scott-Clayton, (2012); Bound et al., (2012)).

Non-cognitive skills comparatively get less attention in the literature than cognitive skills. At the same time, cognitive skills cannot fully explain the endogeneity in the wage equation as there are effects of unobserved personal characteristics on wages (Castex and Dechter, 2014). Castex and Dechter (2014) also observed statistically significant adverse effects of behavioral problems on later earnings. The evidence on the importance of personality and social skills in determining wages has indicated the necessity of related policy implications. The study on non-cognitive skills also creates optimism about the efficacy of interventions to improve behavioral instead of cognitive functioning (Cawley, Heckman, and Vytlacil, 2014). In recent years, few other significant studies focused on non-cognitive skills. Lee and Ohtake (2012) used agreeableness, openness to experience, conscientiousness, emotional stability, and extraversion as personal traits to measure the outcome variations in schooling and the labor market. Among them, agreeableness and conscientiousness have the most influence on an individual's earnings (Lee and Ohtake, 2012). A contrasting result is also found between the two countries and gender. For example, in Japan, women with higher confidence are preferred for managerial positions, whereas this is different for the USA (Lee and Ohtake, 2012). The five variables that Lee and Ohtake (2012) used in their paper are the five-factor model or Big Five, which is quite popular in the literature on personal traits and job performance. Mueller and Plug (2006) found a statistically significant effect of those five variables on both male and female individual earnings. Moreover, Ramos et al. (2004) describe non-cognitive skills as generic skills and categorize them into nine skill indices: leadership, literacy, physical, influencing, problem-solving, teamwork, numeracy, planning s, and emotional labor skills. Making strategic or logical decisions(decisiveness), staff development and resource management are the main factors of leadership skills. Besides, teamwork skills refer to factors, e.g., extraversion, listening to others' abilities, and helpfulness. They also described problem-solving as a logical and detailed situation analysis ability (Ramos et al., 2004). Among those skills, they found the different significance of those skills for the various working groups. The higher-income group enjoyed significant positive relationship between wage and several ability traits – leadership, problem-solving, and planning skills. In contrast, the lower-income group observed significant positive relationships between wage and physical, numerical, and influencing skills (Ramos et al., 2004). Though it was expected to get a significant positive result for influencing skill, the importance is equal for all income groups (Felstead et al., 2002). Besides, emotional labor and teamwork are mostly utilized in the low-wage working group, e.g., retail shops, food production, etc. However, Ramos et al. (2004) found utilization of all generic skills for a particular working group, indicating diverse effects on generic skills for different income groups.

2.3 Social background’s influence on wage:

Oaxaca (1973) first applied the wage decomposition method to find the gender pay discrimination in the USA by using the data of 1960 and found that the lower wage rate of females was the main reason for this discrimination. He also found that experience has more effect on earnings than age, education, and those factors explained the earning variation the most. Altonji and Blank (1999) also used the wage decomposition method to investigate the racial and gender discrimination in the labor market outcome and found an increasing trend in wage gap due to discrimination. They stated that the other indicators of the labor market e.g., unemployment rates, labor force participation, occupational location, job characteristics, non-wage compensation, and job mobility, have also faced racial and gender discrimination (Altonji and Blank, 1999). Furthermore, Bacolod and Hotz (2005) found that family background prepares an individual for his future career and notably affects future earnings. Their main focus was to find the transition from early career development through education, experience, and its future consequences as earnings. They also estimated the wage growth rate in terms of age and used the age group of 13 to 27 to estimate the result (Bacolod and Hotz, 2005). They found an improvement in educational attainment for females across the cohorts. Moreover, a female with higher education and experience has higher earnings than a male (Bacolod and Hotz, 2005; Ashworth et al., 2021). Buchinsky (1994) also observed wage inequality among different gender and skills groups. He also found evidence of changing returns of education and experience across time but experiencing similar changing trends. In fact, the gender wage gap became more extensive in the mid-1990s than in the earlier two decades (Katz, 1999).

However, those skills jointly affect the returns to education significantly. Along with the social background and cognitive ability, non-cognitive skill's significance on wage composition is also found in the literature (Lee and Ohtake, 2012; Mueller and Plug, 2006; Ramos et al., 2004). Most of the studies have some limitations to non-cognitive ability due to data availability. So, for addressing the problem of endogeneity, we are interested to add non-cognitive ability variable as otherwise the returns to education estimate will be biased. This paper tries to develop a non-cognitive ability variable by using a set of behavioral variables from the PSID data set to measure non-cognitive ability. In literature, there is evidence of using those variables partially or directly.

Chapter 3: Data

This study uses the Panel Study of Income Dynamics (PSID) data from 1968 to 2017. The dataset contains information on the social background and non-cognitive skill attainment, and demographic composition of each household in the survey. The dependent variable of this study is the log of maximum inflation-adjusted annual income (2016 dollars), which I use as a proxy of wage due to data unavailability. The independent variables of this study are sex, race, education, father's education, mother's education, age, father's occupation, first job, potential experience, and non-cognitive ability.

Non-cognitive ability variable is formed with four variables (leading, logic, independence, decisive). The ability measures variables are self-reported (score 1-7). Those variables represent, compared to other, how good an individual at those skills.

$$\text{Non-cognitive ability} = (\text{leading}+\text{logic}+\text{independence}+\text{decisive})/\ 4$$

We compute potential experience (potential experience= (Age – total years of education – 6)) (Mincer, 1974). This paper also includes race (White, Black, Hispanic, Asian); occupation (labor, operatives, sales, professionals); and educational qualification (school, high school, college, post-college).

Table 1: Descriptive Statistics

	Total		Male		Female	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Sex	1.488	.5	1	0	2	0
Race	1.359	.496	1.346	.494	1.372	.497
Father's occupation	2.293	1.091	2.29	1.09	2.296	1.092
Parent economic status	1.565	.717	1.564	.716	1.566	.718
Father's Education	1.251	.605	1.251	.6	1.251	.609
Mother's Education	1.445	.663	1.446	.664	1.443	.662
First Occupation	1.793	.802	1.793	.799	1.792	.804
Education	13.028	2.476	12.854	2.542	13.21	2.392
Age	57.089	17.781	57.187	17.658	56.987	17.909
Potential Experience	38.061	18.487	38.333	18.294	37.776	18.683
Maximum real income	38490.89	52888.627	48151.265	68224.882	28355.55	25457.608
Leading*	5.608	1.097	5.612	1.136	5.604	1.056
Logic*	5.653	1.072	5.782	1.03	5.519	1.099
Independence*	5.77	1.164	5.685	1.217	5.858	1.099
Decisive*	4.974	1.392	5.209	1.315	4.729	1.429
Mean ability*	5.501	.837	5.572	.819	5.427	.849
N	19047		9752		9295	

Note: *Total observation number: 1254 (total);641(male);613(female)

Table 1 represents the descriptive statistics of this data set. The mean value of the dependent variable, the real value of an individual's yearly income, is 38490.89 Dollars. The standard deviation for this variable is so high that the values of this variable are scattered. In our dataset, 51.20 percent of individuals are male, 64.64 percent are white, and 38.65 percent are high school graduates (Table-2). As the mean age is 57.08 which indicates a large number of mid-aged interviewees in this survey.

Table 2: Descriptive statistics for categorical variables

Variables	Dummy	Frequency	Percentage
Sex	1= male	9752	51.20
	2= female	9295	48.80
Race	1 = white	12312	64.64
	2 = black	6676	35.05
	3 = Hispanic	13	0.07
	4 = Asian	46	0.24
Father's occupation	1 = laborers	4966	26.07
	2 = operatives / kindred workers	7938	41.68
	3 = sales	1741	9.14
	4 = professionals	4402	23.11
Parental economic status	1=below average	10838	56.90
	2=average	5657	29.70
	3=above average	2552	13.40
Current_occupation	1 = laborers	3678	19.31
	2 = operatives / kindred workers	7925	41.61
	3 = sales	2089	10.97
	4 = professionals	5355	28.11
Father's education	1 = Some High School	15774	82.82
	2 = High School Graduate	1964	10.31
	3 = Some College	1117	5.86
	4 = College Graduate	192	1.01
Mother's education	1 = Some High School	12237	64.25
	2 = High School Graduate	5326	27.96
	3 = Some College	1310	6.88
	4 = College Graduate	174	0.91
First occupation	1 = laborers	8475	44.50

	2 = operatives / kindred workers 3 = sales 4 = professionals	6078 4464 30	31.91 23.44 0.16
Education	1-11 = Less than HS 12 = HS graduate 16 = College Graduate 17 = Post graduate study	2754 7362 7140 1791	14.46 38.65 37.49 9.40

Another interesting observation comes from the descriptive analysis; in the case of the first occupation, 44.50 percent of individuals were involved with labor work, whereas, currently, 19.31 percent of individuals are engaged with labor work (Table-2). This indicates the wage mobility of the working group population. Moreover, in case of family characteristics, 41.61 percent individual's father is involved with operative work. In our dataset, an individual's mother is more educated than his father and on average, individual's parents are school graduate (Table-1). On the other hand, on average individuals are high school graduate. The mean of the ability variable is 5.5 which represents that individual think, they have higher non-cognitive ability. Among the four ability measures, on average they scale lowest for decisiveness and highest for independence.

Chapter 4: Methodology

Mincer (1974), used a simple equation to estimate the effect of education and experience on income. He excluded the other factors due to data limitation. As a result, endogeneity problem created. However, later studies addressed this limitation, as with time, the data availability has increased. Moreover, as there is no fixed measure for ability, different methods were used to measure the non-cognitive skill. This paper will also try to mitigate the endogeneity problem of the mincer model by estimating several models to examine the return of different factors.

In Mincer equation, they especially focused in the return of education and experience. In our model we will estimate the effect of different educational attainments on the outcome.

$$(1)\ y_i = \ln(Y_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{2i}^2 + u_i$$

Here, y is the logarithm of the maximum reported inflation adjusted income, x_1 is the number of years of total schooling, x_2 is the potential experience (potential experience= (Age – total years of education – 6)); and u_i is the error term. Here, i represents the individuals.

We also add demographic endowments e.g. sex (x_3), race (x_4) and social endowments e.g. father's occupation (x_5), parent's economic status (x_6), father's education (x_7), mother's education(x_8) (Castex and Dechter, (2014); Bacolod and Hotz (2005)).

$$(2)\ y_i = \ln(Y_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{2i}^2 + \beta_4 x_{3i} + \beta_5 x_{4i} + \beta_6 x_{5i} + \beta_7 x_{6i} + \beta_8 x_{7i} + \beta_9 x_{8i} + u_i$$

In addition, in this paper, we add the individual's first occupation (x_9) and non-cognitive skill(x_{10}), which is highly likely to affect an individual's income. For the non-cognitive variable, we use four variables from the PSID data set (Logic, leading, independence, and decisive) to create an ability index and measure those variables' combined effect.

Our third model control for first occupation,

$$(3)\ y_i = \ln(Y_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{2i}^2 + \beta_4 x_{3i} + \beta_5 x_{4i} + \beta_6 x_{5i} + \beta_7 x_{6i} + \beta_8 x_{7i} + \beta_9 x_{8i} + \beta_{10} x_{9i} + u_i$$

Lastly, our full model is –

$$(4)\ y_i = \ln(Y_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{2i}^2 + \beta_4 x_{3i} + \beta_5 x_{4i} + \beta_6 x_{5i} + \beta_7 x_{6i} + \beta_8 x_{7i} + \beta_9 x_{8i} + \beta_{10} x_{9i} + \beta_{11} x_{10i} + u_i$$

Table- 3: Dependent and independent variables of the models

Models	M1	M2	M3	M4
Explanatory Variables/Dependent Variables	Log of annual real income	Log of annual real income	Log of annual real income	Log of annual real income
Education	□	□	□	□
Experience	□	□	□	□
Experience^2	□	□	□	□
Sex	□	□	□	□
Race	□	□	□	□
Father’s occupation	□	□	□	□
Father’s education	□	□	□	□
Mother’s education	□	□	□	□
Parent’s economic status	□	□	□	□
First occupation	□	□	□	□
Non cognitive ability	□	□	□	□

To measure the sheepskin effect, we run all the models for different educational attainment, except the full model. As the non-cognitive variables are collected for only few years, the observation number is small. So, when we run the full model and control for ability, the observation number gets smaller, which doesn’t measure the sheepskin effect correctly. We also do a likelihood ratio test to determine the better fit of the model.

Chapter 5: Findings

We have run an ordinary least square (OLS) regression analysis to estimate our model. The following findings have come out from our analysis.

5.1 Returns to education:

Table-4 represents the estimates of returns to education for different models and specification. This table also shows the sheepskin effect of graduating from school to high school. Panel (a) of the table represents the returns to an additional year of schooling for four different specifications. Firstly, for the Mincer specification, the real income increases by 11.2 percent for an additional year of education, holding all other variables constant. If we control for socioeconomic endowments in this model, the return slightly changes, and it becomes 11.3 percent. However, adding first occupation does not change the returns of education of the Mincerian equation. If controlled for ability, the return to schooling is the highest and increases to 16.4 percent. As my ability variable is self-reported, there might be upward self-reported bias which can explained this increase in the returns to schooling.

Table 4: Measures of wage returns to schooling across specification

	Coefficient	Std. Error
a)Return to years of schooling		
i. Mincer	.112***	.004
ii. Background	.113***	.004
iii. First occupation	.112***	.004
iv. Ability	.164***	.021
b)Return to less than High School education		
i. Mincer	.054***	.012
ii. Background	.069***	.011
iii. First occupation	.069***	.011
c)Return to at least high school graduation		
i. Mincer	.10***	.009
ii. Background	.098***	.009
iii. First occupation	.097***	.009

Note: *** *p<.01*, ** *p<.05*, * *p<.1*

From Table-4, section(b) and (c) show the returns to less than high school education and at least high school education, respectively, for the three different specifications. For less than high school education, the returns to schooling varies from 5.4 percent to 7 percent across the specifications.

If an individual graduate from high school (section c), his return will increase to 10 percent for the Mincer model. For the other two specifications, the return to graduating from high school is 9.8 and 9.7 percent, respectively. So, if an individual graduate from high school, his income will increase by 3 to 4.6 percent, holding all other variables constant. So, in case of an individual with less than high school education, the Mincerian specification estimates a lower return of schooling than other models. Moreover, for all the models, the coefficient of the education variable is significant at one percent level. For addressing heteroscedasticity problem, we report the robust standard error.

5.2 Returns to experience:

Table-5 estimates the returns to experience across different specifications for different educational attainment. Panel (a) shows the return of experience for all education levels. In that case, we find the highest return to experience in Mincer specification. If we include socioeconomic endowments and first occupation, the returns to education remain almost similar at 7.9 percent.

Table -5 : Measures of returns to experience across specification

	Coefficient	Std. Error
a) Return to Experience		
i. Mincer	.08***	.001
ii. Background	.079***	.001
iii. First occupation	.079***	.001
b)Returns to Graduation from High School		
i. Mincer	.072***	.002
ii. Background	.072***	.002
iii. First occupation	.072***	.002
c)Returns to Graduation from College		
i. Mincer	.10***	.003

ii. Background	.10***	.003
iii. First occupation	.10***	.003

Note: *** *p<.01, ** p<.05, * p<.1*

In panel (b) and (c), the return remains the same across specifications. However, for an individual with college degree, the real income increases to 10 percent with an additional year of experience, ceteris paribus. A college graduate earns 2.8 percent more than a high school graduate with an extra year of experience holding all other variables constant. Here, for all the models, the coefficient of the experience variable is significant at one percent level, and for addressing the heteroscedasticity problem, we report the robust standard error too.

5.3 Returns to social endowments:

Along with education and experience, literatures have found the significance of demographic and social background on earnings. In this paper, we include sex, race, father's occupation, parental education, and parental economic status to determine the effect of social background. In table-6, we estimate the social endowments without controlling for ability and first occupation. For father's occupation, we use four categories, our reference category is laborers, and this variable is significant only for two categories. An operative’s child earns 3 percent more than a laborer's child, holding all other things constant. A professional's child earns 3.9 percent more than a laborer's child, ceteris paribus. This result is quite natural as a person with a higher income can provide more facilities and opportunities, so the probability of his child's higher-income comes automatically. However, if we control for ability, the probability increases drastically; for an operative's child it becomes 24.9 percent, and for a sales person's child it becomes 29.5 percent (Table-7). This drastic change can be caused by our full model's limited number of observations. Only one category of father's education is statistically significant (Table-6). Mother's education is not statistically significant for our third model. However, for the full model the estimation results are different. In our full model (Table-7), father's education is not significant, but the mother's education is significant only for the high school graduate category. The children of parents with higher education earns higher income. The children of a high school graduate mother earn 20.6 percent more than a less than high graduate mother, holding all other things constant. Parental economic status is statistically insignificant in the full model. Ashworth et al. (2020) also found the same result for this variable. Moreover, we have used race and gender as demographic variables and both of them are statistically significant. A white individual earns 12.4 percent more than a black individual, holding all other things constant. Lastly, males lead females in earnings, and females earn 47.7 percent less than males, ceteris paribus.

Table-6 : Measures of wage returns to social background

	Coefficient	Std. Error
Father's Occupation (ref: laborers)		
Operatives	.030	.019
Sales	.039	.03
Professionals	.039	.024
Father's Education (ref: less than high school)		
High School Graduate	.060**	.025
Some College	-.034	.035
College Graduate	-.012	.074
Mother's Education (ref: less than high school)		
High School Graduate	.024	.018
Some College	-.001	.034
College Graduate	.081	.077
Socio Economic Group (ref: below average)		
Average	.017	.018
Above Average	-.068***	.025
Race (ref: white)		
Black	-.124***	.018
Hispanic	.327**	.197
Asian	.159	.164
Gender (ref: male)		
Female	-.477***	.015

Note: *** *p<.01, ** p<.05, * p<.1*

5.4 Other observations:

Our paper has some other important observations. We have added two more important variables in our model to measure their effect on individual's real earning. We include individual's first occupation in full model. We have categorized the first occupation into three categories, and all of them are statistically significant at 1 percent level. The earning increases with the level of higher position. The first occupation has significant effect on an individual's earnings. As first occupation is the starting of an individual's career, it works as a determinant of future profession. An individual whose first occupation is in the professional category earns 55.9 percent more than an individual whose first profession is laborer, ceteris paribus. We also add an ability variable to measure the effect of the non-cognitive ability. We have added this variable to our full model specification. This variable is statistically significant at 1 percent level. As this ability index is a composition of leading, logic, independence, and decisive; an individual's earning is increased by 12.8 percent with the level increase by one unit. So, with higher level of non-cognitive skills, an individual's income will also increase. We also found that the square term of the experience always belongs to the negative coefficient; this represents the diminishing marginal return of potential experience and the concavity nature of the function. After a certain age, with the higher age and years of experience, the rate of earning growth decreases.

Table-7: Regression Output: Full Model

ln_income	Coef.	St.Err.
Education	.164***	.021
Experience	.231***	.027
Experience Square	-.007***	.002
Ability	.128***	.045
Gender (ref: male)		
Female	-.189***	.069
Race (ref: white)		
Black	-.397***	.087
Hispanic	-.057	.134
Asian	-.413	.296
Father's Occupation (ref: laborers)		

Operatives	.249*		.135
Sales Professionals	.295* .09		.158 .15
Parent's Economic Status			
Average	-.065		.082
Above Average	-.089		.093
Father's Education (ref: less than high school)			
High School Graduate	.104		.095
Some College	.013		.12
College Graduate	-.065		.137
Mother's Education (ref: less than high school)			
High School Graduate	.206**		.084
Some College	.022		.116
College Graduate	.06		.133
First Occupation (ref: laborers)			
Operatives	.479***		.103
Sales	.516***		.101
Professionals	.559***		.146
Constant	4.767***		.44
Mean dependent var	9.200	SD dependent var	1.307
R-squared	0.211	Number of obs	1236
F-test	13.997	Prob > F	0.000
Akaike crit. (AIC)	3921.381	Bayesian crit. (BIC)	4039.133

Note: **** p<.01, ** p<.05, * p<.1*

We test for heteroskedasticity and detect heteroskedasticity problem. We report robust standard error in our data table to mitigate the problem. We have also tested the likelihood ratio to examine the better fit of our models. Among the four models, our full model has the best fit among all other models and the dependent variable is explained better by the independent variables.

Chapter 6: Conclusion

The main objective of this study is to estimate the contribution of different factors on earnings. We estimate our models by using PSID data across various specifications. Our regression results show that we get the highest return to education for our full model, where we include the demographic variables, non-cognitive ability, and an individual's first occupation. Returns to experience is quite similar across the specifications and slightly higher in the Mincer equation. Also, the returns to education is higher than the returns to experience across specifications. Though with a higher level of education, the returns to experience increases. So, with an additional year of experience, the earning increases more for highly educated individuals than for less educated individuals. For both education and experience, a high school graduate earns more than a non-graduate. Few of the variables of our socioeconomic endowment set were found significant. Also, if we include all social endowments, this gives our model a better fit. Race and gender are significant at 1 percent level. Aligned with the literature, we found that males earn higher than females, holding all other variables constant. Moreover, whites earn more than non-whites. Father's occupation has a significant effect on an individual's earnings. It represents that if one's father is a Professional, s/he gets more opportunities. In comparison, parental education has insignificant effect on an individual's earnings in our model. Also, our results show that parent's economic status is statistically insignificant. Furthermore, we introduced a new non-cognitive combined ability variable in our model, and the result was statistically significant. If a person has better leadership skills, more logical, work independently, and a quick decision-maker, he earns more than individuals who has less of these skills. When a person has better non-cognitive skills, he performs better and works effectively in the workplace. This paper investigates the major factors that contribute to an individual's real earnings, estimates the truer rate of return to education by reducing endogeneity, and uses a non-cognitive ability variable to find its impact on income. A rigorous analysis will be required to see the detailed sectoral contribution of those factors, which can be one significantly important research avenue.

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