LONG TERM DETERMINANTS OF INCOME: EARLY CAREER CHOICES AND THEIR EFFECT ON FUTURE INCOME

by

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ABSTRACT

BRIAN DICKERSON. Long term determinants of income: early career choices and their effect on income. (Under the direction of DR. HWAN LIN)

The purpose of this thesis was to examine how early career decisions by young adults can affect their long term career outcomes, specifically income twenty years in the future. Previous research dedicated to this area looked at short-term effects. Data was gathered from the NLSY79, which followed young adults from 1979, when each individual was between 14 and 22, through 2010. This was used to create a log-linear OLS model that contained regressors of income, unemployment, educational attainment, intelligence, gender, and race demographics.

The results showed that income, unemployment, educational attainment, and intelligence each had a statistically significant effect on income as far out as twenty years. A one hundred dollar increase in income is associated with income twenty years out by a .147% increase. A week-spent unemployed is associated with 0.813% decrease in income twenty years later. Educational attainment results suggest that an additional year of education is associated with a 6.28% increase in income and a one percent increase in AFQT percentile is associated with a .715% increase in income twenty years out. Income, education, and intelligence results held significance at a 0.001 level while unemployment held significance at a 0.05 level.

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CHAPTER 1: INTRODUCTION

I entered college during one of the worst economic climates of the past 100 years. As I was graduating in 2012, the unemployment rates for recent college graduates had gone up and stayed there while underemployment for recent college graduates hit 44% in 2012 (Abel et. al 2014). For me, and others like me, these economic conditions led to our peers taking jobs for which they were overqualified and under paid, as well as not taking jobs at all and remaining unemployed. It was this experience that led me to exploring if these choices would have long lasting effects. Would choosing to enter the job market as an underemployed college graduate who earns less than they should be an indicator of depressed wages in the future. Would choosing to remain unemployed be a signaling mechanism to future employers and lead to depressed wages? Was it still worth it to get a college education, or was the wage gap small enough that lifetime income was unaffected by educational attainment? It is these, and questions like these, that I will explore in this paper.

Past research has looked at the short-term effects of these indicators, but this paper will examine them in the long term, specifically twenty years. Also in the past, ability bias has often been overlooked or not considered fully. The effect of ability on educational returns and attainment has been explored, but its affect on income has not been examined as closely. By controlling for ability, education, and risky behavior, I examine whether lagged income and past unemployment experiences still affect income as far out as twenty years.

I am going to choose 1984 as my base year for determinants and use 2004 as my "future" income year. The base year of 1984 was chosen for two reasons. The first is that the individuals entering the labor market at that time faced similar economic conditions to those entering the labor force in the past few years. The recession in the United States created rising unemployment and a stagnated economy. The second reason to choose 1984 was that all of the individuals were between the ages of 19 and 27. This is the age at which most people enter the labor force with their first post-college jobs or their post high school jobs.

1.1 Research Question

This paper will seek to answer the following research question: Do current job and career choices affect income as far out as twenty years?

This report will answer the preceding question by exploring the relevant research to further understand the problem at hand and seek to analyze the problem most efficiently. Proper data to address the question will be gathered and manipulated for analysis. Data will come form the National Longitudinal Survey of Youth in 1979. This is a panel data set that followed young adults and teens from 1979 through 2010. A wide variety of data were gathered, including data on education, employment, income, family demographics, and aptitude testing. A model with appropriate variables will be developed using ideas and previous models found in research. Six primary explanatory variables will be considered: lagged income, past unemployment, educational attainment, intelligence, hours worked, and a risk factor. An appropriate analysis technique will be formulated and guided by theory and the data available. A log-linear OLS model was

chosen after rejecting the use of a fixed effects panel model. Finally, the analysis will be presented, along will further robustness checks, and then discussed.

1.2 Structure

The paper will be laid out in the following order. Chapter 2 will be background and literature reviews. The main papers I used as references and pulled ideas from will be laid out in detail, followed by secondary papers. Chapter 3 will be data presentation and sample statistics. I will detail the collection of the data, as well as how it was transformed for use. Chapter 4 will be methodology and I will explain the choice of my model as well as address potential drawbacks. Additionally I will present alternative models that were not useable. Chapter 5 will be results and discussion of results. These will include full robustness checks and justification for each check. Chapter 6 will conclude by recapping the findings and methods of the paper.

CHAPTER 2: LITERATURE REVIEW

In the following section, selected research and empirical studies will be reviewed and discussed. Previous research into this field has focused on the immediate and short term effects of unemployment, hours worked, income, and education on future wages and employment. This research will be detailed below. The main papers that influenced me will be introduced first, and secondary papers will follow them.

2.1 Arulampalam, Booth, and Taylor (2000)

Arulampalam, Booth, and Taylor (2000) seek to separate the effects of unobserved individual heterogeneity and state dependence in unemployment occurrences in British men.

2.1.1 Data

The used came from the British Household Panel Survey (BHPS), which is a nationally representative sample of British households. It is an annual survey that began in 1991 and continued for seven years. All sample participants were over 16 at the time of the first interview in 1991, under aged 60 at the beginning of the fifth wave, and active in the labor market in wave one. Once an individual exits the labor force, they exit the sample. This creates an unbalanced panel since individuals can only exit, not enter, the sample. Conditional probabilities of unemployment were given for wave one (1991), as well as each subsequent wave.

2.1.2 Methodology

The dependent variable, unemployment, is binary and is regressed on a vector of coefficients. To model state dependence, a one period lag of unemployment is used as a regressor. This can create a spurious regression. To control for this, a series of different lag structures are used.

2.1.3 Results

The results indicate that state dependence effects are present regarding past unemployment experiences, particularly for men aged 25 or older. This finding holds with the scarring theory of unemployment, which says that past unemployment experiences affect future labor market behavior. Additional results conclude that local labor market conditions have a negligible effect on unemployment, but rather age, health, and qualifications are more likely to affect unemployment.

2.2 Arulampalam (2001)

This is one of the main papers I used for reference. It examined one of the three main issues I looked at and used a data set very similar to the one I used. Following the findings of Arulampalam (2000), the author sought to investigate the degree of wage loss associated with spells of unemployment. Secondary questions answered include: was the wage loss temporary and if so, how long does it last; does the type or work interruption affect the wage loss; do multiple spells of interruption have increased effects on wages lost; and does only the incidence matter, or does the length of the spell matter also.

2.2.1 Data

The data used for the paper came from the British Household Panel Survey (BHPS), a nationally representative survey of 5,500 households and 7,291 observations.

The data covered the years from 1991 to 1997 and includes retrospective information on labor market history.

2.2.2 Methodology

One important econometric issue that had to be dealt with was unobserved individual heterogeneity. In the standard human capital model, tenure and experience returns are interpreted as human capital returns. Workers who have been with a firm longer are paid a higher wage because their productivity rises over time and they gain more experience in their job. Additionally, unobserved job-match heterogeneity has to be dealt with. An alternative explanation for returns to tenure and experience are selectivity and matching arguments. The selectivity argument is that better workers have better promotions and this results in higher tenure. The matching argument is that good matches between employer and employee will last longer, and with more experience comes more time to find a good match.

Tenure and experience variables are then functions of past unemployment spells and are therefore correlated with unobservable job specific and match specific variables. (Arulampalam 2001) OLS estimation produces biased estimates of the wage growth due to tenure and experience.

Given all of the above, a within group estimation is used of a log-linear wage equation. The estimation requires at least two wage observations and as a result needs individuals with employment in at least two of the waves. This creates an issue of sample selection bias, which is the second econometric issue. To correct this, a model for the probability of being in the selected sample is estimated using a reduced form probit. “A correction term (Heckman’s) is constructed using the generalized residuals (inverse

Mill's ratio) form the probit and used as an additional regressor in the wage equation to correct for selection. " (Arulampalam 2001)

2.2.3 Results

The study had three main results. First, an unemployed individual will see a decrease in wages of 5.7% in the first year, 13.5% in the next three years, and then 11.4% and falling in the years after. Second, the paper found that the first spell of unemployment has the largest effect and subsequent spells of unemployment have a less pronounced effect. Third, men who had a spell of unemployment due to a redundancy were less scarred compared to men who had a spell of unemployment due to other reasons.

2.3 Gicheva (2012)

This paper examines the relationship between weekly hours and growth in wages. Specifically, the paper looks at those individuals in the start of their careers, and who hold college degrees and work white-collar jobs. While other papers have examined the relationship between longer hours and higher pay (Charness 2004, Charness and Kuhn 2007, Fehr and Goette 2007), this paper focuses on "the intertemporal relationship between labor supply and earnings and examines the slope of the wage profile." (Gicheva 2012)

2.3.1 Data

Two sources of data were used for the paper. The main data source was a survey of those who registered for the Graduate Management Admission Test, or GMAT. The GMAT was a good primary data source because the group of people in this panel has similar backgrounds and all have college degrees. Most held white-collar jobs and are

more likely to work longer hours. Controls for ability can be gathered from educational institution and major choice.

The secondary data source used was the NLSY79. The data was restricted to college-educated workers. The secondary source was used to supplement the first and to show that the results hold outside the universe of the first data set. All wages were measured in 1991 dollars and the average age of the workers was 28 years old.

2.3.2 Methodology

The theoretical model of promotions used is a simplified version of the complete information framework model that Gibbons and Waldman (1999) used. Two job levels and two time periods are used in the model. The empirical model used to examine the relationship between long hours and wage growth follows the method used by Robinson (1988) and estimates a partial linear model.

2.3.3 Results

The relationship between hours and wage growth is not linear but rather convex. For employees who work 48 hours or more per week, working an additional five hours a week is associated with a one percent increase in wages. The relationship exists, but is much weaker, among those with less than 16 years of school, which is a college degree. Secondary findings are that the odds of receiving a promotion increase with hours worked and learning on the job.

2.4 Ferber and Waldfogel (1998)

Ferber and Waldfogel (1998) set out to investigate the effects of nontraditional employment on income and benefits. Additionally, they look at whether the returns to nontraditional work experience are different than the returns to traditional work

experience. And last, they examine to what degree are the estimates biased by unobserved heterogeneity among the workers.

2.4.1 Data

Data for the paper came from the NLSY79 and had a span of 15 years. The NLSY contains data on whether or not the respondent was employed in a nontraditional job as well as lengths of time in nontraditional jobs. The data also contains information on the jobs before and after a nontraditional job, allowing the author to examine how switching in and out of nontraditional jobs affects wage growth. Both men and women were used, ranging in age from 28 to 36.

2.4.2 Methodology

A multivariate analysis is used to examine the effect of nontraditional employment on wages. OLS models are used for the effect on wages, while probit models are used to examine the effect on benefits. To differentiate the returns between traditional and nontraditional work experience, earnings functions are re-examined with experience separated out into full-time and part-time pieces. This type of analysis is used to examine self-employment and non-self-employment experience. To examine how nontraditional employment affects wage growth instead of wage levels, a wage growth model (which has the log of wages as the dependent variable) is used and has all of the variables expressed as a first year difference.

2.4.3 Results

The results suggest that nontraditional employment in the past does have a significant effect on wages as well as benefits. Among the self-employed, the men had higher wages but were less likely to have benefits than their counterparts who held

traditional jobs. Part-time workers had lower wages and benefits. The returns to part-time experience were zero, while the returns to self-employment were positive. Additionally, the returns to incorporated self-employment were even higher. This suggests that the longer an individual is self-employed, the higher the returns. These results persist even when controlling for potential heterogeneity bias.

2.5 Further Research

Maurin and Xenogiani (2007) present evidence from the annual Labor Force Survey (LFS) that shows that French men a fall in educational attainment and achievement is associated with lower entry wages when entering the labor market. Marcotte (1998) found that the wage premium paid to senior employees has declined since the 1980s. Serneels (2005) found that seniority wage premiums were larger in bigger companies. This implies that individual characteristics like intelligence and education are becoming more important role in wage growth and levels. Serneels also finds that job level allocations are largely influenced by education.

Bachmann, Bauer, and David (2010) present evidence that labor market conditions at the time of entry can affect wage levels, which in turn can affect job mobility and turnover rate. Specifically, employees earning a below average starting wage are more likely to change jobs, both directly and indirectly. Not only that, but they are also more likely to change occupations. The results held for high, medium, and low skilled workers.

Kunze (2002) used a German longitudinal data set and found that male and female workers had a wage gap of 22%, with males earning more. Bredtmann and Otten (2010) further expand upon previous research in the gender gap in wages. The authors

found evidence that even among a homogenous group of labor market entrants, a wage gender gap still persists. The authors used a dataset comprised of university graduates in economics to eliminate some of the problems of unobserved heterogeneity.

Corcoran, Gordan, Laren, and Solon (1989) use the NLSY to examine the effects of family and community influences on men's economic status. They present evidence that black men, men from lower-income families, and men from more welfare-dependent families or communities face significant economic disadvantages. Weiss (1985) presents evidence of a wage premium associated with high school graduation. In addition, a high school degree is also associated with a lower propensity to quit one's job and lower job turnover, compared to those without the same degree.

2.6 Summary Of Findings

To summarize, unemployment has a scarring effect and future employment status, as well as depresses wages in the immediate future after the first spell. Working longer hours, among higher hour workers, is associated with wage growth and higher wage levels. Nontraditional forms of employment have varying effects on wages and benefits, and differ for men and women. Women face depressed pay when entering the labor market compared to men. More education is linked to higher entry wages and less job turnover. And family and community factors can influence wages, such as minorities receiving less in wages.

2.7 Link To Analysis

Going forward, my paper will expand upon this research and use the findings to focus my scope and analysis. I will focus on the longer-term consequences of unemployment, entry wages, and job turnover than has already been examined. I will also

include controls for gender, race, background, and educational attainment to account for the biases and wage gaps found in previous research.

CHAPTER 3: DATA

In this section, the data sample's origins, properties, and limitations will be described. A justification for the choice of variables will be given and the timeframe chosen will be justified. Then the manipulations required for using the data will be outlined. Finally, descriptive statistics for the sample will be presented and their meaning will be discussed.

3.1 Origin Of Data

All of the data in the sample were gathered from the National Longitudinal Survey of Youth (NLSY) database. The NLSY is a national representative sample of over 12000 men and woman, who range in age from 14 to 22 at the time of the first interview. There are two samples, one beginning in 1979, and on that begin in 1997. The sample chosen for this paper was the NLSY beginning in 1979 (NLSY79). This allowed for the full long term effects to be examined and tested. The survey followed the young men and women from 1979 to 2010, with new surveys every year until 1994, when the surveys began taking place every two years.

There were 12,686 individuals who participated in the original interview in 1979. Of those, 6,403 respondents were male and 6,283 respondents were female. Additionally, 2,002 respondents were Hispanic or Latino, 3,174 respondents were Black, and 7,510 respondents were non-Black and non-Hispanic. The survey questions covered topics such as geography, education history, family dynamics, income and labor, and employment status.

3.2 Description Of Data

For the purposes of this paper, only variables that inform on income, labor status and employment, or education and demographics were chosen. These variable types gave a wide-ranging view of an individual's labor market characteristics.

The income variables chosen were the respondent's family income, the respondent's income, the spouse's income, and the amount of unemployment received. These four variables give a good overview of the amount of income available to the respondent as well as the source of the income. The respondent's income variable is the primary variable for this group of variables, showing the information required for the analysis and testing. The spouse's income variable gives partial information on the income dynamics in a household while the family's income variable completes the information. This information is important to understanding where the income comes from and whether or not the respondent can afford to work less or change jobs more frequently. A respondent with no other source of income in the family is more rigid in their job and has less flexibility in looking for change. This information is important because it gives more information on the lifetime income dynamics of the respondent.

The labor status and employment variables chosen were weeks worked, hours worked, weeks unemployed, weeks out of the labor force, weeks in the military, number of jobs, occupation, and industry. These variables give an overview of whether a respondent is working or unemployed; if they are unemployed, they show for how long were they unemployed and looking for a job versus unemployed and not looking. This information is used to determine how they affect jobs, income, and employment and whether those effects persist into the long term. The occupation variable measures which

type of job the respondent has, such as a managerial job or a manual labor job. The industry variable gives the industry that the respondent works in. The occupation variable is used as a filter for the expectation the different job types will have different incomes or a higher turnover. The industry variable is used as a way to control for different incomes in different industries for the same occupation. Occupation and industry variable both came from the 1980 CPS codes. There were dozens of occupations and industries in these codes, but only a few more broad categories that each specialized industry or occupation fell into. So both variables were recoded into their broader categories to keep the codes and dummy variables from being too much to work with.

The education and demographic variables chosen were the type of home the respondent lived in, the highest amount of education achieved, family size, geographic region, marriage status, number of children, race, gender, drug use behavior, aptitude, and parent's education. These variables were all chosen to determine whether family demographics and background, educational background, and geographic region affect labor market characteristics. The drug use variables are used to create a variable to will represent a respondent's propensity for risky behavior. This information should inform on risk taking preferences, as well as potential attitude problems that could affect work performance.

One of the main goals of the paper is to find how far into the future these labor characteristics follow a person and test for potential lifelong affects to lifetime labor characteristics. In order to achieve this, the NLSY79 was chosen as it gave the longest timeframe.

3.3 Summary Statistics

To begin, basic gender and race demographics of the data sample will be examined and discussed. As seen below in table 1, basic gender and race demographics, as well as foreign language demographics are presented.

TABLE 1: Demographics by gender

		MALE	FEMALE	TOTAL
Race				
	Hispanic	49.95%	50.05%	15.78%
	Black	50.82%	49.18%	25.02%
	White	50.47%	49.53%	59.20%
Birth Country				
	U.S.	50.43%	49.57%	93.11%
	Other	51.03%	48.97%	6.89%
Home Language				
	English	50.63%	49.37%	78.03%
	Other	49.91%	50.09%	21.97%

As shown, there is a near even split across genders for all three demographic categories. The demographic categories are more varied. The majority of respondents are U.S. born English speakers, but there exists enough of a minority that a discernible difference should be recognizable if it exists. These differences will be examined in the analysis and used as dummy variables to control for any biases and differences that are present. Table 2 presents AFQT percentiles, which show scores that are more weighted towards the bottom. This is unusual because since this is a nationally representative same the percentiles should also reflect this. Instead, a majority of individuals scored below the 50^{th} percentile.

TABLE 2: AFQT percentile by gender

		MALE	FEMALE	TOTAL
AFQT Percentile				
	1% - 10%	1157	910	17.40%
	11% - 20%	837	902	14.64%
	21% - 30%	685	797	12.48%
	31% - 40%	535	618	9.71%
	41% - 50%	570	601	9.86%
	51% - 60%	444	515	8.07%
	61% - 70%	415	436	7.16%
	71% - 80%	477	442	7.74%
	81% - 90%	430	381	6.83%
	91% - 99%	401	325	6.11%

Shown in tables 3 and 4 below are demographics for 1980, as well as employment and income statistics. Except for the marriage statistics, the difference in each category between genders is minimal. This gives a good subset of respondents for each category as well as ample observations for each control group. It shows the initial starting point for each category, which will show how they evolve over time. However, this time period can't be used for analysis yet as many respondents are not 18 yet and many are still in school, so income and employment statistics are atypical for what they would experience over their professional lifetimes. Shown in table 5 is the same table for 1984, the year that will be examined to see how it affects income twenty years later in 2004.

TABLE 3: 1980 Demographics by gender

		MALE	FEMALE	TOTAL
Age				
	14-17	51.3%	48.7%	4,078
	18-20	49.8%	50.2%	4,816
	21-26	50.5%	49.5%	3,792
Geographic Region				
	Northeast	51.3%	48.7%	2,401
	North Central	50.7%	49.3%	2,874
	South	48.8%	51.2%	4,516
	West	51.1%	48.9%	2,314
Type of Living				
	Urban	50.9%	49.1%	10,249
	Rural	48.7%	51.3%	2,437
Marriage Status				
	Never Married	53.8%	46.2%	10,025
	Married	34.4%	65.6%	1,827
	Separated	24.5%	75.5%	278
	Widowed	11.1%	88.9%	9
Employment Status				
	Employed	52.7%	47.3%	5,733
	Unemployed	53.0%	47.0%	1,766
	Out of Labor Force	40.6%	59.4%	3,648
	Armed Forces	66.1%	33.9%	994

TABLE 4: 1980 Employment and income statistics

Variable	Obs	Mean	Std.Dev.	Min-Max
Hours Worked	9432	836.2429	805	0 - 4669
Weeks Worked	9691	25.30358	20	0-52
Weeks Unemployed	8149	3.948705	8.200023	0-52
Weeks Out of Labor Force	8149	22	20.456	0-52
Weeks in Military	1201	45.73272	11.65723	2-52
Income	8246	3257.446	4267.454	0-67500
Spouse Wage	1622	5887.263	6611.068	0-75001
Family Income	9891	16,939	13920.79	0-75001

TABLE 5: 1984 Demographics by gender				
		1984		
		MALE	FEMALE	TOTAL
Age				
	19	53.16%	46.84%	948
	20	51.53%	48.47%	1,566
	21	49.94%	50.06%	1,564
	22	50.10%	49.90%	1,505
	23	50.61%	49.39%	1,634
	24	48.66%	51.34%	1,677
	25	50.09%	49.91%	1,667
	26	49.11%	50.89%	1,682
	27	57.11%	42.89%	443
Geographic Region				
	Northeast	51.48%	48.52%	2,263
	North Central	50.15%	49.85%	2,690
	South	48.58%	51.42%	4,487
	West	51.60%	48.40%	2,444
Type of Living				
	Urban	50.61%	49.39%	10,525
	Rural	49.79%	50.21%	2,161
Marriage Status				
	Never Married	56.83%	43.17%	7,093
	Married	42.06%	57.94%	4,099
	Separated	34.04%	65.96%	855
	Widowed	42.86%	57.14%	21
Employment Status				
	Employed	53.48%	46.52%	7,562
	Unemployed	54.09%	45.91%	1,394
	Out of Labor Force	30.13%	69.87%	2,406
	Armed Forces	75.25%	24.75%	707

Parents Education Attainment		
	Mom	Dad
HS Graduate	53.56%	49.07%
College Graduate	6.90%	12.02%

CHAPTER 4: METHODOLOGY

This section will detail the model selection process and discuss alternative approaches that were considered but discarded.

First, a clear objective had to be obtained. Future income was chosen as the factor to examine twenty years out because as far as job characteristics go, it is the most prominent, the easiest to identify and catalog, as well as the most objective. Other factors considered were unemployment and job turnover. The most glaring problem with each of these was the lack of information about the cause of the unemployment or job turnover. This is a very important distinction. An individual choosing to become unemployed or to leave the labor force versus a person who is forced to do so should have different reasons for doing so, and therefore have a different set of both observable and unobservable characteristics. With no way to identify who is who, the model would be biased.

Once income was established as the long-term factor that will be explored, a model had to be created. The creation of the model pulled from various models that were discussed in detail in the research section of this project. The first regressor chosen for the model was lagged income. This was a natural choice since income is often lag-dependent, as most time series financial variables are. Additionally, without income as a regressor, it is likely that the effect of all other regressor could be overstated. Income should act as a signaling device to future employers about perceived worth.

The second regressor chosen was unemployment. Arulampalam (2001) showed that unemployment followed individuals through time and inflicted a negative penalty on

income. While the study only followed individuals for a couple of years, I will attempt to extend this further by going out twenty years.

The third regressor chosen was educational attainment. Julian and Kominski (2001) show that education levels can affect income by as much as $ 40,000 a year when comparing high school dropouts to college graduates. This variable will help control for biases in income and unemployment, as without a check on education, these would be biased. For example, an individual with more unemployment or lower income could also have less education. By controlling for that, the bias is partially eliminated.

The fourth regressor chosen was aptitude, which, for the purposes of this project, will be synonymous with intelligence. This is required to eliminate any ability bias that exists without it. If this variable was missing, the effect of education could be overstated. Willis and Rosen (1979) showed that unobservable characteristics such as intelligence could cause estimators to be erroneous. This variable should, in conjunction with the educational attainment variable, eliminate the bias in income and unemployment that arises from unseen characteristics.

The remaining regressors are all dummy variables that contain information on gender, race, and whether the individual was born in a foreign country or spoke a foreign language at home. These were added to control for gender and race biases. Additionally, a foreign language and birth variable was created to control for those who were born outside the United States or who were raised in a home speaking a language other than English. This could lead to this group having lower income if employers held a bias against foreign-born workers. The other possibility is that foreign-born workers have a job visa and are more likely to stay with their job or work harder to keep it knowing that

losing their job puts their immigration status in question. This in turn means longer tenure with a company and higher income.

Once the model had been set, the type of analysis used had to be chosen. One issue that had to be dealt with in the model selection was unobserved variable bias. My first thought on dealing with this was to use a simple first difference model. However, this was later rejected, as lag dependent variable models are not static and therefore not applicable to fixed effects models. Since I defined income as an essential part of the model, any fixed effects model is unavailable to use.

In light of this fact, a log-linear OLS model was used as it allowed for the use of lagged income as a regressor. Since unobserved variable bias could very well still be present, I will attempt to control for this by including enough explanatory variables to catch unobserved variable bias. The primary purpose of the model extensions was to further this goal. They included numerous other explanatory variables, each exploring a new factor of income determination. These factors were varied, and involved checks for geographic region, types of home living, industry, and occupation checks, as well as other employment and job characteristics.

Another potential issue with the model was multicollinearity. If income in the future were influenced by intelligence and educational attainment, it makes sense that income would be influenced by those factors early in an individual's career also. Although they are not substitutes for one another, they might be correlated enough to pose problems. Despite this risk, educational attainment and intelligence factors had to be in the model for it to be complete. Also, they kept the effect of income on future income

from being overstated or biased. However, to check that no large or critical issues existed, variance inflation factors were checked and can be seen below in table 6.

TABLE 6: VIF		
Variable	VIF	1/VIF
AFQT	1.69	0.59024
Education Attainment	1.38	0.726029
Black	1.27	0.78576
1984 Income	1.1	0.912304
1984 Weeks Unemployed	1.09	0.913545
Foreign	1.06	0.946535
Female	1.03	0.974916
Mean VIF	1.23	

It is clearly shown that each explanatory variable in the primary model has a low VIF and therefore is no cause for concern.

As mentioned previously, additional factors were introduced into the main model to add explanatory variables and to check for other income determination factors. The two primary model extensions came from adding hours worked for the income year being tested and adding a risk factor variable to control for unobserved behavior problems and decision making skills.

The hours worked variable was added purely because it is a strong determining factor in assessing income. Obviously for hourly employees, but also for salaried employees, longer hours are associated with higher pay. This was important to add because once it was added, the model had to be retested to examine whether the previously used model still held.

The risky behavior variable added a crucial missing factor to the model. Unobserved characteristics such as behavior or attitude problems could adversely affect income as well as employment. Individuals who can't keep a job because they drink, or those who can't get along with their co-workers, will likely have more unemployment and lower income because they are more likely to have been passed over for promotions and bonuses. The risk variable allowed me to capture this type of affect and control for it.

CHAPTER 5: ANALYSIS

In this section, the results of the primary model will be presented and discussed. Relevant findings will be highlighted. Following that, robustness checks will be presented and reviewed. These will include additional potential determinants of wage, as well as additional model specifications.

5.1 Model Specification

The main question examined in this paper is whether future wages are affected by current wages and employment status. To answer this, the following model specification is used.

$$\ln W_{i25} = \beta W_{i5} + \beta U_{i5} + \beta E_{i5} + \beta Z_i + \varepsilon_i \qquad (1)$$

In equation 1, ln (W_{i25}) is the log of income in 2004 for individual i, W_{i5} is income in 1984 for individual i, U_{i5} is weeks spent unemployed in 1984 for individual i, E_{i5} is educational attainment in 1984 for individual i, and Z_i is a vector of variables for individual i that include gender, race, and intelligence scores.

That income is a determinant of future income is a safe assumption, as previous research has found that income is certainly lag dependent; however, the length of the effect is what I am trying to determine here. I also include unemployment, which Arulampalam (2001) showed has a persistent negative effect on income. However, only a few years after the unemployment occurrence were examined; I seek to examine a longer timeframe. Educational attainment is another important factor to consider when analyzing income, and as such it is included here. The remaining variables are time invariant and

include dummies for gender and race as well as AFQT percentile scores to measure aptitude, which will substitute for intelligence.

It is expected that both income in 1984 as well as educational attainment will have positive coefficients, since increasing income early should lead to higher income later and receiving more education should increase lifetime income. Conversely, unemployment in 1984 should lead to negative future income and as such should have a negative coefficient. This again has been shown to have negative impacts on income. Additionally, a higher AFQT percentile score is expected to have a positive effect on income, as more intelligent individuals and those with a higher aptitude for learning will gain job specific and firm specific knowledge quicker and more efficiently, as well as use that knowledge more efficiently.

Equation (1) will be the starting point from which further equations will be based. Another explanatory variable that will affect income in 2004 is the time spent working in 2004. To account for this, hours worked in 2004 will be added as an explanatory variable in model 2. The third model will also include a risk variable, which will ideally capture whether or not a respondent can't keep a job or has depressed job performances due to behavior and attitude issues. As stated previously, the dependent variable for each of the three models will be the log of income in 2004. The full results of the three models can be seen below in table 7.

TABLE 7: Primary results

	Model (1)	Model (2)	Model (3)
Income 1984	0.0000147***	0.0000114**	0.0000113**
	(4.16)	(3.30)	(3.28)
Unemployed 1984	-0.0106*	-0.00809*	-0.00832*
	(-2.55)	(-2.25)	(-2.31)
High Grade Completed	0.0628***	0.0514***	0.0521***
	(4.33)	(3.72)	(3.77)
Female	-0.456***	-0.324***	-0.319***
	(-10.05)	(-7.79)	(-7.61)
Foreign	0.192**	0.143*	0.152*
	(2.62)	(2.17)	(2.30)
Black	0.146**	0.0877	0.0952
	(2.61)	(1.63)	(1.77)
AFQT Percentile	0.00715***	0.00714***	0.00700***
	(7.04)	(7.58)	(7.36)
Hours Worked 2004		0.000355***	0.000358***
		(8.30)	(8.33)
Risky Behavior			0.0709
			(1.65)
Constant	9.499***	8.887***	8.845***
	(53.32)	(45.41)	(44.66)
Observations	1079	1065	1065

t statistics in parentheses
Source: NLSY79
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As shown above, income in 1984 is always individually statistically significant at the 0.01 level, with model one being significant at the 0.001 level. In addition, as

predicted, the coefficients were positive in each model. A one-dollar increase in 1984 income is associated with a .00147% increase in 2004 income. Or a more practical interpretation is a one hundred dollar increase in 1984 income would signify a .147% increase in 2004 income. The coefficients on AFQT percentile score and educational attainment were also positive, as predicted, as well as individually statistically significant at the 0.001 level. They suggest that an additional year of education results in a 6.28% increase in income and a one percent increase in AFQT percentile results in a .715% increase in income. This suggests that it is possible that educational attainment is more important to income than intelligence. The coefficient on the dummy variable for female was negative, as would be expected, and was individually statistically significant at the 0.001 level.

As shown, income, unemployment, education, and intelligence have a lasting effect on income for young adults, going out at least as far as twenty years. One explanation for this is that income is acting as a signaling device for the market. An individual's entry wage is an objective numerical evaluation of an employee's worth at that time, and future employers might look to this and come to conclusions based on this number. An underpaid young adult entering the labor force might be viewed as having a lower perceived worth, and that perceived worth acts as a signal to future employers.

A lengthy spell of unemployment also potentially acts as a signaling device to the market that there is something missing or wrong with a particular candidate. As the length of the unemployment spell increases, employers might wonder why it took so long for the individual to find another job. It potentially signals some unobservable trait or set of traits that employers would find undesirable.

Education can act as a signaling device of a combination of intelligence and work ethic. Since intelligence can't be quantified on a resume, or fully discovered through an interview, education can often be viewed as a proxy for it, where more educational attainment means higher intelligence. In addition to specific training and knowledge received in college, a degree might also signal the ability to adapt and to learn new material quickly. This is important for all jobs, but especially more technical jobs, where the information learned on the job is very specific and can be challenging. Therefore, a candidate with a certain perceived level of intelligence is more likely to get the job and, as a result, be paid more for it.

In the second model, once hours worked is added in, the magnitude of the effects on 2004 income is slightly dampened, but it still exists and is still significant at the same level. This is true of all of the variables except for the dummy variable representing whether or not the respondent was black. This variable loses significance when hours worked are accounted for, suggesting no statistical difference between the incomes of black and non-black individuals. This all fits with what would be expected. The amount of time spent working in a year will likely always be strongly correlated with income. For an hourly employee, more hours mean higher wages. For a salaried employee, higher wages are associated with longer hours. In this case, there might exist a phenomenon where an individual is paid a high wage, and as a result feels some unseen pressure to work longer hours to justify their pay.

The third model adds the risk variable, seeking to capture those more prone to risky behavior and attitude problems. This variable would ideally capture this effect and account for individuals who can't hold a job for unseen reasons, or those who are passed

over for promotions and bonuses because of unobservable characteristics. After running the third model, the risk variable is found to be statistically insignificant, thereby not adding any more information. The previous explanatory variables keep their signs and remain just as statistically significant as they were previously.

5.2 Recap

When all of the information is analyzed, it becomes clear that forces going as far back as twenty years affect future income in young adults. All of the individuals in 1984 were between the ages of 19 and 27, which gives a good mix of college graduates and those who went to work at age 18, with and without high school diplomas. This age group of young adults was chosen because the explanatory variables for this group should be the most relevant to future income. They have no work history, and these variables should be best at signaling for future employers. Later in life once the respondents are older, intelligence and education should matter less and past work performances along with income will be more prominent a factor in future income.

Income in the past, educational attainment, intelligence, unemployment, and gender each had the same level of significance in each of the three models. From this, it can be safely assumed that they are significant determinants of future income for young adults. Going forward, I will check to see that these results remain when other explanatory variables are added and additional models are examined.

5.3 Robustness Checks

Now that the main model has been examined and tested, additional models and extensions of the first model will be explored.

The first model extension I will examine will control for industry and occupation.

The variables for industry and occupation do not extend out into 2004, so a new model will be created to test that income, unemployment, educational attainment and aptitude still factor into future income when accounting for industry and occupation. The new model will keep the same 1984 variables, but will look ten years out at income in 1994. The industry and occupation variables will also be 1994 variables. While this is not a perfect check to examine whether the results still hold when adding occupation and industry factors, it will provide sufficient enough data to make a safe assumption that they will.

First, occupation will be added and discussed. There were seven major occupation categories in the data; so six dummy variables were created. Each of the six dummies is compared against someone in a managerial service job. As shown in table 8 below, three of the six occupations have a statically significant impact on income. The three occupation categories were technical jobs, service jobs, and farming jobs. Both service jobs and farming jobs had negative coefficients, while technical jobs had a positive coefficient. This makes sense, because when compared to someone in a managerial job, those working farming and service jobs would be expected to earn less. Also, those in technical jobs often earn more income because of the advanced training required to obtain them.

It is shown clearly that even when accounting for occupation, the early life factors are still relevant. Previous income and unemployment are still very highly statically significant, as are education and aptitude.

TABLE 8: Robustness checks - occupation

	Model (4)	
Technical Job	0.168**	(2.71)
Sales Job	-0.0523	(-0.81)
Administrative Job	-0.0506	(-0.98)
Service Job	-0.370***	(-4.16)
Farming Job	-0.714**	(-3.13)
Production/Manual Labor	-0.0686	(-1.07)
Hours Worked 1994	0.000698***	(12.71)
Income 1984	0.0000113***	(3.31)
Unemployed 1984	-0.00892**	(-2.83)
High Grade Completed	0.0329*	(2.37)
Female	-0.151***	(-3.89)
Foreign	0.153*	(2.51)
Black	0.0153	(0.30)
AFQT Percentile	0.00443***	(4.79)
Constant	7.963***	(38.35)
Observations	1231	

t statistics in parentheses
Source: NLSY79
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Now that occupation has been added and explored, and it has been found to have no impact on the previous results, industry factors will be added. The industry against which all others will be compared is retail trade. It was chosen because it was the most common industry for the individuals. Results will be shown in table 9 below.

TABLE 9: Robustness checks - industry

	Model (5)	
Agriculture	-0.340	(-1.42)
Mining	0.433***	(3.33)
Construction	0.131	(1.03)
Manufacturing	0.362***	(4.46)
Transportation/Comm/Utilities	0.377***	(4.10)
Wholesale Trade	0.274	(1.77)
Finance/Insurance/Real Estate	0.345***	(3.93)
Business Services	0.105	(1.03)
Personal Services	-0.413*	(-2.14)
Entertainment/Rec Services	0.214	(1.30)
Professional Services	0.186*	(2.19)
Public Administration	0.260**	(2.62)
Hours Worked 1994	0.000683***	(12.98)
Income 1984	0.00000990**	(2.97)
Unemployed 1984	-0.0102**	(-3.27)
High Grade Completed	0.0393**	(2.75)
Female	-0.135***	(-3.48)
Foreign	0.172**	(2.82)
Black	-0.00330	(-0.06)
AFQT Percentile	0.00472***	(5.36)
Constant	7.655***	(40.14)
Observations	1231	

t statistics in parentheses
Source: NLSY79
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As previously mentioned, there were 13 distinct industry classifications, meaning 12 dummy variables were created. Of those 12 variables, seven were statistically significant. Those seven were (1) mining, (2) manufacturing, (3) transportation, communications, utilities, (4) finance, insurance, real estate, (5) personal services, (6) professional services, and (7) public administration. Of the seven industries that had a statistically significant effect on income, six had a positive effect, while only the personal services industry had a negative effect. This is a reasonable outcome given the industry classifications. The retail trade category, against which all other categories are compared, often has employees who are paid hourly near the minimum wage (Addison et. al 2008). This is about the lowest wage an individual can be paid, so having other industries paid more makes sense. It also fits that the personal services industry would earn less, since those in that industry are often paid a flat rate for a job, regardless of hours spent on the job. Also, those in this category that do earn an hourly wage would also make the minimum wage.

Conversely, the same logic follows that those in the other six industries would make more, since they earn above the minimum wage. Each of the six categories has employees who either earns an annual salary, or is paid hourly but above the minimum wage. In the mining industry, workers are paid well to compensate for dangerous working conditions. In general, working in each of the significant categories requires specialized skills and industry specific knowledge that rewards employees with higher wages.

It is clearly shown, as is the case with occupation, that adding industry controls for income does not affect previous results. Lagged income, past unemployment,

educational attainment, and aptitude still remain relevant to future income. However, it is worth noting that the effect of past income is slightly dampened by adding industry factors, and is only statistically significant at the 0.01 level instead of the 0.001 level it had been significant to previously.

Now results that include both industry and occupation factors will be examined in table 10 below.

TABLE 10: Robustness checks -occupation and industry

	Model (4)	
Technical Job	0.139*	(2.25)
Sales Job	-0.0384	(-0.53)
Administrative Job	-0.123*	(-2.38)
Service Job	-0.228**	(-2.66)
Farming Job	-0.651***	(-3.45)
Production and Manual Labor	-0.146*	(-2.07)
Agriculture	0.0895	(0.45)
Mining	0.413**	(3.12)
Construction	0.178	(1.29)
Manufactoring	0.372***	(4.18)
Tran/Comm/Utilities	0.405***	(4.14)
Wholesale Trade	0.301	(1.93)
Fin/Insur/Real Estate	0.348***	(3.82)
Business Services	0.112	(1.06)
Personal Services	-0.286	(-1.44)
Ent/Rec Services	0.206	(1.22)
Professional Services	0.159	(1.69)
Public Administration	0.282**	(2.66)
Hours Worked 1994	0.000680***	(12.85)
Income 1984	0.00000952**	(2.83)
Unemployed 1984	-0.0100**	(-3.20)
High Grade Completed	0.0328*	(2.29)
Female	-0.140***	(-3.57)
Foreign	0.151*	(2.47)
Black	0.00314	(0.06)
AFQT Percentile	0.00394***	(4.35)
Constant	7.852***	(38.21)
Observations	1231	

t statistics in parentheses
Source: NLSY79
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When industry and occupation factors are added together into the model, the results change slightly, but have a negligible impact. In the industry factors, both personal and professional services industries lose significance. In the occupation factors, administrative and production and manual labor jobs gain significance. The same logic discussed above applies to this new model. Also, just as above, the same income, unemployment, education, and aptitude factors remain significant.

The next model extension will look for differences in income based on geographic region in the United States. There are four primary geographic regions: northeast, north central, south, and west. The base group will be those in the northeast. Additionally, controls for an urban environment versus a rural environment will be added. Cost of living in urban areas is higher than rural areas, so wages should mirror this. Table 11 will explore this possibility.

TABLE 11: Robustness checks - region

	Model (7)	
Lived in Urban Area	0.0249	(0.56)
Lived in North Central US	-0.147*	(-2.06)
Lived in South US	-0.0618	(-0.97)
Lived in West US	-0.0211	(-0.29)
2004 hourswork	0.000356***	(8.29)
Income 1984	0.0000109**	(3.13)
Unemployed 1984	-0.00801*	(-2.22)
High Grade Completed	0.0508***	(3.69)
Female	-0.327***	(-7.79)
Foreign	0.120	(1.72)
Black	0.0864	(1.56)
AFQT Percentile	0.00723***	(7.55)
Constant	8.939***	(44.02)
Observations	1056	

t statistics in parentheses
Source: NLSY79
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The only added geographic region that has statistical significance is living in the north central region of the country. The four main explanatory factors of income, unemployment, education, and aptitude remain significant.

5.4 Additional Checks And Models

In this section, additional models will be shown and briefly discussed, but not as in depth as previous models. The models shown and discussed here impacted the primary model in a discernable sense.

One thought had been to explore how parent's educational attainment affected income for the individual. The thought behind it was that more successful parents would have more education, leading them to earn a higher income. This would translate to more successful children, who would themselves attain more education and therefore a higher wage. These variables were excluded because they were captured in the individual's educational attainment variable. Table 12 shows this relationship.

TABLE 12: Robustness checks - educational attainment

	Model (4)	
Mom HS Graduate	0.246***	(3.53)
Mom College Graduate	0.305***	(3.54)
Dad HS Gradute	0.0710	(1.02)
Dad College Graduate	0.164*	(2.16)
AFQT Percentile	0.0284***	(26.83)
Constant	11.84***	(199.85)
Observations	3172	

t statistics in parentheses
Source: NLSY79
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

One more check to examine is how the addition of job turnover affects income. Those with higher job turnover could be signaling to employers a lack of dedication to a job, or lack of ability, either of which could lead to lower wages. Also, individuals with

higher job turnover don't have the time at a single company to accumulate raises and bonuses, or the time to acquire the firm specific knowledge often required for promotions. Each additional job an individual held in 2003 is associated with a 28.5% decrease in 2004 income. Table 13 below shows full results for this model.

TABLE 13: Job turnover

	Model (1)	
Number of Job Changes 2003	-0.285***	(-7.00)
Risky Behavior	0.0600	(1.42)
Hours Worked 2004	0.000418***	(9.95)
Income 1984	0.0000110**	(3.27)
Unemployed 1984	-0.00813*	(-2.25)
High Grade Completed	0.0539***	(3.92)
Female	-0.297***	(-7.16)
Foreign	0.154*	(2.27)
Black	0.107*	(2.03)
AFQT Percentile	0.00684***	(7.26)
Constant	9.032***	(46.14)
Observations	1065	

t statistics in parentheses
Source: NLSY79
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.5 Sub-conclusion

To recap, job and employee decisions and factors can influence income as far out as twenty years. A one hundred dollar increase in income is associated with income twenty years later by a .147% increase. A week spent unemployed is associated with 0.813% decrease in income twenty years later. Educational attainment results suggest that an additional year of education is associated with a 6.28% increase in income and a one percent increase in AFQT percentile is associated with a .715% increase in income twenty years out.

These results hold significance, although are slightly dampened, when industry

and occupational factors are considered. The same is true when geographic and regional factors are considered, as well as job turnover and

CHAPTER 6: CONCLUSION

The purpose of this thesis was to examine whether early career decisions made by young adults have long lasting effects on income, and if so, what types of decisions have the most significant effects.

If decisions made in young adulthood, typically those made after graduating college or high school, do affect income as far as twenty years out, then it is as important as ever to be sure to make those decisions wisely. Take for example young adults in the last six years since the economic downturn of 2008. College graduates have seen increased unemployment rates, which have led them to find jobs for which they are over qualified. As this underemployment of college graduates grows, they push those without college degrees out of jobs that they had previously been employed in. This unemployment and underemployment leads to negative income effects that persist as far out as twenty years, just like that unemployment for those being pushed out of jobs or those not finding jobs will affect their careers for a long time going forward.

Using data collected from the NLSY79, I created a log-linear OLS model to explore and analyze the effects of income, unemployment, educational attainment, intelligence, as well as other control factors on income twenty years out. I used 1984 as my base year and 2004 as my "future" year. The purpose of this was to see how early career decisions made by young adults affect their future career outcomes much later in life. I found that income, unemployment, educational attainment, and intelligence each affect income as far out as twenty years at a high statistical significance. A one hundred

dollar increase in income is associated with income twenty years out by a .147% increase. A week-spent unemployed is associated with 0.813% decrease in income twenty years later. Educational attainment results suggest that an additional year of education is associated with a 6.28% increase in income and a one percent increase in AFQT percentile is associated with a .715% increase in income twenty years out. Income, education, and intelligence results held significance at a 0.001 level while unemployment held significance at a 0.05 level.

I then introduced more controlling factors and potential determinants of income and found that even after the introduction of these controls the previous four factors remained significant determinants of income. Of particular note was that control for risky behavior did not have a significant effect on income. This could be due to the limited data available for this behavior, as I used drug use as a teenager as a proxy for risky behavior. One additional regressor that once added remained significant was hours worked in the future.

6.1 Further Research

Going forward, there are certainly areas to improve upon research done in this paper. The first would be to find a better and more complete substitute for the risky behavior variable. My variable was based on drug use as teenagers. However, since all respondents would have been teenagers in the 1980s, it is possible that since the full dangers of marijuana and cocaine were not realized or that the knowledge was not widespread, and as such teenagers would not have viewed their use as a risk.

Another area of improvement would be to also gather data on college major, college GPA, and college attended. These effects could contribute highly to entry wages, which in turn would affect future income.

A third area of improvement could come from a more thorough breakdown of income in the base year. If, for example, bonuses could be differentiated from base salary, a clearer picture of the type of employee the individual is could be gather. For instance, a worker with high bonuses each year could have some workplace characteristics that are unobservable that influence their income. This distinction would help with the unobserved variable bias problems.

Overall, the model could benefit from a more thorough data source that includes the previously mentioned variables. This would eliminate the biggest shortcoming of the model, which is unobserved variable bias. Although numerous explanatory variables were added, and the number of observations for each model tested was high, it is likely there is still some amount of unobserved variable bias. With that said, the model still holds weight as the main results were corroborated in every model, adding strength to the conclusion that early career decisions do indeed affect young adults as far out as twenty years.

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