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Determinants of Income : Hours, Alcohol and Non-cognitive Skills

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DETERMINANTS OF INCOME : HOURS, ALCOHOL AND NON-COGNITIVE SKILLS

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ABSTRACT

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The determinants of income has been a key area of research in labor economics, and a large part of this has focused on the relationship between education and wages. This ignores the many other ways that income is influenced. I explore additional avenues by which income is determined. I examine how education affects income by influencing the hours of work rather than wages directly. Next explore the mechanism that determines the relationship between drinking and income. And finally I continue exploring the importance of non-cognitive and other skills, particularly as they relate to job sorting and therefore determine income

The first chapter uniquely documents the emerging role of education in the well known decline in U.S. male working hours. An insignificant hours difference between high school and college graduates becomes a highly significant 2 hours/week advantage for college graduates within a generation. This growing *college hours premium* is confirmed in alternate data over a longer time period. Moreover, the growing premium exists throughout the distribution and is not generated by the tails. The increasing premium persists across a wide variety of robustness checks and presents as a widespread phenomenon. The emerging college hours premium increases the overall *college earnings premium* despite recent trends in the *college wage premium*.

The second chapter uniquely shows that the returns to drinking in social jobs exceed those in non-social jobs. While workers' social skills yield higher returns in social jobs, controlling for these skills does not change the returns to drinking. This suggests a return beyond sorting on measured social skills. The higher returns in social jobs remain when including individual fixed effects and in a series of robustness exercises. The findings fit the hypothesis that drinking assists the formation of social capital in social jobs. The social capital associated with drinking represents both general and specific capital with a higher return to each in social jobs.

The third chapter examines the relationship between education and the changes to occupational sorting in the US. I show a college degree is associated with sorting into all high skill occupations, but is less associated with sorting into high social skill occupations within one generation. I uniquely show that when considering the importance in skills in job sorting, the relationship between both social and math skills determines sorting for the latter generation.

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Lastly, I dedicate this dissertation to my mother Kavitha, father Venkatesh, and sister Shraveena who were always with me despite the distance between us.

Chapter 1

THE EMERGING COLLEGE HOURS PREMIUM FOR MEN

1.1 Introduction

The returns to college have been under increasing scrutiny as the demand for skills has changed. The most common focus has been the *college wage premium*. Yet, any labor income difference depends on both relative wages and relative hours (Kuhn and Lozano, 2008). Men working in the U.S. are working fewer hours than they used to, particularly younger workers (Ramey and Francis, 2009). Left unexplored is how education might influence this decline.

This paper uses two cohorts of the National Longitudinal Survey of Youth (NLSY) to uniquely document the emergence of a *college hours premium*. Among young male workers in the NLSY79 there exists no difference in hours by college degree status. In the NLSY97 college graduates work two hours per week more than high school graduates. The college hours premium is statistically significant and present across the entire distribution of hours worked. It is not driven only by those working part-time or overtime. The college hours premium is in fact greatest in the middle of the distribution of hours worked.

The American Community Survey (ACS) and Current Population Survey (CPS) data confirm the results. Ten five-year birth cohorts between 1940 and 1990 in the ACS and 6 five-year birth cohorts between 1960 and 1990 in the CPS show a steady increase in the college hours premium. The premium is three hours for the latest cohort in the ACS (born 1985-1990) suggesting that the trend between the NLSY cohorts continues.

I also look explanations for the college hours premium. The college hours premium increases more for salaried workers than hourly worker providing some insight. I also show that an increase in involuntary part time employment among high school graduates explains a small portion of the college hours premium. The increase in the college hours premium does not differ by union

status, sector of employment, industry or occupation. While I identify several partial sources, no single and pervasive source is found. The college hours premium is general and widespread.

The increasing college hours premium influences labor earnings. Increases in the college wage premium between the NLSY cohorts may have stopped or reversed (Ashworth and Ransom, 2019; Venkatesh, 2019). Yet, this paper emphasizes that the growing college hours premium dominates any slowing or reversing of the college wage premium so that the *college earnings premium* continues to increase. The emerging hours premium rather than the wage premium appears to be taking center stage increasing the earnings differences by college degree.

The source of the college hours premium has not been identified. This paper attempts to shed light on some possibilities by splitting workers by observable job characteristics. The college hours premium is not a result of high school graduates working more jobs. The type of job however does have an effect. Workers paid by the hour do not experience a college hours premium in the latter cohort.

The rest of the paper is structured as follows. Section 2 explores past research related to hours, wages and returns to education. Section 3 describes the data from both the NLSY, CPS and ACS as well as empirical strategies. Section 4 presents the results. Section 5 concludes.

1.2 Past Research

The returns to college education have been intensely studied for several decades. Goldin and Katz (2009) use Census and CPS data to show an increasing *college wage premium* over the last century. Card and Lemieux (2001) suggest that the growth of the college wage premium reflects the meager growth in the supply of educated workers. Castex and Dechter (2014) use workers from two cohorts of the NLSY to show increasing college wage premiums for workers between 18 and 29 years old. Ashworth et al. (2017, 2020) use the NLSY to show that this increase can be attributed to differences between older and younger workers in the NLSY79, as younger workers in the NLSY79 have similar returns to education as those in the NLSY97. Ashworth and Ransom (2019) examine ages 25 to 35 finding no increase in the college wage premium between the NLSY79 and NLSY97. They confirm this in other data sources. Venkatesh (2019) finds that for ages 18 to 35, there is no change in the premium between the NLSY79 and NLSY97. Fuentes and Leamer (2019) use the ACS between 1980 and 2016 confirming that only those with advanced

degrees working more than 40 hours a week have seen a wage increase.

The above research does not examine hours worked. Yet, annual labor earnings are influenced by both wages and hours worked. The hours worked per week in the US for all workers has been roughly stable since 1950. McGrattan et al. (2004) show that this hides underlying changes. The decline in hours worked by men is offset by an increase in hours worked by women. Similarly, Aguiar and Hurst (2007) examine five time use surveys between 1965 and 2003 to show a dramatic increase in the hours of leisure for men and a large reduction in hours of work.

Aguiar et al. (2017, 2021) use the CPS to show a decline in the average hours worked by men between 2000 and 2015. This decline is largest for young workers (Ages 21 to 30). They argue that innovations in leisure technology explain half the increase in leisure for young men. These innovations (largely electronic devices) increase leisure demand among young men at the cost of hours of work. They include workers not employed so combine the hours and participation decision. Instead I examine the role of education in explaining the decline in male hours among only those participating.

Even and Macpherson (2019) use CPS data to show that the ACA increased involuntary part time employment for those most affected by the mandate during 2011 to 2014. The act was passed in 2009, coincident with the Great Recession, though the insurance exchange became available only in 2013 and employers did not face fines until 2015. While not focusing on the general link between education and reduced hours, they highlight the importance of controlling both for macroeconomic conditions and for changes in involuntary part time. Despite their showing, Lalé (2016) demonstrates that between 1995 and 2015 American workers become less likely to hold multiple jobs. Thus, hours worked at the primary job increasingly captures the total hours worked.

Kuhn and Lozano (2008) focus exclusively on employees who work 30 or more hours per week. They show that these men became more likely to work 50 or more hours in the 1980s. This change is concentrated among salaried workers, those with higher wages and higher education levels. They show an increase in working more than 50 hours between 1979 and 1989, but they do not find a significant change beyond 1989. I find the increase is concentrated in the heart of the hours distribution and not exclusively working long hours and find a role that persists after 1989.

As this review suggests, male working hours declined and this decline is concentrated among

younger men. At the same time the likelihood of working more than 40 hours a week for salaried men has increased. The role of education in this pattern of hours has not been studied.

The more general literature on the link between wages and hours of work is extensive. Starting with the theory of labor supply, the substitution effect increases hours worked when wages increase. Yet, at higher income levels the income effect takes over, reducing labor supply as wages increase (Barzel, 1973; Moffitt, 1982, 1984). Costa (2000) confirms that for most of the 20th century high wages were associated with fewer hours. But, from the 1970's high wages were no longer associated with fewer hours Costa (2000). Gicheva (2013) shows that wage growth and hours of work are positively related. This is non linear with particular increases in wage growth for those who work more than 48 hours a week. Mohanty and Golestani (2017) show that the relationship between hours worked and its relationship with wages changes over a persons life. The substitution effect is actually greater later in life conditional on working.

Following past work, I focus on the reported usual hours worked per week. Earlier research compares the reported hours to the actual hours by comparing survey responses to time use surveys and employer records. Frazis and Stewart (2004) find the reported usual hours to be similar to the actual hours. Frazis and Stewart (2010) find somewhat different magnitudes of reported hours by data source but very similar trends over time across sources.

The evidence I present of an emerging college hours premium coincides with evidence that the growth in the college wage premium may be fading. Yet, the college earnings premium continues to rise even as the wage premium may not. This increases differences in earnings between US male high school and college graduates despite the stagnation of the college wage premium. I now turn to the data and the empirical approach used to document the emerging college hours premium.

1.3 Data

I use data from the National Longitudinal Survey of Youth (NLSY), the American Community Survey (ACS) and the Current Population Survey (CPS). The primary dependent variable, the usual number of hours worked per week data sources report usual hours worked per week. The NLSY uniquely allows controlling for cognitive ability and the CPS and ACS provide data over a longer time frame.

The NLSY79 follows 6,403 men born between 1957 and 1964, first interviewed in 1979. The most recent wave was in 2014 when respondents were between 49 and 57. The NLSY97 follows 4,599 men born between 1980 and 1984, first interview in 1997. The latest available data is for 2015 at which point the subjects were between 29 and 35. The sample I use includes men between 18 and 35 from 16 survey waves each for the NLSY79 and NLSY97. The survey waves are selected to make sure the individuals in the two cohorts are observed for the same amount of time and during the same ages.[1] I exclude women from the analysis as large structural changes occur between these cohorts for women such that their hours were increasing and not declining.[2]

The usual hours worked per week is common to both cohorts of the NLSY. Workers are also asked hours worked each week of the survey year. Where usual hours is missing, I compute an average hours worked based on reported hours worked in each week in the previous year. Individuals enrolled in school are excluded from the analysis. Educational attainment is the highest degree attained at the time of observation.For individuals with no reported degree I use years of education. So I use education dummies for not completing high school (no High School diploma or fewer than 12 years of education), completing some college (an associates degree or between 13 and 16 years of education), college completion (a college degree or 16 or 17 years of education) and graduate degree completion (masters degrees, doctoral degrees, professional degrees or more than 17 years of education). This follows Castex and Dechter (2014). All estimated values are compared to high school graduates.

I control for cognitive ability using the Armed Forces Qualification Test (AFQT) scores.[3] This is important as cognitive ability plays a large role in college completion affecting labor market success indirectly, if not directly (Caviglia-Harris and Maier, 2020). I also control for race, region, residence in an Metropolitan statistical area (MSA), age, year, birth year and marital

[1] I exclude all observations of individuals in the military. The response rate for NLSY97 is lower than for the NLSY79 and may affect the results as well.

[2] The pooled results for women suggest no change in the college hours premium between cohorts. The individual fixed effects estimate however shows the emergence of a college hours premium, but one smaller than that found for men.

[3] The AFQT scores in the NLSY79 and NLSY97 have been adjusted to account for type of test and age at testing using the procedures suggested by Altonji et al. (2012) as used in Castex and Dechter (2014), and all test scores are scaled to have a mean of zero and a standard deviation of one. The AFQT scores do not account for cognitive ability completely but is the only available measure.

status. All estimates apply traditional individual sampling weights.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		College Graduates		High School Graduates	
	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
High School	0.483	0.611				
Some College	0.175	0.057				
College Degree	0.132	0.198				
Graduate Degree	0.056	0.045				
Hours Worked/Wk	44.417	38.70	44.886	40.86	44.328	37.887
Black	0.13	0.147	0.075	0.084	0.141	0.172
Other	0.024	0.115	0.011	0.106	0.020	0.113
Msa	0.781	0.917	0.872	0.97	0.750	0.9
Age	27.33	25.62	28.3	26.87	26.93	25.09
Paid hourly	0.462	0.345	0.221	0.201	0.538	0.389
Cognitive Ab.	0.052	0.015	0.789	0.744	-0.206	-0.152
N	49,058	19,425	5,045	3,230	23,613	12,332

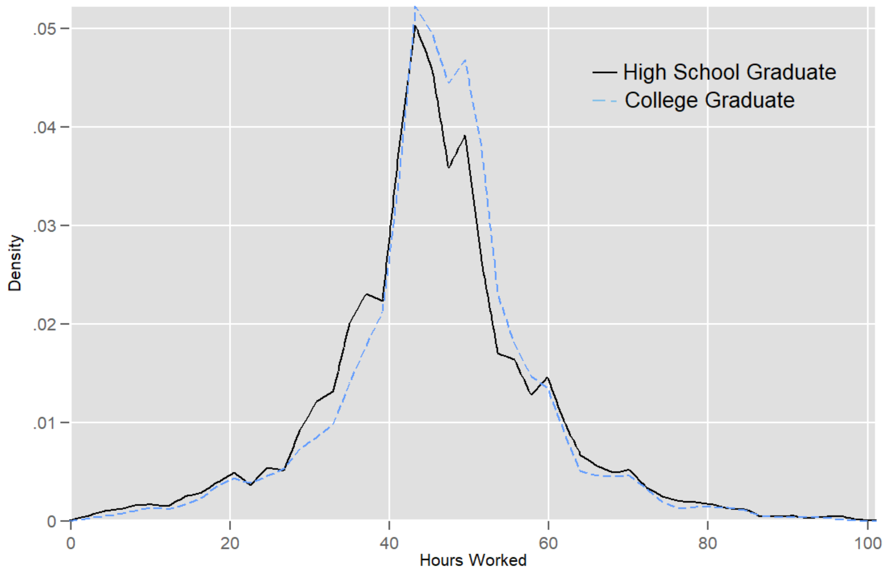
The last four columns are sub-samples of workers with a high school degree or an undergraduate degree. Individuals between the ages of 18 and 35 are included in the sample. Hourly pay may not capture everyone who is not salaried it is based on pay-rate reported. An equal number of waves of both the NLSY79 and NLSY97 are included in the sample. Sample weights are used to calculate means.

Table 1.1: Descriptive statistics for men in the NLSY79 and NLSY97

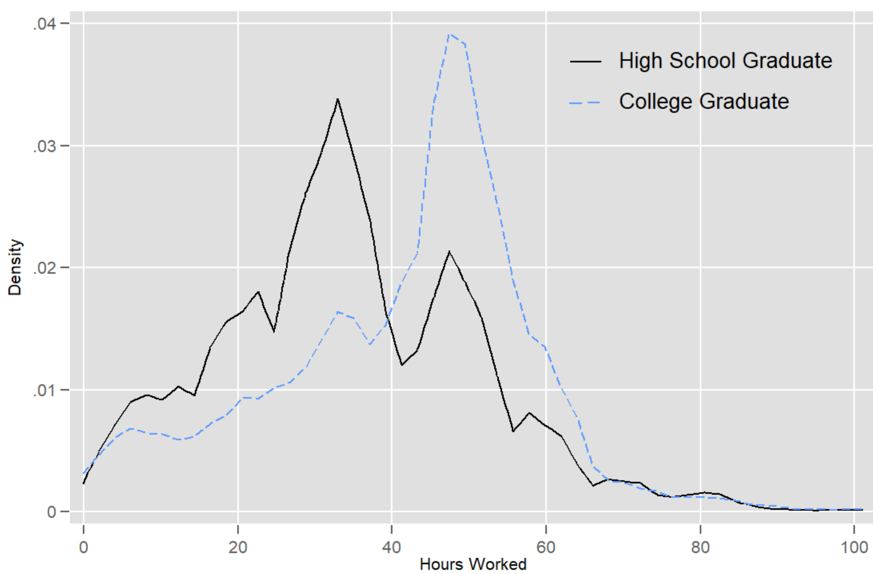
Table 1.1 shows the mean hours worked declines from 44 hours a week to 39 hours a week between cohorts. This decline is consistent with previous research. Both High school and college graduates work slightly more than 44 hours a week in the NLSY79. In the NLSY97 however, a college graduate works 41 hours a week compared to 38 hours a week for high school graduates.

Figure 1.1 shows the distribution of the usual hours worked by high school graduates and college graduates in both the NLSY79 and NLSY97 excluding those who work exactly 40 hours a week.[4] For workers in the NLSY79, the distributions of the two groups are similar. In the NLSY97 the distribution for college graduates is substantially to the right of that for high school graduates.

[4]Including workers who work exactly 40 hours results in large spikes at 40 masking the other differences in the distribution. Excluding them allows us to clearly see the differences in the distribution. I will however examine the pattern of those who work exactly 40 hours later.



(a) NLSY79



(b) NLSY97

Workers who work exactly 40 hours are excluded from this distribution. They form a large portion of workers and therefore mask changes to the rest of the distribution if included.

Figure 1.1: Distribution of hours worked in the NLSY79 and NLSY97 for male workers with a high school education and college education.

I combine waves of the American Community Survey (ACS) from 1960 to 2016. I match the NLSY variables to their counterparts in the ACS. The educational attainment variable again allows construction of the same dummy variables for education again. Other controls include race, age, region, birth year, residence in MSA and marital status. Table 1.2 reports the descriptive statistics for the NLSY equivalent cohorts from the ACS. These variables are constructed to be comparable to their NLSY counterparts.[5] The dependent and independent variables in both sets of data are nearly identical. Table 1.2 shows the mean hours worked declines from 43 hours a week to 41 hours a week between the two cohorts in the ACS. This decline is consistent with the decline in the hours worked by workers from the same birth cohorts surveyed in the NLSY.

	(1) 79 Birth Cohort	(2) 97 Birth Cohort
High School	0.377	0.37
Some College	0.274	0.219
College Degree	0.168	0.215
Graduate Degree	0.058	0.078
Hours Worked	43.13	41.14
Black	0.10	0.11
Other	0.08	0.17
Msa	0.77	0.88
N	689,246	548,869

Individuals between the ages of 18 and 35 are included in the sample.

Sample weights are used to calculate means.

Table 1.2: Descriptive statistics for the NLSY79 and NLSY97 male birth cohort equivalents in the ACS.

[5]As mentioned, there is no control for cognitive ability in the ACS.

I combine waves of the Current Population Survey (CPS) from 1986 to 2016. Once again, I match the NLSY variables to their counterparts in the CPS. The educational attainment variable again allows construction of the same dummy variables for education again. Other controls include race, age, region, birth year, residence in MSA and marital status. Table 1.3 reports the descriptive statistics for the NLSY equivalent cohorts from the CPS. These variables are constructed to be comparable to their NLSY counterparts.[6] The dependent and independent variables in all sets of data are nearly identical. Table 1.3 shows the mean hours worked declines from 44 hours a week to 39 hours a week between cohorts. This decline is consistent with previous research. Both High school and college graduates work slightly more than 44 hours a week in the NLSY79. In the NLSY97 however, a college graduate works 41 hours a week compared to 38 hours a week for high school graduates. Table 3 shows the mean hours worked declines from 43 hours a week to 41 hours a week between the two cohorts in the CPS. Once again, this decline is consistent with the decline in the hours worked by workers from the same birth cohorts surveyed in the NLSY and ACS.

[6]As mentioned, there is no control for cognitive ability in the CPS either.

	(1) 79 Birth Cohort	(2) 97 Birth Cohort
High School	0.379	0.356
Some College	0.242	0.255
College Degree	0.194	0.199
Graduate Degree	0.074	0.065
Hours Worked	43.30	41.47
Black	0.11	0.10
Other	0.04	0.08
Msa	0.75	0.86
N	47,599	92,833

Individuals between the ages of 18 and 35 are included in the sample.

Sample weights are used to calculate means.

Table 1.3: Descriptive statistics for the NLSY79 and NLSY97 male birth cohort equivalents in the CPS.

1.4 Empirical Approach

The empirical approach used follows those estimating the changes in hours of work and the education wage premium (Aguiar and Hurst, 2007; Kuhn and Lozano, 2008; Castex and Dechter, 2014; Ashworth et al., 2017; Ashworth and Ransom, 2019). I describe changes in the association between education and hours of work over time.

To calculate the college hours premium in both the NLSY, CPS and ACS I estimate the following model.

$$Hours = \beta_0 + \beta_1 EDU_i + \beta_k X_i + \varepsilon_i \tag{1.1}$$

where $Hours$ is the usual hours worked per week, EDU is the vector of dummy variables for each level of education, and X is the vector of controls.[7] The NLSY includes the measure of cognitive ability and standard errors clustered by individual.

I also create an ordinal hours variable. The variable separates working fewer than 40 hours, working exactly 40 hours and working more than 40 hour. The controls from (1) are included in the ordered probit estimates.

A quantile regression version of (1) is estimated. This excludes individuals working exactly 40 hours. They form a large portion of the sample and quantiles. When included, the quantiles estimated provide no relevant information and hide the pattern in the rest of the distribution.[8] The quantile regression investigates the extent to which the college hours premium is observed throughout the distribution of hours. This is done to confirm that estimations at the point of means are not driven by the tails. The tails might drive the mean estimate if the only educational differences are in extreme overtime and/or in minimal part-time.

Finally I estimate the college earnings premium. This follows a similar structure to (1). The dependent variable is the log annual labor income. In this specification I show the role of hours by first excluding and then including it as a control variable.

1.5 Results

Table 1.4 reports the results of estimating (1) for the two NLSY cohorts. Column 1 shows that a college degree is not associated with additional hours of work in the NLSY79. Column 2 shows a college degree is associated with 2.2 more hours of work than a high school degree in the NLSY97. This college hours premium is significantly different from zero. Controls for race, age, msa, region and marital status take statistically significant coefficients.[9]

[7] These controls are in the form of a dummy variable for each unique value of the above controls to account for any non-linear variation.

[8] Appendix Figure A1 includes those working exactly 40 hours in the estimates to make this clear.

[9] Appendix Table A3 includes the coefficient of the control variables.

Hours Worked/Week in the	(1) NLSY79	(2) NLSY97	(3) NLSY79	(4) NLSY97
No diploma	-0.497	-0.578	-0.150	-0.284
	(0.342)	(0.484)	(0.372)	(0.523)
Some College	-0.0901	0.0481	-0.306	-0.0146
	(0.334)	(0.775)	(0.342)	(0.772)
College Degree	-0.0958	2.215***	-0.506	1.898***
	(0.365)	(0.460)	(0.401)	(0.480)
Graduate Degree	0.784	4.292***	0.275	3.919***
	(0.550)	(1.043)	(0.577)	(1.049)
Cognitive Ability			0.434**	0.383*
			(0.181)	(0.214)
N	49058	19425	49058	19425

All estimates include controls for race, birth year, year, region, msa status and marital status.

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.4: Estimates of the college hours premium for male workers in the NLSY79 and NLSY97.

Controlling for cognitive ability does not change the pattern of these results. Column 3 shows a college degree in the NLS79 is not associated with additional hours of work. Column 4 shows that in the NLSY97 a college degree is associated with 1.9 more hours of work. This 2.5 hour difference between cohorts is statistically significant (s.e. = 0.338).[10] The college educated work similar hours to high school graduates in the early cohort but significantly more hours in the latter cohort, a college hours premium emerges between these two cohorts. To identify the source of the hours premium I first turn to a simple linear probability model estimating the effect of

[10]The coefficient and standard error are computed by stacking equations for the two cohorts while allowing all the controls to vary by cohort by using cohort-control interaction terms.

college on working more than 40 hours and fewer than 40 hours.

Table 1.5 presents the linear probability estimates of the association between education and working more than 40 hours a week. Columns 1 and 2 show that a college graduate is 5% more likely to work more than 40 hours a week than a high school graduate in the NLSY97, this has changed from the NLSY79 where college graduates were 3% less likely to do so. Columns 3 and 4 include controls for cognitive ability and show that a college graduate is 5% more likely to work more than 40 hours a week than a high school graduate in the NLSY97, this has changed from the NLSY79 where college graduates were 5% less likely to do so. The 10% change between the two cohorts is statistically significant. The pattern of results does not change when estimating a probit using an indicator for working more than 40 hours a week as shown in Appendix table A4.

	(1)	(2)	(3)	(4)
Hours Worked/Week in the	NLSY79	NLSY97	NLSY79	NLSY97
No diploma	-0.0262***	-0.0409**	-0.0142	-0.0431**
	(0.00861)	(0.0188)	(0.00967)	(0.0199)
Some College	-0.0329***	-0.0249	-0.0404***	-0.0244
	(0.00898)	(0.0260)	(0.00932)	(0.0260)
College Degree	-0.0337***	0.0482***	-0.0478***	0.0506***
	(0.00966)	(0.0149)	(0.0104)	(0.0160)
Graduate Degree	-0.0451***	0.0520**	-0.0627***	0.0548**
	(0.0129)	(0.0252)	(0.0137)	(0.0263)
Cognitive Ability			0.0149***	-0.00287
			(0.00502)	(0.00762)
N	49940	19687	49940	19687

All estimates include controls for race, birth year, year, region, msa status and marital status.

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: Linear probability estimates for male workers working more than 40 hours a week in the NLSY79 and NLSY97.

Table 1.6 presents the linear probability estimates of the association between education and working fewer than 40 hours a week. Columns 1 and 2 show that a college graduate is 15% less likely to work fewer than 40 hours a week than a high school graduate in the NLSY97, this has changed from the NLSY79 where college graduates were just 7% less likely to do so. Columns 3 and 4 include controls for cognitive ability and show that a college graduate is 14% less likely to work fewer than 40 hours a week than a high school graduate in the NLSY97, this has changed from the NLSY79 where college graduates were just 4% less likely to do so. The 10% change between the two cohorts is statistically significant. The pattern of results does not change

when estimating a probit using an indicator for working more than 40 hours a week as shown in Appendix table A5.

	(1)	(2)	(3)	(4)
Hours Worked/Week in the	NLSY79	NLSY97	NLSY79	NLSY97
No diploma	0.0230*	-0.00726	-0.00419	-0.0226
	(0.0139)	(0.0148)	(0.0148)	(0.0154)
Some College	-0.0245*	-0.0167	-0.00768	-0.0134
	(0.0148)	(0.0263)	(0.0152)	(0.0262)
College Degree	-0.0669***	-0.154***	-0.0349*	-0.137***
	(0.0167)	(0.0182)	(0.0182)	(0.0188)
Graduate Degree	-0.104***	-0.257***	-0.0642***	-0.238***
	(0.0223)	(0.0334)	(0.0238)	(0.0338)
Cognitive Ability			-0.0339***	-0.0199***
			(0.00736)	(0.00590)
N	49940	19687	49940	19687

All estimates include controls for race, birth year, year, region, msa status and marital status.

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: Linear probability estimates for male workers working fewer than 40 hours a week in the NLSY79 and NLSY97.

Table 1.7 shows the ordered probit estimates of association between education and the likelihood of working fewer than 40 hours, exactly 40 hours or more than 40 hours a week when including the control for cognitive ability. Focusing on college, row 6 shows that in the NLSY97 a college degree is associated with a 9.8 percentage point reduction in the probability of working fewer than 40 hours a week, a 1 percentage point increase in the likelihood of working exactly 40 hours, and an 8.8 percentage point increase in the likelihood of working more than 40 hours,

whereas row 5 shows that in the NLSY79 a college degree does not affect the likelihood of working fewer than 40 hours, exactly 40 hours or more than 40 hours. A college degree is associated with an increased likelihood of working 40 hours or more in the NLSY97 but not the NLSY79.

	(1)	(2)	(3)
	Hours<40	Hours=40	Hours>40
No High School Diploma			
NLSY79	0.0027	0.0019	-0.005
	(0.004)	(0.003)	(0.007)
NLSY97	0.0109	-0.001	-0.01
	(0.009)	(0.001)	(0.008)
Some College			
NLSY79	0.01***	0.0069***	-0.0169***
	(0.004)	(0.003)	(0.007)
NLSY97	0.006	-0.001	-0.006
	(0.012)	(0.001)	(0.011)
Undergraduate Degree			
NLSY79	0.00008	-0.00006	0.00014
	(0.0053)	(0.0037)	(0.009)
NLSY97	-0.098***	0.01***	0.088***
	(0.008)	(0.001)	(0.007)
Post-Graduate Degree			
NLSY79	-0.009	-0.006	0.015
	(0.008)	(0.006)	(0.014)
NLSY97	-0.157***	0.016***	0.141***
	(0.017)	(0.002)	(0.015)

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

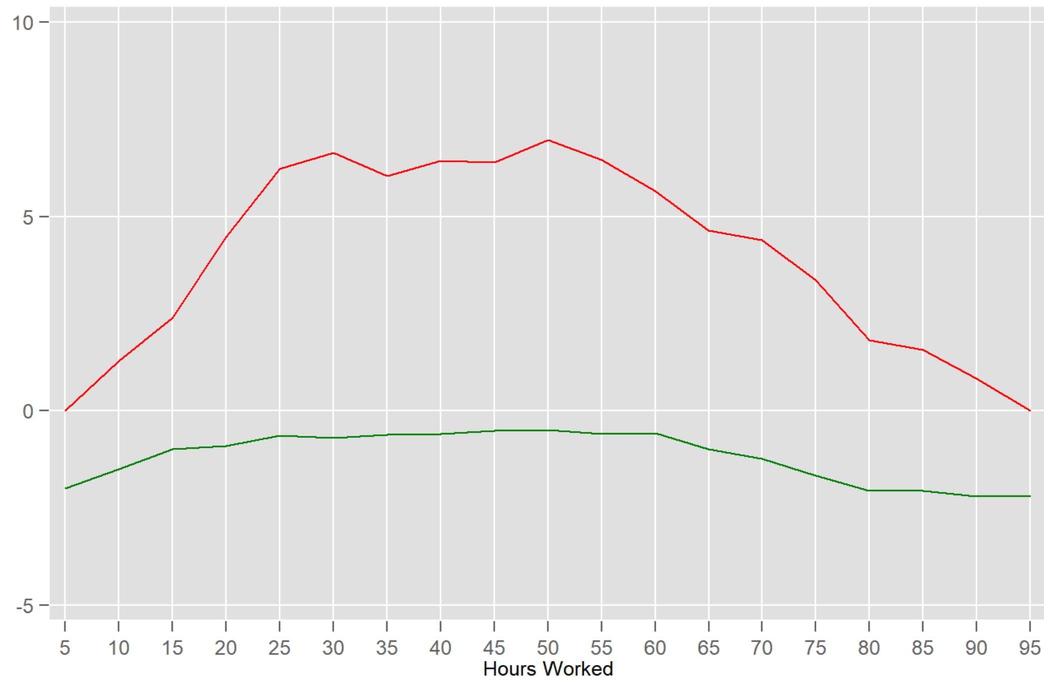
Table 1.7: Estimated marginal effects using an ordered probit to examine the effect of a college education on working fewer than 40 hours, 40 hours and more than 40 hours a week for male workers in the NLSY79 and NLSY97.

The increase in the likelihood of working exactly 40 hours a week associated with a college degree is only around 10% the size of the increase in likelihood of working more than 40 hours or the decline in the likelihood of working fewer than 40 hours a week relative to high school graduates. This suggests college hours premium may be associated with changes in the tails of the distribution. I now test this hypothesis using a quantile regression. Using a quantile regression allows measurement of the association of a college degree at each point in the distribution of hours worked.

Figure 1.2 presents the results of a quantile regression of (1). The figure includes the coefficient on college degree at each integer quantile between 5 and 95. In both cohorts I exclude those who work exactly 40 hours. This aids in interpretation. Also, the ordered probit shows there is little influence of a college degree on the likelihood of working exactly 40 hours.[11]

The x axis translates the quantiles into the corresponding hours of work. I include labels for every 5th quantile between 5 and 95 inclusive. The y axis shows the magnitude of the influence of a college degree on hours of work at each quantile.

[11] Figure A1 in the appendix presents the quantile regression for the entire sample. Here over 40 of the integer quartiles are associated with working exactly 40 hours and the differences between cohorts across these quartiles are not significant. Yet, the graph confirms Figure 2 showing that both sides of 40 hours, the NLSY97 shows a significant hours premium that fades in the extreme tails.



The vertical axis represents the college hours premium. The horizontal axis logs hours associated with each 5th quantile of the hours distribution. Workers who work exactly 40 hours are excluded from this distribution. The difference between the two cohorts is statistically significant for the entire distribution. The difference is calculated by a stacked equation with a dummy variable for a cohort and interaction term between the dummy variable and all the dependent variables.

Figure 1.3: Estimates of the quantile regression of college graduation on hours worked by men in the NLSY79 and NLSY97.

From Figure 1.2 it is clear that the mean estimate in Table 1 of 2.5 more work hours in the NLSY97 does not represent large portions of the distribution. In the NLSY79 a college degree is associated with fewer hours in the tails and essentially no difference in hours in the heart of the distribution. The NLSY97 differs dramatically. There exists a college hours premium throughout the distribution that is largest for those working between 30 and 45 hours. The college hours premium in the NLSY97 is not a phenomenon driven by the tails of the distribution.

The increase in the college hours premium between cohorts is statistically significant throughout the distribution although concentrated by size in the middle of the distribution. For example, at the 50^{th} quantile which is 45 hours the coefficient on college is -0.70 (s.e. = 0.22) for the NLSY79 and 6.7 (s.e. = 0.57) for the NLSY97. This enormous difference of 7.5 hours (s.e. = 0.85) between cohorts is about three times the mean difference between cohorts. For the 25^{th} quantile at 36 hours there is nearly as large a difference of 6.9 hours (s.e. = 1.06) between cohorts. This gap begins to narrow past the 65^{th} percentile at 48 hours. At the 75^{th} percentile the difference between the cohorts is 5 hours (s.e. = 0.89).

This shows that the emergence of a college hours premium is not a tail phenomenon, i.e. not driven by those working extremely long hours or working relatively few hours. The increase in the college hours premium is largest in the middle of the distribution although present throughout the distribution.

1.5.1 Robustness checks

While the above results clearly confirm the existence of the college hours premium, the source of this premium is still not clear. I use the data to examine several possibles sources of the premium. I begin by estimating the association between education and number of jobs worked. Next I split the sample based on whether the worker is paid by the hour or salaried, their union status, whether they are employed by the private sector or the public sector, broad industry group of their primary job and finally broad occupation group of the job.

The primary dependent variable is the usual number of hours worked at the primary job. If high school graduates are more likely than college graduates to work multiple jobs in the NLSY97, the college hours premium could be explained by high school graduates working multiple part time jobs. I present estimates of the relationship between education and the number of jobs worked in each of the NLSY cohorts in the 1st row of Table 1.8. Columns 1 and 2 show that a college degree is associated with working 0.05 more jobs than high school graduates in the NLSY97 compared to less than 0.01 in the NLSY79. Columns 3 and 4 show that a college degree is associated with working 0.04 more jobs than high school graduates in the NLSY97 compared to no effect in the NLSY79 with the inclusion of a control for cognitive ability. The difference

between the two cohorts is not statistically significant. A change in the number of jobs worked by workers at each education level is not driving the emerging college hours premium, infact college graduates may be likely than high school graduates to work multiple jobs in the NLSY97 compared to the NLSY79.

Next I turn to splitting the sample. Kuhn and Lozano (2008) show salaried workers earning a higher premium for each hour worked over full-time. Workers who are paid by the hour might have less of an incentive to work long hours if they are paid a low wage. I examine if this results in differences in the college hours premium for salaried workers and hourly workers. Row 2 of Table 1.8 presents estimates of the college hours premium for salaried workers. Columns 1 and 2 show the college hours premium increasing to 2.38 hours in the NLSY97 from negative 0.95 hours in the NLSY79. This increase of 3.33 hours is statistically significant. Columns 3 and 4 include controls for cognitive ability and show the college hours premium for salaried workers increasing to 1.9 hours in the NLSY97 from negative 1.25 hours in the NLSY79. This increase of 3.15 hours is once again statistically significant.

Row 3 of Table 1.8 presents estimates of the college hours premium for workers paid by the hour. Columns 1 and 2 show the college hours premium increasing to negative 0.95 hours a week in the NLSY97 from negative 2.08 hours in the NLSY79. This increase of 1.13 hours is statistically significant. Columns 3 and 4 include controls for cognitive ability and show the college hours premium for hourly workers increasing to negative 0.84 hours a week in the NLSY97 from negative 2.37 hours in the NLSY79. This 1.53 hour increase between the two cohorts is statistically significant but half that for salaried workers.

Among hourly workers, what was an hours disadvantage for the college educated in the NLSY79, grows to rough equality in the NLSY97. Among salaried workers, what was an hours disadvantage for the college educated in the NLSY79 grows to a very large advantage in the NLSY97. The college hours premium grows between the two cohorts for both groups of workers but is larger for salaried workers than hourly workers. The result I show is more general than simply salaried workers becoming more likely to work more than 50 hours as shown in Kuhn and Lozano (2008).

Next I examine differences in the college hours premium for workers with different union status. Table 1.8 row 4 presents the college hours premium for workers in a union. Columns

1 and 2 show the college hours premium increases to 0.43 hours a week in the NLSY97 from 0.12 hours in the NLSY79. This increase of 0.31 hours is not statistically significant. Columns 3 and 4 include controls for cognitive ability and show the college hours premium declines to negative 0.01 hours a week in the NLSY97 from 0.01 hours in the NLSY79. Once again this 0.02 hour change between the two cohorts is not statistically significant. None of the estimates of the college hours premium for union workers are statistically significant, this is partially due to the small sample size in both cohorts[12]

[12]As shown in Appendix table A11, the NLSY79 sample includes 4,833 observations and the NLSY97 includes 2,059 observations, compared to 49,058 observations in the full NLSY79 sample and 19425 in the full NLSY97 sample.

	(1)	(2)	(3)	(4)
	NLSY79	NLSY97	NLSY79	NLSY97
Association between college and number of jobs				
No. of Jobs	0.00717	0.0521*	-0.0000371	0.0427
	(0.0158)	(0.0285)	(0.0176)	(0.0307)
Workers split by rate of pay				
Salaried	-0.954**	2.382***	-1.259***	1.921***
	(0.423)	(0.516)	(0.464)	(0.549)
Hourly	-2.083***	-0.946*	-2.368***	-0.840
	(0.556)	(0.533)	(0.588)	(0.544)
Workers split by union membership				
Union	0.121	0.431	0.00908	-0.00888
	(1.117)	(0.849)	(1.111)	(0.912)
Non-Union	1.048	2.727***	0.938	2.412***
	(0.689)	(0.480)	(0.749)	(0.515)
Workers split by employer type				
Public	-0.400	2.003*	-1.706	1.422
	(1.339)	(1.136)	(1.506)	(1.153)
Private	-0.0746	2.322***	-0.478	2.070***
	(0.367)	(0.486)	(0.404)	(0.507)

Appendix Tables A9, A10, A11 and A12 presents expanded results of the above estimates. All estimates include controls for race, birth year, year, region, msa status and marital status. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.8: Association between college and number of jobs worked and estimates of the college hours premium for subsamples of male workers in the NLSY79 and NLSY97.

Table 1.8 row 5 presents the college hours premium for workers not in a union. Columns 1 and 2 show the college hours premium increases to 2.73 hours a week in the NLSY97 from 1.05 hours in the NLSY79. This increase of 1.68 hours is statistically significant. Columns 3 and 4 include controls for cognitive ability and show the college hours premium increases to 2.41 hours a week in the NLSY97 from 0.94 hours in the NLSY79. Once again this 1.47 hour increase between the two cohorts is statistically significant.

The college hours premium increases for non-union workers between the NLSY79 and NLSY97. There is no change in the college hours premium between the two cohorts for union workers. Workers included in the sample for the NLSY79 responding to the question are observed later in their life and may affect the lack of an increase between the two cohorts.

Next I examine differences in the college hours premium for workers by sector of employment. Table 1.8 row 6 presents the college hours premium for workers employed in the public sector. Columns 1 and 2 show the college hours premium increases to 2 hours a week in the NLSY97 from negative 0.40 hours in the NLSY79. This increase of 1.6 hours is statistically significant. Columns 3 and 4 include controls for cognitive ability and show the college hours premium increases to 1.4 hours a week in the NLSY97 from negative 1.71 hours in the NLSY79. Once again this 3.11 hour change between the two cohorts is statistically significant.

Table 1.8 row 7 presents the college hours premium for workers employed in the private sector. Columns 1 and 2 show the college hours premium increases to 2.32 hours a week in the NLSY97 from negative 0.08 hours in the NLSY79. This increase of 2.38 hours is statistically significant. Columns 3 and 4 include controls for cognitive ability and show the college hours premium increases to 2.07 hours a week in the NLSY97 from negative 0.47 hours in the NLSY79. Once again this 2.55 hour increase between the two cohorts is statistically significant. The college hours premium increases for both public and private sector workers between the NLSY79 and NLSY97.

Next I turn to separating workers by industry of employment. In order to maximize sample sizes I group industries into three broad categories. Agriculture, forestry, fisheries, mining, construction, manufacturing, utilities, transportation and public services make up industry group IND-A, education, health, social services, public administration, entertainment and recreation make up industry group IND-B and finance, insurance, real estate, business and professional

services make up industry group IND-C.

Table 1.9 row 1 presents the college hours premium for workers employed in industry group IND-A. Columns 1 and 2 show the college hours premium increases to 1.65 hours a week in the NLSY97 from 0.78 hours in the NLSY79. This increase of 0.87 hours is statistically significant. Columns 3 and 4 include controls for cognitive ability and show the college hours premium increases to 1.54 hours a week in the NLSY97 from 0.19 hours in the NLSY79. Once again this 1.35 hour increase between the two cohorts is statistically significant.

Table 1.9 row 2 presents the college hours premium for workers employed in industry group IND-B. Columns 1 and 2 show the college hours premium increases to 1.98 hours a week in the NLSY97 from negative 1.16 hours in the NLSY79. This increase of 3.14 hours is statistically significant. Columns 3 and 4 include controls for cognitive ability and show the college hours premium increases to 1.83 hours a week in the NLSY97 from negative 1.1 hours in the NLSY79. Once again this 2.93 hour increase between the two cohorts is statistically significant.

Table 1.9 row 3 presents the college hours premium for workers employed in industry group IND-C. Columns 1 and 2 show the college hours premium increases to 4.87 hours a week in the NLSY97 from 0.31 hours in the NLSY79. This increase of 4.55 hours is statistically significant. Columns 3 and 4 include controls for cognitive ability and show the college hours premium increases to 3.51 hours a week in the NLSY97 from 0.25 hours in the NLSY79. Once again this 3.26 hour increase between the two cohorts is statistically significant.

The college hours premium increases for workers in all three broad industry groups between the NLSY79 and NLSY97. The increase in the college hours premium is largest for industry group IND-C followed by IND-B and finally IND-C. These differences in magnitude however are not statistically significant.

Next I turn to separating workers by occupation. In order to maximize sample sizes I group occupations into three broad categories. Group OCC-A consists of professional workers, technical workers, manager, officers and proprietors, OCC-B consists of clerical, sales and service workers and OCC-C consists of farmers, laborers, craftsmen and operatives.

Table 1.9 row 4 presents the college hours premium for workers employed in occupation group OCC-A. Columns 1 and 2 show the college hours premium increases to 2.7 hours a week in the NLSY97 from negative 2.05 hours in the NLSY79. This increase of 4.71 hours is statistically

significant. Columns 3 and 4 include controls for cognitive ability and show the college hours premium increases to 2.2 hours a week in the NLSY97 from negative 1.57 hours in the NLSY79. This increase of 3.77 hours is statistically significant.

Table 1.9 row 5 presents the college hours premium for workers employed in occupation group OCC-B. Columns 1 and 2 show the college hours premium increases to 2.3 hours a week in the NLSY97 from 0.89 hours in the NLSY79. This increase of 1.41 hours is statistically significant. Columns 3 and 4 include controls for cognitive ability and show the college hours premium increases to 1.69 hours a week in the NLSY97 from negative 0.28 hours in the NLSY79. Once again this 1.97 hour increase between the two cohorts is statistically significant.

	(1)	(2)	(3)	(4)
	NLSY79	NLSY97	NLSY79	NLSY97
Workers split into Industry groups				
IND-A	0.782	1.647**	0.192	1.539**
	(0.565)	(0.639)	(0.615)	(0.668)
IND-B	-1.162	1.982**	-1.093	1.833*
	(1.281)	(0.900)	(1.345)	(0.941)
IND-C	0.310	4.867***	0.247	3.509***
	(0.781)	(0.870)	(0.878)	(0.889)
Workers split into Occupation groups				
OCC-A	-2.046***	2.661***	-1.574**	2.198**
	(0.540)	(1.014)	(0.619)	(1.060)
OCC-B	0.889	2.301***	-0.282	1.685***
	(0.541)	(0.652)	(0.585)	(0.652)
OCC-C	-0.145	-0.506	-0.357	-0.478
	(0.905)	(1.239)	(0.921)	(1.273)

Appendix Table A13 and A14 present the expanded estimates.
All estimates include controls for race, birth year, year, region, msa status and marital status. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.9: The college hours premium for male workers in the NLSY79 and NLSY97 separated by broad industry and occupation groups.

Table 1.9 row 6 presents the college hours premium for workers employed in occupation group OCC-C. Columns 1 and 2 show the college hours premium decreases to negative 0.51 hours a week in the NLSY97 from negative 0.15 hours in the NLSY79. This decrease of 0.36

hours is not statistically significant. Columns 3 and 4 include controls for cognitive ability and show the college hours premium decreases to negative 0.48 hours a week in the NLSY97 from negative 0.38 hours in the NLSY79. Once again this 0.12 hour decrease between the two cohorts is not statistically significant.

The college hours premium increases between the NLSY79 and NLSY97 for workers in occupation groups OCC-A and OCC-B. The increase in the college hours premium is largest for occupation group OCC-A followed by OCC-B. There is no change in the college hours premium for workers in occupation group OCC-C.

The increase in the college hours premium is larger among salaried workers than among hourly workers. The college hours premium is also larger for workers in occupation group OCC-A and OCC-B than among workers in occupation group OCC-C. Splitting the sample by union status and sector of employment does not provide strong evidence for different increases in the college hours premium between the two groups. Splitting the sample into broad industry groups once again does not provide strong evidence for differences in the increase in the college hours premium between the two cohorts. The addition of 2-digit industry and occupation controls to equation (1) in estimating the college hours premium between the two cohorts does not change the pattern of results.[13]

1.5.2 The college hours premium beyond the NLSY

While the NLSY has superior controls, particularly cognitive ability, the CPS and ACS cover a longer period[14] and the CPS uniquely includes information on involuntary part-time employment. Neither are limited by the cohorts considered by the NLSY. Workers born before, after and between the two NLSY birth cohorts can be observed.

Using data from the CPS I create five year birth cohorts beginning in 1960 and ending in 1990. Once again I limit the sample to non-students between the ages of 18 and 35 at the time of observation to match the NLSY. The results of estimating the college hours premium

[13]Table A15 in the appendix presents these results in detail.

[14]The ACS data includes workers surveyed in the 1960, 1980, 1990, 2000, and 2010 Census waves and annual waves of the ACS between 2001 and 2016.

for each cohort are presented in Figure 1.3. The vertical axis measures the college hours premium. The horizontal axis is the middle year of each 5 year birth cohort. For example, the college hours premium for the 1981 to 1985 birth cohort is 1.18 hours and plotted at the year 1983.

The vertical axis represents the college hours premium. The horizontal axis logs the birth year with each 5 year birth cohort plotted at the middle year. The dashed lines to either side of the main line represent the 95% confidence interval for the estimate.

Figure 1.5: Estimates of the college hours premium for 5 year birth cohorts of men in the CPS.

It is possible that involuntary part-time work drives the emerging hours premium. In this view, those without a college education are increasingly unable to work the hours they want. Employers reduce hours to improve flexibility or keep hours below those required for health

insurance. The CPS uniquely identifies involuntary part time employment and allows examining a longer period.

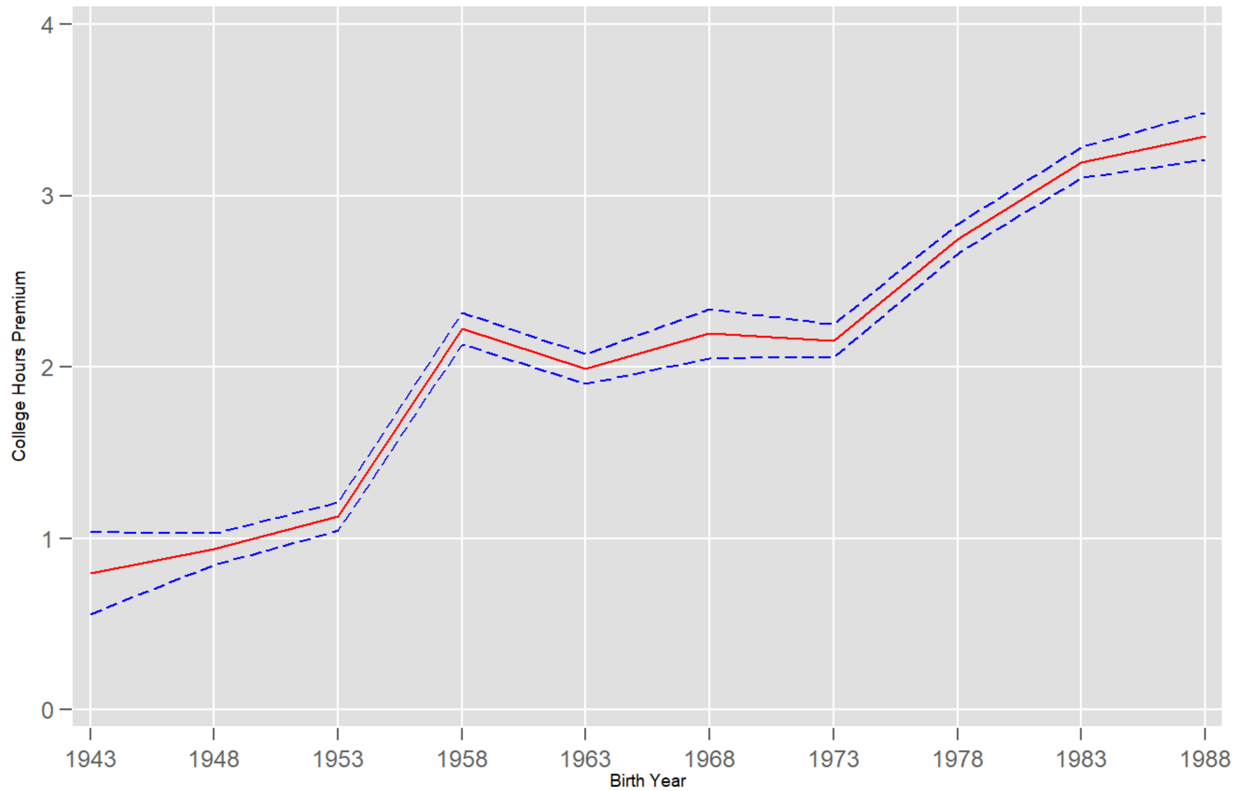
The top line of Figure 3 presents the estimated college hours premium for each five - year birth cohort. In the first cohort (centered on 1963) the premium for the college educated is 0.533 hours. This rises to a 1.164 hour college premium for the 1985-1990 birth cohort. The graph shows a clear increase in the college hours premium over time, but the ultimate size of the hours premium emerges as smaller than in the NLSY or than will be shown in the ACS.

In order to examine the role of involuntary part-time employment, it is included as a regressor in the hours equation for each birth cohort. In every birth cohort it takes a negative and statistically significant coefficient. Those reporting involuntary part-time employment tend to work approximately 11 hours less than would otherwise be predicted. The college educated are less likely to report involuntary part-time work. The bottom line of Figure 3 illustrates the consequence of these facts by showing the college hours premium after controlling for involuntary part-time work. The hours premium for the college educated is reduced, but not dramatically. It is now 0.495 in the first birth cohort (1960-1965) and 0.957 in the final birth cohort (1985-1990). Thus, while accounting for involuntary part-time work reduces the size of the college hours premium, it neither eliminates it nor changes its pattern of growth over time.[15]

Using the much larger ACS data, I once again create five year birth cohorts, but I am able to begin in 1940 and end in 1990.[16] Once again I limit the sample to non-students between the ages of 18 and 35 at the time of observation to match the NLSY. The results of estimating the college hours premium for each cohort are presented in Figure 1.4. The vertical axis measures the college hours premium. The horizontal axis is the middle year of each 5 year birth cohort. For example, the college hours premium for the 1951 to 1955 birth cohort is 1.13 hours and plotted at the year 1953.

[15]While the CPS measure identifies those working involuntarily part-time, there might also be those working more hours than they desire as well as working less hours than they desire.

[16]The first few birth cohorts (before 1980) the individuals included come primarily from Census waves rather than the ACS. The latter cohorts include individuals surveyed in both the Census and ACS.



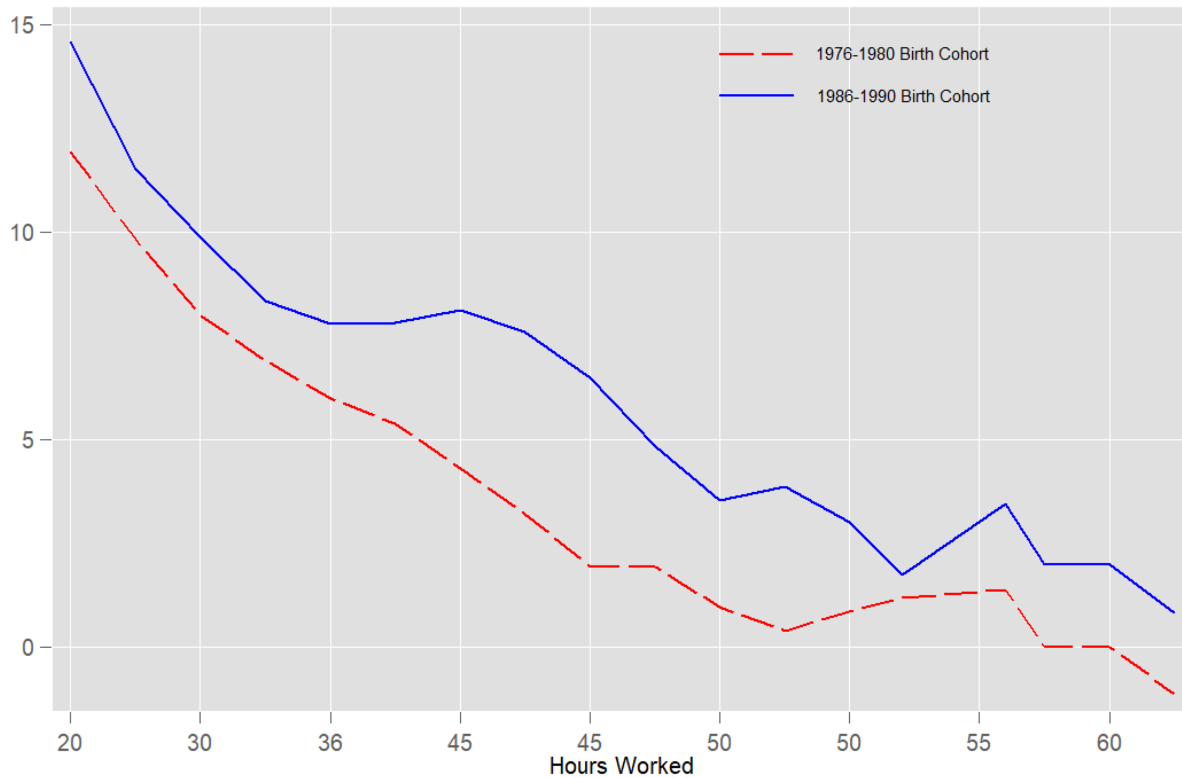
The vertical axis represents the college hours premium. The horizontal axis logs the birth year with each 5 year birth cohort plotted at the middle year. The dashed lines to either side of the main line represent the 95% confidence interval for the estimate.

Figure 1.7: Estimates of the college hours premium for 5 year birth cohorts of men in the ACS.

As in NLSY and CPS, the college hours premium increases across the birth cohorts in the ACS. This steady increase in all three sets of data shows a long term phenomenon. The earliest birth cohort (1940-1945) has a college hours premium of 0.93 hours, this increases more than three times to a 3.4 hours in the last birth cohort (1986-1990). The 2.5 hours increase in the college hours premium between these cohorts is statistically significantly.

I once again turn to quantile regressions to examine whether this longer term phenomenon is driven by changes in the tails of the distribution. Here, I focus on the ACS data to examine

changes in the college hours premium across the distribution. Figure 5 presents the quantile regressions for the 1976-1980 and 1986-1990 birth cohorts from the ACS.[17]



The vertical axis represents the college hours premium. The horizontal axis logs hours associated with quantiles of the hours distribution. Workers who work exactly 40 hours are excluded from this distribution. The difference between the two cohorts is statistically significant for the entire distribution. The difference is calculated by a stacked equation with a dummy variable for a cohort and interaction term between the dummy variable and all the dependent variables.

Figure 1.9: Estimates of the quantile regression of college graduation on hours worked by men in the ACS.

[17] Again, I do not include those who work exactly 40 hours a week as that creates large un-interpretable horizontal lines in the middle of the distribution.

The results differ from the NLSY in one way but confirm it in two others. The primary difference is the steady decline with lower hours premiums at the top of the distribution. This is true of all of the ACS birth cohorts. Despite this difference the ACS results confirm that the 1986-1990 birth cohort has a higher college hours premium than the 1976-1980 birth cohort throughout the distribution.[18] Moreover the largest difference in the college hours premium remains in the heart of the distribution not in the tails. For example at the 10th quantile the college hours premium is 14.6 hours in the 1986-1990 birth cohort compared to 11.9 hours in the 1976-1980 birth cohort. This is a 2.7 hour increase in the college hours premium. At the 50th quantile, around 45 hours, a college degree is associated with a 6.5 hours premium over high school graduates in the 1986-1990 birth cohort and 1.9 hours in the 1976-1980 birth cohort. This is a 4.6 hour increase in the college hours premium. At the 80th percentile the college hours premium for the 1986-1990 birth cohort is 3.5 hours and in the 1976-1980 birth cohort the college hours premium is 1.4 hours. There is a 1.1 hour increase in the college hours premium at this point in the distribution between cohorts. The quantile regressions estimated using the CPS show a similar pattern to the ACS results described here.

The ACS and CPS largely confirm the NLSY results. The ACS shows a long term trend of an increasing college hours premium beginning with those born in 1940 until those born in 1990. Quantile regressions comparing these cohorts again show that the increase in the college hours premium happens throughout the distribution of hours but is greatest in the heart of the distribution. The growth of a college hours premium and its effect across the distribution are not specific to the NLSY.

1.5.3 College Earnings Premium

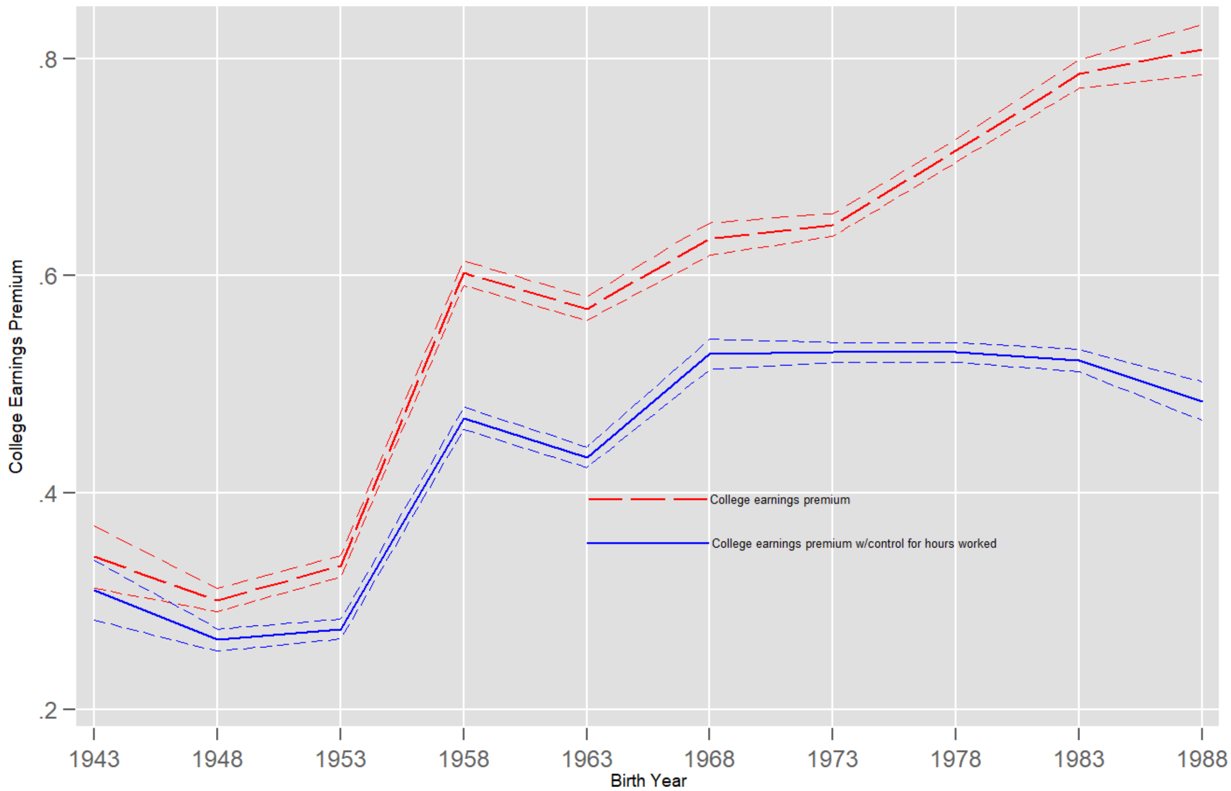
The influence of a college degree on annual labor earnings consists of both the influence of college on hours of work and on the wage.[19] To make this point I examine the college earnings premium in the NLSY cohorts and in each of the 5 year ACS cohorts. The analysis replaces

[18]For any two five year cohorts, the latter cohort has a larger college hours premium throughout the distribution.

[19]The earnings here includes all earnings in that year from wages, salaries, commissions, cash bonuses, tips, and other money income received from an employer.

hours with earnings in (1). Inclusion of a control for hours worked is not meant to be an indirect calculation of the college wage premium.

Two college earnings premia are presented in the Figure 5. One controls for hours worked and the other does not. The aggregate labor returns to college both with and without a control for usual hours worked in a week are plotted in Figure 1.5. These are plotted at the middle year of each birth cohort. For example, the college earnings premium for the 1961-1965 birth cohort is plotted at 1963 but reflects the entire five year cohort.



The vertical axis represents the college aggregate labor income premium. The horizontal axis logs the birth year with each 5 year birth cohort plotted at the middle year. The thin lines to either side of the main lines in the legend represent the 95% confidence interval for the estimate.

Figure 1.11: Estimates of the college aggregate labor income premium for men for each 5 year cohort in the ACS with and without a control for hours worked.

The upper line plots the college earnings premium when not controlling for hours of work. The lower line plots the college earnings premium when controlling for usual hours worked each week. The distance between the two lines reflects the effect of hours of work on the earnings premium. Controlling for hours of work in the early cohorts leaves the earnings premiums essentially unchanged. For the first cohort the college earnings premium is reduced from 0.34 to 0.31 when controlling for hours of work. This difference is not statistically significant. Over

time the difference grows. By the 1961 to 1965 birth cohort the college earnings premium is 0.57 and is reduced to 0.43 when controlling for hours worked. The difference for this cohort is a statistically significant 25% of the college earnings premium. The growing gap in hours becomes increasingly important. In the final cohort (born 1986 to 1990), the college earning premium is 0.81, which reduces to 0.48 when controlling for hours worked. Thus, the hours difference increasingly drives the earnings difference.

Without a control for hours there exists a clear trend of an increasing college earnings premium. When controlling for hours worked, those born after the 1970's see no increase in the college earnings premium. It remains stable or actually declines during this period.

The effect of the college hours premium on the college earnings premium in both data sets point to the importance of the growing college hours premium in determining the college earnings premium. Failure to account for this growing premium generates a misleading trend in the college earnings premium. This emphasizes the growing college income premium despite a slowdown in the growth of the college wage premium.

1.6 Conclusion

The *college wage premium* has risen for much of the last century. However, recent evidence suggests the growth may have stopped. At the same time there has been a decline in hours worked per week by men. I show this decline is concentrated among those without a college degree. Thus the growth of the college hours premium is reflected in the *college earnings premium*.

The NLSY allows a comparison of men from two birth cohorts. The distribution of hours worked is similar for both college graduates and high school graduates in the first cohort. However, in the second cohort college graduates work more hours than high school graduates. The increase in the college hours premium exists throughout the hours distribution. Yet, the increase in the hours premium is largest in the centre of the distribution, as much as 8 hours. This is more than 3 times the mean increase of the college hours premium between cohorts.

I show that the college hours premium is not explained by high school graduates working a greater number of hours than college graduates in the NLSY97. Splitting the sample based on a worker's union status, sector of employment, industry or occupation does not provide greater insight into the source of the college hours premium. However, the increase in the college hours

premium is substantially larger among salaried workers than among hourly workers. There is also an increase in involuntary part time employment among the less educated. Yet, this explains only a modest portion of the emerging college hours premium. There appears to be no single source for the premium and it clearly remains widespread.

I also demonstrate a long term trend of increasing college hours premiums for workers born between 1940 and 1990 using the ACS. The data mirrors the NLSY by showing that this increase in the college hours premium happens across the entire hours distribution and is largest in the heart of the distribution.

The data also allows examination of the *college earnings premium*. The five year ACS birth cohorts show increasing college earnings premiums. Re-examining this college earnings premium when controlling for hours worked shows that the college earnings premium stops growing for those born in the 1970s and after. This confirms a clear increase in the influence of hours worked on the college earnings premium. Particularly for the later birth cohorts more than a third of the college earnings premium is driven by the college hours premium.

The education wage premium is not the only channel through which education affects income. The education hours premium is of increasing importance. Thus, education may still drive income inequality, but now based on a growing education hours premium. An increasing college hours premium, particularly one generated by a reduction in hours worked by those without a college degree, may further increase inequality if it the reduces the likelihood of formal full time employment and the associated fringe benefits of health insurance and pensions.

Chapter 2

THE RETURNS TO DRINKING - SOCIAL WORKERS OR SOCIAL JOBS?

2.1 Introduction

The labor market outcomes associated with alcohol consumption remain in doubt. Conventional wisdom argues that alcohol consumption, especially excessive consumption, leads to adverse outcomes. These include worse health (Schmidt and Popham, 1975), increased likelihood of unemployment (Mullahy and Sindelar, 1993), workplace conflict (French et al., 2011), and lower human capital accumulation (Williams et al., 2003). However, one vein of economics research, at least since Berger and Leigh (1988), shows that drinking is associated with higher income than abstaining.

Several mechanisms have been offered for this positive association. First, the health benefits associated with moderate consumption, including both improvement in physical health (Kannel and Ellison, 1996) and reduced social isolation and stress (Peele and Brodsky, 2000). While these benefits might raise earnings, the social aspects of drinking may also dramatically increase social capital increasing the returns to work. Eckardt et al. (1998) argue that social networks expand, communication skills improve and valuable job information is exchanged during social drinking.

I match the NLSY97 worker data with O*NET data to examine the differences in the return to drinking in social and non-social jobs to show a substantially higher return to alcohol consumption in *social jobs*. I follow Deming (2017) by recognizing that individual worker *social skills* (measured by extraversion) have returns. While the returns to social skills are greater in social jobs, accounting for them does not meaningfully change the returns to drinking. This suggests that the returns to drinking reflect more than workers sorting on social skills. Accounting for individual fixed effects only increases the returns to drinking in social jobs. These results fit with

Glaeser et al. (2002) who show workers in social jobs invest more in social capital because they can expect higher returns for that capital. Drinking is an important channel for generating social capital.

In the next section I review studies examining the relationship between earnings and drinking during periods of employment. Yet, drinking prior to the labor market also has consequences. Drinking during high school and college is linked to lower GPA, lower likelihood of graduation and a lower likelihood of future employment (Mullahy and Sindelar, 1993; Chatterji and DeSimone, 2006; Balsa et al., 2011; Williams et al., 2003; Renna, 2007). However, Bray (2005); Bray et al. (2018) show that drinking during school and college may increase income once students become workers.

At issue in studies of earnings and drinking is the role of self selection. This is true for studies focusing on either school age drinking or drinking during periods of employment. On the one hand, drinking may facilitate the creation of social capital as has been contended. On the other hand, those with social capital and social skills may naturally be attracted to drinking. Henderson et al. (1996) and Buvik (2020) study the effect of drinking on work. They suggest that besides reducing stress, the social element of drinking is an important part of its effect on workers. Peters and Stringham (2006) emphasize that it is not drinking per se but the social aspect of drinking in groups that has returns. This fits with the model of Haucap and Herr (2014) who argue that social drinking builds trust facilitating future social and business interactions.

Empirical studies show that associations between earnings and drinking in cross-sections often fade with the introduction of worker fixed effects (Lye and Hirschberg, 2004; Peters, 2004). This argues that sorting may be crucial and that those brought together in drinking have greater social capital inherently or would find ways to build it other than drinking. Controls for social skills, individual fixed effects and the ability to divide jobs into social and non-social allow me to show that drinking is routinely associated with additional earnings and dramatically so in social jobs.

Additionally I find that the returns to an additional year of drinking while employed at the same employer is common to workers in both social and non-social jobs. This suggests the generation of employer specific social capital from drinking. Years of drinking before the current employer is rewarded at much higher rates in social jobs suggesting that the social capital generated from drinking may also be transferred between jobs in social occupations and therefore be general

social capital as well.

In what follows section 2 provides a look at past evidence on the returns to drinking during periods of employment and social skills. Section 3 presents the data used and Section 4 the empirical strategy used to analyze that data. Section 5 describes the results and a series of robustness checks. Section 6 concludes and suggests future research.

2.2 Past Evidence and Theory

Past research documents the association between drinking during periods of employment and higher wages[1]. Berger and Leigh (1988) use the 1972-1973 Quality of Employment Survey to show a positive relationship between alcohol use and wages. They correct for selection in their cross section using the Heckman (1979) two stage estimator. Using job repetitiveness and obesity as first step instruments does not change the positive relationship between drinking and wages.

Hamilton and Hamilton (1997) and Auld (2005) use Canadian cross-sectional data. They use a Heckman type two stage estimator to account for selection into three categories; abstainers, moderate drinkers and heavy drinkers.[2] Hamilton and Hamilton (1997) confirm that moderate drinkers earn more than abstainers. They suggest that this reflects health benefits to moderate drinking. Auld (2005) uses six waves of the Canadian General Social Survey, finding moderate drinkers earn 10% more than abstainers. He also accounts for individual smoking behaviour, a potential omitted variable. He suggests that occupational sorting may generate the returns to drinking, but does not explore it further.

Lye and Hirschberg (2004) use the 1995 Australian household survey to examine the effects of alcohol and smoking on wages. They again control for sample selection. They find a positive relationship between drinking and wages for non-smokers. But an insignificant relationship for smokers.

[1]Not all past studies look at the effect of alcohol on earnings. Mullahy and Sindelar (1993) look at effects across the life cycle. However, they only look at excessive alcohol use. They show that alcoholism at any point in someone's life negatively affects many labor market outcomes including wages. Alcoholism indirectly affects income by affecting characteristics such as educational attainment. Others such as Dave and Kaestner (2002); French et al. (2011); Kandel et al. (1995) also look at labor market outcomes. It is mostly excessive alcohol use that affects non-wage labor market outcomes.

[2]Both papers use the price of alcohol, religiosity and Catholicism as instruments.

French and Zarkin (1995) study the relationship between drinking and wages using detailed data from four work sites. They find a non-linear relationship between drinking and wages. The returns diminish or reverse with higher levels of alcohol consumption. Zarkin et al. (1998) use the 1991 and 1992 National Household Surveys on Drug Abuse, a repeated cross-section. They measure alcohol use multiple ways but all measures reveal a positive relationship between drinking and wages. MacDonald and Shields (2001) use the Health Survey for England using illness indicators, parent's smoking behavior and a self assessed opinion of alcohol consumption as instruments. Again, the results confirm a positive relationship between drinking and wages.

Kenkel and Ribar (1994) use the panel nature of the NLSY79 to control for individual fixed effects. They find a positive relationship between earnings and days of drinking per month. However, when using individual fixed effects the association is no longer statistically significant. Tekin (2004) uses six waves of the Russia Longitudinal Monitoring Survey. Saffer and Dave (2005) uses six waves of the Health and Retirement study. Both studies find a positive relationship between drinking and wages that disappears with the inclusion of individual fixed effects.

Bray (2005) also uses the NLSY79, but does not directly study the relationship of drinking with wages. Instead, he finds increased returns to education and experience when drinking. Bray et al. (2018) follows the same structure but uses the NLSY97. This is important as the NLSY97 asks individuals about alcohol use in every survey wave unlike the NLSY79. The authors define moderate drinking as drinking but not binge drinking. Binge drinking is 5 or more drinks in each instance. I also use this Center for Disease Control definition (CDC, 2018). The results suggest that drinking reduces the returns to education. The returns to drinking are positive but not significant when accounting for human capital development while drinking.

As suggested, the positive relationship between drinking and earnings may reflect the ability of social drinking to build social capital. Henderson et al. (1996) reviews past research noting that social drinking has benefits in the workplace. It creates informal groups at work and improves working relationships within these groups. It improves relationships between managers and employees. It helps with team-building.

Buvik (2020) summarizes in-depth surveys of Norwegian managers and employees who emphasize the importance of drinking. Drinking facilitates networking and fosters positive relationships with colleagues. Both managers and employees consider drinking an investment

in the workplace. Drinking with colleagues after work represents an important "transition ritual" out of work. It reduces reported stress and helps employees deal with their day. Drinking strengthens group cohesion and builds trust among colleagues.

While drinking may improve performance within the workplace, it may also generate social capital outside the workplace. Networks outside the workplace may be expanded, valuable information exchanged with competitors, customers and suppliers. Social skills can be developed and knowledge of job possibilities improved (Eckardt et al., 1998).

Peters and Stringham (2006) differentiate between those who drink at a bar or tavern and those who do not. They emphasize that drinking in public rather than at home leads to larger social networks and social capital. It also develops social skills. They find a 10% increase in income associated with drinking, that rises to 17% for those who drink in public. This they take as evidence that social capital growth plays a role in the returns to drinking.

Social capital is the interpersonal element of human capital. Glaeser et al. (2002) provide a theoretical framework for explaining the formation of social capital. Social capital represents an individual's intrinsic social skills and contacts and subsequent investments in building those skills and contacts. They show that workers in social occupations should gain more from social capital. As a consequence, workers in these occupations will invest more in social capital.[3]

Deming (2017) provides a test of the Glaeser et al. (2002) model. Using the NLSY97, he measures social skills with the big 5 personality measure for extraversion. He shows that there has been a 12% increase in the demand for social skills over the last generation. Using O*Net skill intensities, he matches jobs with the importance of social skills. He shows that workers with greater social skills are more likely to sort into social jobs. Moreover, workers earn more from social skills in social jobs.

This paper introduces measures of alcohol use into a framework of social skills and social jobs. I use the measure from Deming (2017) for each. I confirm that social skills have higher returns in social jobs, but find that the return to drinking remains unchanged when I control for social skills. Alternatively, I introduce individual fixed effects, their inclusion only increases the differences in the returns to drinking between social and non-social jobs. This suggests that

[3]Putnam (1995) defines investments in social capital as those that expand the features of social life -networks, norms and trust- that enable participants to act together more effectively to pursue shared objectives".

even when controlling for observable but fixed individual characteristics, job type matters. The social nature of the job plays an important role in determining a worker's return to drinking in exactly the way the Glaeser et al. (2002) model would predict if drinking represents, in part, an investment in social capital.

Investments in social capital, like investments in all human capital, can be expected to have both specific and general components (Becker, 1962). Having found returns to drinking that may reflect social capital investment, I examine this distinction. Current returns to drinking during previous jobs would represent a return to general investments in social capital. Returns to drinking during the current job would more nearly represent a return to specific investments in social capital.

2.3 Data

I use the National Longitudinal Survey of Youth (NLSY97) for data on income, education, alcohol consumption, ability and demographic characteristics. The NLSY97 surveys 8,984 individuals born between 1980 and 1984. The survey is ongoing with the latest available data for 2015 at which point the subjects were between the ages of 30 and 36. I include workers over the age of 21 and not enrolled in either school or college. Drinking before 21 may also be indicative of other traits.[4] The final sample includes 41,021 observations of 6,332 workers.

The primary dependent variable is annual labor earnings. Using an hourly wage measure does not meaningfully change the pattern of results.[5]

Respondents are asked about their alcohol consumption in the month preceding the interview. They report if they consume alcohol, and if so, the quantity consumed. Following the previous literature (Bray et al., 2018; CDC, 2018; SAMHSA et al., 2016; DHHS and USDA, 2015; NIAAA, 1997), individuals who typically consume five or more drinks in one instance are "binge" drinkers. Those who drink but do not binge drink are the primary focus of this study and are labelled "regular" drinkers.

[4]Using all 18 year olds and counting drinking after 18 does not meaningfully change the results.

[5]This is consistent with the use of annual income as the dependent variable in past research (Auld, 2005; Kandel et al., 1995; MacDonald and Shields, 2001; Mullahy and Sindelar, 1993). Other papers do use hourly wage as well but do not find different results. (Berger and Leigh, 1988; French and Zarkin, 1995; Bray, 2005)

Years of alcohol use after workers turn 21 and when not enrolled form the basis of our independent variable. The focus is on drinking while employed, thus, the primary variable measures the number of years of regular drinking prior to the survey year. I also control for number of years of binge drinking prior to the survey year.

I also split years of drinking into those before the current employer and those at the current employer. This separation is based on the unique employer identification number assigned to each employer in the NLSY97. I count every year an individual is associated with that particular employer in calculating the number of years of regular drinking and binge drinking.

The big five personality measure, extraversion measures social skills. The NLSY97 asks two questions answered on a 1-7 scale.[6] I normalize the response to each question, add the normalized values and re-normalize the sum. This follows Deming (2017). I then create a dummy for a high level of social skills, based on a level of extraversion above the mean. Using the continuous measure does not change the results.

The O*NET provides detailed information about tasks for each occupation. It contains information about task intensities and importance, skill, knowledge and ability required for a job among other details. This information is collected for each narrow occupation by surveying individuals in the occupation. I match the NLSY occupation code to the O*Net data. The O*Net defines occupations at a finer level than the NLSY. When multiple O*Net occupations correspond to a single NLSY occupation, the mean for the corresponding occupations is used.

The importance of work skills required for a job to differentiate between social and non-social jobs. Specifically I use a combined measure consisting of "social perceptiveness", "coordination", "persuasion" and "negotiation". O*NET survey respondents rate the importance of each of these factors to their job on a scale of 1-5 with 5 being the most important. I normalize the values for each of the skills, add them and re-normalize to create a continuous distribution of the importance of social ability within each occupation. This follows Deming (2017). Occupations with a level above the mean are considered social occupations.

I include other controls commonly used in income regressions, education, cognitive ability, race, age, sex, region of residence, residence in an urban area, health status and marital status.

[6]The first question asks respondents to rate how closely extraversion and enthusiasm apply to them. The second question does the same with reserved and quiet.

Educational attainment for each worker is based on their highest education level. For workers with no reported degree, highest grade completed is used to fill in the gaps. Education dummies are created for no high school diploma, some college or an associate degree, college graduates and advanced or professional degrees. Armed Forces Qualification Test (AFQT) scores are used as a cognitive ability measure. Race is controlled for by including dummy variables for White, Black, American Indian (or Eskimo or Aleut), Asian (or Pacific Islander) and other races. Region of residence is split into South, West, North East and North Central. Health status is based on an individuals self reported health on a scale of 1-5.[7] Finally, marital status is separated into never married, married, separated, divorced and widowed.

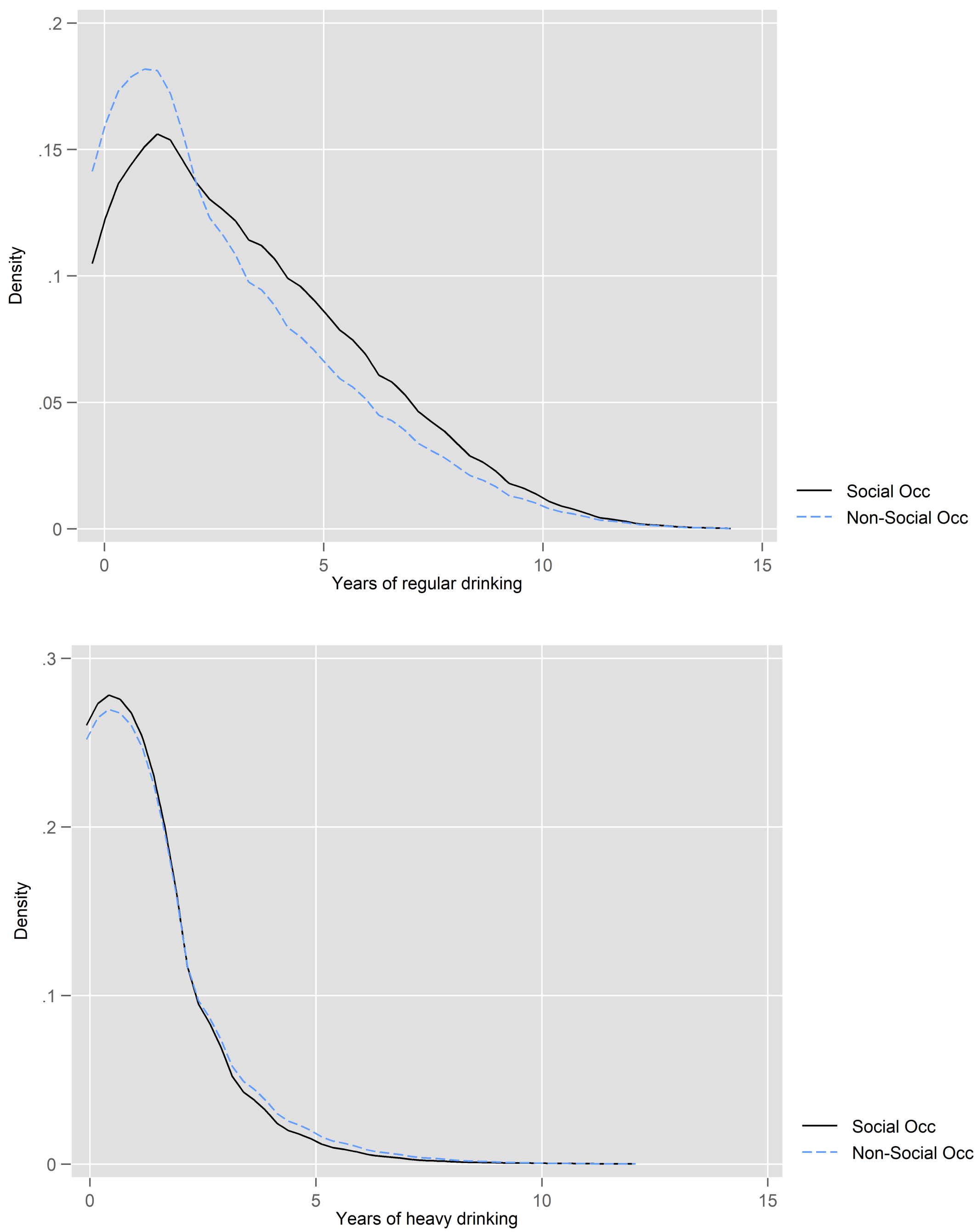
Table 2.1 shows the descriptive statistics for the entire sample and split by social and non-social jobs. The mean income is $28,970 for the full sample, $33,884 for workers in social jobs and $24,652 for workers in non-social jobs. The average years of experience is 7.2 for workers in both social jobs and non-social jobs. 29% of workers in social jobs have an undergraduate degree compared to only 10% of workers in non-social jobs.

[7] 1 refers to excellent health and 5 refers to poor health. I use indicators for each of the 5 levels.

	Full sample	Social Jobs	Non-Social Jobs
Income	$28,970	$33,884	$24,652
Years of regular drinking	2.7	2.9	2.5
Years of binge drinking	1.0	1.0	1.1
Age	26	26	25
Years of Experience	7.2	7.2	7.2
High School	0.10	0.05	0.14
Some College	0.06	0.07	0.05
Bachelors Degree	0.19	0.29	0.10
Graduate Degree	0.04	0.08	0.01
Race:Black	0.25	0.23	0.27
Race:Other	0.13	0.13	0.13
North East	0.16	0.16	0.15
North Central	0.23	0.22	0.23
South	0.39	0.39	0.40
West	0.22	0.23	0.21
Urban	0.83	0.86	0.80
N	38,535	18,766	19,769

The final sample consists of 6,332 individuals who have no missing data for extraversion and any of the other control variables. All observations are of workers who are 21 or older. Income is all income from wages, salary and tips in a year. Drinking more than 5 drinks in each instance is coded as "binge" drinking. Drinking, but drinking fewer than 5 drinks in each instance is coded as "regular" drinking.

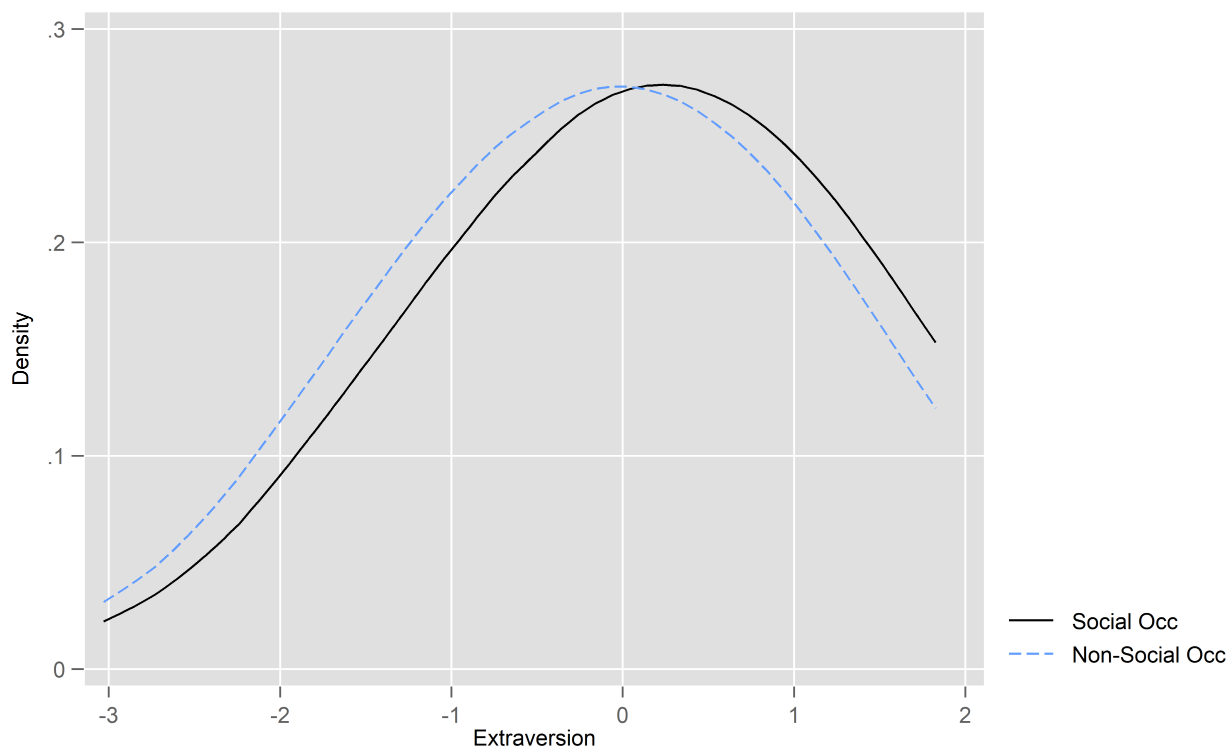
Table 2.1: Descriptive Statistics



Regular drinking is defined as drinking fewer than 5 drinks in each instance. Binge drinking is defined as drinking 5 or more drinks in each instance. Job types are based on O*NET measures of the importance social skill.

Figure 2.1: Distribution of years of regular and heavy drinking drinking by job type.

On average workers drink "regularly" for 2.7 years and "binge" for 1 year. The distribution of the number of years of regular drinking looks very different by job type. The top graph in Figure 2.1 shows that workers in social jobs drink regularly for a greater number of years than those in non-social jobs. This is an initial indication that those in social jobs may invest more in drinking as it may build more social capital. The bottom graph in Figure 1 shows that the number of years of binge drinking does not differ by job type. The distributions are also essentially identical. This suggests the focus on regular drinking may be the appropriate one for examining social capital.



Social skills are constructed using the big 5 personality measure "Extraversion". Job types are based on O*NET measures of the importance social skill.

Figure 2.3: Distribution of social skills by job type.

Figure 2.2 presents the distribution of social skills by job type. Workers in social jobs clearly have a higher level of social skills. This would be predicted by Glaeser et al. (2002). The pattern of social skills and regular drinking are similar across job types. They are each more prevalent in social jobs. This argues for the analysis that examines the returns to drinking controlling for the extent of social skills.

2.4 Empirical Approach

The analysis differentiates between job types, I include the returns to drinking for the entire sample as a baseline for comparison to past research. I then show the returns separately for those working in social and in non-social jobs.

I estimate variations of the following equation:

$$ln(income_{it}) = \beta_0 + \beta_1 Drink_{i(t)} + \beta_2 Binge_{i(t)} + \beta_3 Soc.Ski._i + \beta_k X_{it} + \varepsilon_i \tag{2.1}$$

where the primary dependent variable, $income$ is the annual labor income of the individual "i" in year "t". The two primary independent variables are $Drink$ and $Binge$. $Drink$ is the number of years of drinking but not binge drinking i.e. "regular" drinking before year "t". $Binge$ is the number of years of binge drinking before year "t". $Soc.Ski$ is the dummy variable for a high level of social skills.[8] The vector X represents year and individual specific controls including education, cognitive ability, age, race, sex, residence in an urban area, survey year, experience, region, health, and marital status.[9] All estimates are weighted using sampling weights.

I use three estimation strategies. The first is comparable to past research using demographic controls. It is estimated for the full sample and separately for social and non-social jobs. The second strategy uniquely includes the measure of social skills for the entire sample and social and non-social jobs separately. At issue is whether this inclusion reduces or eliminates the returns to drinking, especially for social jobs. The final strategy includes individual fixed effects. The inclusion of fixed effects controls for abilities or characteristics that are fixed over time and otherwise unobservable. These may be correlated with both drinking and earnings generating a

[8]I show very similar results with a continuous measure of social skill in Appendix table B2. I also include that continuous measure as both a linear term and as a quadratic term, once again that does not affect the pattern of results.

[9]The controls are included with dummies for each of the values allowing for any non-linear variation.

misleading correlation between these variables. I continue to uniquely examine the influence of fixed effects separately for social and non-social jobs.

As workers may switch between social and non-social jobs, I present two fixed effects estimates. The first includes all workers. Thus, the same worker may appear for some observations in the social job estimate and for others in the non-social job estimate. The second limits the sample to workers who do not switch job types. Therefore it only compares workers who have worked only in social jobs to those who have worked only in non-social jobs.

After initially examining theses three strategies I engage in a variety of robustness tests. I first examine men and women separately as social skills have sometimes been thought to differ by gender. Second, I alter the treatment of both the critical dependent and independent variables. Next, I examine hourly wages and use multiple methods of classifying drinking. Next I examine whether critical sub-samples of occupations drive our results, specifically I eliminate sales workers and restaurants and bars staff. These occupations may be thought to be uniquely associated with alcohol consumption. I show that none of these robustness tests cause a substantial variation in the basic results but do present some nuance.

After the robustness checks, I examine the distinction between general and specific investments in social capital. I use the distinction between years of drinking prior to the current employer and years of drinking with the current employer to distinguish between general and specific investments.

2.5 Results

Table 2.2 reports estimates for the entire sample, workers in social jobs, workers in non-social jobs and the difference between the latter two groups of workers. Row 1 Column 1 shows a year of "regular" drinking is associated with 5.6% higher income in the entire sample. Row 1 Columns 2 and 3 show that "regular" drinking is associated with 6.2% higher income in social jobs and 4.4% higher income in non-social jobs. This difference of 1.8 percentage points is statistically significant.

	(1)	(2)	(3)	(4)
	Full sample	Social Jobs	Non-Social Jobs	Difference
Years of regular	0.0560***	0.0623***	0.0443***	0.0180***
Drinking	(0.00295)	(0.00416)	(0.00418)	(0.00590)
Years of Binge	0.0188***	0.00523	0.0329***	-0.0276***
Drinking	(0.00451)	(0.00700)	(0.00589)	(0.00915)
Returns to drinking with a control for social skills (extraversion)				
Years of regular	0.0555***	0.0616***	0.0442***	0.0174***
Drinking	(0.00295)	(0.00416)	(0.00418)	(0.00590)
Years of Binge	0.0186***	0.00490	0.0328***	-0.0279***
Drinking	(0.00451)	(0.00699)	(0.00590)	(0.00914)
Social Skills	0.0733***	0.0952***	0.0140	0.0812***
	(0.0136)	(0.0172)	(0.0223)	(0.0281)
N	38535	18766	19769	38535

Regular drinking is defined as drinking fewer than 5 drinks and binge drinking as drinking 5 or more drinks in in each instance. Controls used include year, age, health, region, msa status, AFQT score, marital status, gender and education. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.2: Returns to regular and binge drinking

Thus, not only is regular drinking more common in social jobs but it appears to be better rewarded as would be anticipated if it reflects social capital. At issue is whether drinking is simply a proxy for social skills and not an independent measure of social capital. The NLSY97 allows a measure of social skills to test this.

The second set of estimates (rows 3, 4 and 5) in Table 2.2 include a control social skills measured by extraversion. Row 3 Column 1 shows a year of "regular" drinking is associated with 5.6% higher income for the entire sample. Row 3 Columns 2 and 3 show that in social jobs a year

of “regular” drinking is associated with a 6.2% higher income and in non-social jobs a year of “regular” drinking is associated with 4.4% higher income. This 1.7 percentage point difference is virtually identical to that in Row 1 of Table 2 and remains statistically significant.

Row 5 of Table 2.2 presents the return to social skills. A high level of social skill is associated with 7.3% higher income. Columns 2 and 3 show that a high level of social skill is associated with 9.5% greater income in social jobs and 1.4% greater income in non-social jobs. The 8 percentage point difference is statistically significant. The higher return to social skills confirms Glaeser et al. (2002) and Deming (2017). Yet, controlling for social skills does not influence the returns to drinking. This suggests a return that is independent of the measure of social skills and suggests drinking may reflect a separate investment in social capital.

Yet, there remain many other unobserved individual characteristics. These characteristics that do not change over time can be controlled for with individual fixed effects. Table 2.3 reports the fixed effect estimates. Column 1 shows that a year of “regular” drinking is associated with 4.6% higher income for the full sample. This is moderately lower than the estimate without fixed effects. Columns 2 and 3 show that in social jobs a year of “regular” drinking is associated with 6.3% higher income, compared to 2.1% in non-social jobs. The decline in the average is generated almost completely by a steep decline in return to those in non-social jobs. This 4.2 percentage point difference is statistically significant and much larger in magnitude than in the estimates without fixed effects. This suggests that the unobserved characteristics that are captured by fixed effects generate a mutually large returns to drinking in non-social jobs and controlling for them moves the focus even more to social jobs.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					No Job Type Changers		
	Full Sample	Social Jobs	Non-Social Jobs	Difference	Social Jobs	Non-social Jobs	Difference
Years of regular Drinking	0.0464***	0.0630***	0.0211***	0.0419***	0.104***	0.00976	0.0945***
	(0.00502)	(0.00888)	(0.00730)	(0.0115)	(0.0135)	(0.00952)	(0.0165)
Years of Binge Drinking	0.00113	-0.0226	0.0210**	-0.0435**	-0.00167	0.0258**	-0.0275
	(0.00762)	(0.0151)	(0.0100)	(0.0178)	(0.0239)	(0.0131)	(0.0272)
N	38535	18766	19769	38535	8021	9058	17079

Regular drinking is defined as drinking fewer than 5 drinks and binge drinking as drinking 5 or more drinks in each instance. The same controls as Table 2 are used. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.3: Returns to drinking with individual fixed effects

The next three columns in table 3 excludes workers who switch between social jobs and non-social jobs. The estimate may now only include workers appropriately matched to job type. The development of social capital by drinking may also be different for job types. Looking exclusively at workers not changing job type potentially examines the returns to social capital generated for that specific job type.

Columns 5 and 6 show that a year of “regular” drinking in a social job is associated with 10.4% higher income and has no influence on income in non-social jobs. Thus, among the sample of workers who have remained in a job type the return to drinking is exclusively for those in social jobs. Moreover, that return is very large.

The results presented in table 2 and 3 clearly show larger returns to “regular” drinking for workers in social jobs than workers in non-social jobs. Social skills matter to earnings but when included do not change the estimates for drinking. The inclusion of individual fixed effects does not change the pattern of results. In fact, it reinforces the results showing larger returns to drinking in social jobs and small or no returns in non-social jobs.

The controls for binge drinking present interesting patterns. In the initial estimates there appears to be no return to binge drinking in social jobs but a modest one in non-social jobs. In the fixed-effect estimates, binge drinking is associated with declines in earnings in social jobs and little or no change in non-social jobs. This appears to confirm the focus on regular drinking, one that will be maintain while always controlling for binge drinking even when not specifically included in the table of results.

2.5.1 Robustness Checks

Table 2.4 presents the equivalent to tables 2 and 3 split by gender. The first four rows presents the results for men, the next four present the results for women. The broad pattern of results do not substantially differ by gender.

The basic specifications are in rows (a) and (e) and show that an additional year of "regular" drinking by men increases income by 6.9% in social jobs and 4.3% in non-social jobs. An additional year of "regular" drinking by women increases income by 5.5% in social jobs and 4.2% in non-social jobs. The differences are both statistically significant. Controlling for social skills once again does not greatly alter these results as shown in rows (b) and (f).

Rows (c) and (g) present the fixed effects estimates and show that an additional year of "regular" drinking by men increases income by 5.3% in social jobs and 1.5% in non-social jobs. An additional year of "regular" drinking by women increases income by 5.7% in social jobs and 1.6% in non-social jobs. The differences both remain statistically significant. Rows (d) and (h) present the fixed effects estimates for workers not changing job type and show an additional year of "regular" drinking by men increases income by 7% in social jobs, but has no influence on income in non-social jobs. An additional year of "regular" drinking by women increases income by 10% in social jobs and again has no influence on income in non-social jobs. The use of individual effects continues to increase the difference between job types. Critically, there exist only modest gender differences in the returns to "regular" drinking.

		(1) Social Jobs	(2) Non-Social Jobs	(3) Difference
Men	**(a) Basic Specification**			
	Years of regular	0.0686***	0.0428***	0.0258***
	Drinking	(0.00559)	(0.00482)	(0.00738)
	(b) Including social skills			
	Years of regular	0.0674***	0.0427***	0.0248***
	Drinking	(0.00556)	(0.00483)	(0.00736)
	(c) Individual fixed effects			
	Years of regular	0.0533***	0.0150*	0.0424***
	Drinking	(0.0123)	(0.00842)	(0.0153)
	(d) Individual fixed effects - No Job Type Changers			
	Years of regular	0.0724***	-0.00230	0.0745***
	Drinking	(0.0222)	(0.0105)	(0.0224)
Women	**(e) Basic Specification**			
	Years of regular	0.0554***	0.0423***	0.0131
	Drinking	(0.00586)	(0.00773)	(0.00970)
	(f) Including social skills			
	Years of regular	0.0550***	0.0423***	0.0127
	Drinking	(0.00586)	(0.00775)	(0.00971)
	(g) Individual fixed effects			
	Years of regular	0.0573***	0.0156	0.0417**
	Drinking	(0.0119)	(0.0131)	(0.0176)
	(h) Individual fixed effects - No Job Type Changers			
	Years of regular	0.102***	-0.00463	0.107***
	Drinking	(0.0174)	(0.0198)	(0.0262)

The same controls as Table 2 are used. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: Returns to drinking and binge drinking by gender.

Table 2.5 presents the results of several robustness checks involving alternate measures of alcohol use.[10] The CDC defines "moderate" drinking as 2 or fewer drinks. To rule out the possibility that this more restrictive category drives the results I include the number of years of moderate drinking, those of binge drinking and those of neither "binge" drinking nor drinking "moderately" (3 to 5 drinks, labeled "medium" drinking).

[10] I exclude the basic specification as the inclusion of social skill again presents essentially the same returns.

	(1)	(2)	(3)	(4)	(5)	(6)
	Controlling For Social skills		Individual Fixed effects		Individual Fixed effects Single job type	
	Social Jobs	Non-Social Jobs	Social Jobs	Non-Social Jobs	Social Jobs	Non-Social Jobs
(a) Including Moderate drinking						
Years of moderate	0.0618***	0.0518***	0.0658***	0.0263***	0.110***	0.0168*
Drinking	(0.00457)	(0.00503)	(0.00902)	(0.00780)	(0.0137)	(0.0101)
Years of medium	0.0614***	0.0397***	0.0602***	0.0182**	0.0985***	0.00660
Drinking	(0.00451)	(0.00451)	(0.00916)	(0.00748)	(0.0138)	(0.00978)
Years of binge	0.00495	0.0337***	-0.0224	0.0211**	-0.00115	0.0259**
Drinking	(0.00700)	(0.00591)	(0.0151)	(0.0100)	(0.0239)	(0.0131)
(b) Using Heavy drinking						
Years of non	0.0523***	0.0410***	0.0534***	0.0213***	0.0954***	0.0107
heavy Drinking	(0.00412)	(0.00405)	(0.00884)	(0.00790)	(0.0136)	(0.00927)
Years of heavy	0.0528***	0.0441***	0.0394**	0.0192	0.0785**	0.0273*
Drinking	(0.00903)	(0.00719)	(0.0196)	(0.0123)	(0.0317)	(0.0158)
N	18,776	19,769	15,172	18,378	8,021	9,058

The same controls as Table 2 are used. Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$

Table 2.5: Returns to alternate measures of drinking.

Columns 1 and 2 of Table 2.5 show that a year of ”medium” drinking is associated with 6.1% higher income in social jobs and 4% higher income in non-social jobs. Columns 3 and 4 show that a year of “medium” drinking is associated with 6% higher income in social jobs and 1.8% higher income in non-social jobs with the inclusion of individual fixed effects. Columns 5 and 6 show that a year of “medium” drinking is associated with 9.9% higher income in social jobs and has no influence on income in non-social jobs when individual fixed effects are included and the

sample is limited to workers who do not change job types.

The returns to "medium" drinking just described more closely match the returns to "moderate" drinking than those for "binge" drinking. Columns 3 and 4 show that year of "moderate" drinking is associated with 6.6% higher income in social jobs and 2.6% higher income in non-social jobs. Columns 5 and 6 show that a year of "regular" drinking is associated with 11% higher income in social jobs and 1.7% in non-social jobs when individual fixed effects are included and the sample is limited to workers who do not change job types. It is clear that the general results are not simply driven by moderate drinking.

Hamilton and Hamilton (1997) and Auld (2005) define heavy drinking as drinking at least once a week and drinking at least 8 drinks in each instance. Part (b) of Table 2.6 uses this definition. Columns 1 and 2 show that a year of "non-heavy" drinking is associated with 5.2% higher income in social jobs and 4.1% higher income in non-social jobs. Columns 3 and 4 show that a year of "non-heavy" drinking is associated with 5.3% higher income in social jobs and 2.1% in non-social jobs when individual fixed effects are included. Columns 5 and 6 show that a year of "non-heavy" drinking is associated with 9.5% higher income in social jobs and 1.1% in non-social jobs when individual fixed effects are included and the sample is limited to workers who do not change job types. These results again largely match the original results suggesting the exact definition of drinking is not crucial.

The primary dependent variable used in some of the past research is the hourly wage rather than the annual earnings used in this work. To confirm that the results are not specific to the choice of dependent variable I estimate equation with a control for hours of work and using reported hourly wage as the dependent variable.

Row 1 of Table 2.6 controls for the number of hours worked per year.[11] Columns 1 and 2 control for social skills and show that a year of "regular" drinking is associated with 5.4% higher income in social jobs and 4.4% higher income in non-social jobs. Columns 3 and 4 show that a year of "regular" drinking is associated with 6% higher income in social jobs and 2.4% in non-social jobs when individual fixed effects are included. Columns 5 and 6 show that a year of "regular" drinking is associated with 9.8% higher income in social jobs and 1.4% in non-social jobs when individual fixed effects are included and the sample is limited to workers who do not

[11] The hours worked in a year is the usual hours per week multiplied by the number of weeks worked that year.

change job types. These results do not greatly differ from the main results. Workers in social jobs still earn higher returns to drinking.

	(1)	(2)	(3)	(4)	(5)	(6)
	Controlling For Social skills		Individual Fixed effects		Individual Fixed effects Single job type	
	Social Jobs	Non-Social Jobs	Social Jobs	Non-Social Jobs	Social Jobs	Non-Social Jobs
(a) Controlling for hours worked per year						
Years of regular Drinking	0.0543*** (0.00385)	0.0440*** (0.00393)	0.0602*** (0.00875)	0.0241*** (0.00715)	0.0984*** (0.0133)	0.0138 (0.00931)
N	18,524	19,0362	18,524	19,0362	8,021	9,058
(b) Hourly Pay						
Years of regular Drinking	0.0377*** (0.00508)	0.0331*** (0.00523)	0.0522*** (0.0125)	0.0370*** (0.0101)	0.0859*** (0.0169)	0.0409*** (0.0131)
N	18,206	18,889	18,206	18,889	7,820	8,645

The same controls as Table 2 are used. Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$

Table 2.6: Estimates controlling for hours worked and with hourly wages as the dependent variable.

Row 2 of Table 2.6 estimates equation (1) after replacing the dependent variable with hourly wage. Columns 1 and 2 control for social skills and show that a year of "regular" drinking is associated with 3.8% higher income in social jobs and 3.3% higher income in non-social jobs. Columns 3 and 4 show that a year of "regular" drinking is associated with 5.2% higher income in social jobs and 3.7% in non-social jobs when individual fixed effects are included. Columns 5 and 6 show that a year of "regular" drinking is associated with 8.6% higher income in social jobs and 4.1% in non-social jobs when individual fixed effects are included and the sample is limited to workers who do not change job types. Once again the pattern of results is similar

to the primary results, drinking is associated with higher returns for workers in social jobs than workers in non-social jobs. Another concern is that the results may be driven by sales workers who entertain clients and bartenders for whom drinking is part of the job. I present estimates of the returns after excluding sales workers and bartenders from the sample in Table 2.7. Columns 1 and 2 control for social skills and show that a year of "regular" drinking is associated with 6.4% higher income in social jobs and 4.6% higher income in non-social jobs. Columns 3 and 4 show that a year of "regular" drinking is associated with 6.1% higher income in social jobs and 2.5% in non-social jobs when individual fixed effects are included. Columns 5 and 6 show that a year of "regular" drinking is associated with 10.4% higher income in social jobs and no difference in non-social jobs when individual fixed effects are included and the sample is limited to workers who do not change job types. The results are remarkably similar to those for the entire sample, Sales workers and bartenders, while in social jobs, do not drive the estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
	Controlling For Social skills		Individual Fixed Effects		Individual Fixed Effects Single job type	
	Social Jobs	Non-Social Jobs	Social Jobs	Non-Social Jobs	Social Jobs	Non-Social Jobs
Years of regular	0.0643***	0.0462***	0.0607***	0.0251***	0.104***	0.0145
Drinking	(0.00462)	(0.00432)	(0.0102)	(0.00783)	(0.0149)	(0.0100)
N	15,172	18,378	15,172	18,378	6,642	8,594

The same controls as Table 2 are used. Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$

Table 2.7: Estimates for the sample excluding sales workers and Bartenders

In general, the robustness checks in this section show a consistent pattern. The return to drinking in social jobs exceeds that in non-social jobs.[12]

[12] I also replaced the dichotomous social skills measure with a continuous measure (see Appendix Table B2) and added the remainder of the big five personality traits (See Appendix Table B3). Neither change alters the pattern.

2.5.2 General and specific human capital

If drinking reflects, in part, an investment in social capital, this form of human capital can be profitably compared with others. One of the most basic divisions in human capital distinguishes that which is specific to the firm and that which is general to many firms. (Becker, 1962, 1994) Indeed, implicitly the literature makes this distinction when it contrasts alcohol use improving trust and relations with the boss and co-workers (more nearly specific to the firm) and improving social skills and learning about the market and jobs (more nearly general). Yet, none of the previous studies pursues empirical testing of this difference.

Table 2.8 presents estimates of the returns to potentially the general social capital and employer specific social capital generated from drinking. The years of drinking before the current employer should be viewed as general social capital. The years of drinking at the current employer reflect both general and specific social capital. Row 1 shows that an additional year of "regular" drinking at the current employer is associated with 8.5% higher income in social jobs and an essentially identical 8.3% higher income in non-social jobs. However, Row 2 shows that an additional year of "regular" drinking before the current employer is associated with 3.8% higher income in social jobs and 1.3% higher income in non-social jobs. A year of "regular" drinking before the current job is associated with a statistically significant increase in income for workers in social jobs relative to workers in non-social jobs. Rows 3 and 4 show the fixed effect estimates of an additional year of drinking before and while employed at the current employer while controlling for social skills. As in the primary results these results are not different from those in Rows 1 and 2.

Row 5 shows that an additional year of "regular" drinking at the current employer is associated with 8.5% higher income in social jobs and 3.1% higher income in non-social jobs with the inclusion of individual fixed effects.[13] Row 6 shows that an additional year of "regular" drinking before the current employer is associated with 4.1% higher income in social jobs and no effect in non-social jobs with the inclusion of individual fixed effects.

[13]Limiting our sample to those who work only in one job type changes the sample so roughly half do not change employers. This likely skews the results for the estimate.

	(1) Social Jobs	(2) Non-Social Jobs	(3) Difference
(a) Basic Specification			
Years of regular drinking	0.0859***	0.0829***	0.00296
at current employer	(0.00584)	(0.00600)	(0.00838)
Years of regular drinking	0.0383***	0.0131**	0.0252***
before current employer	(0.00538)	(0.00565)	(0.00780)
(b) Including social skills			
Years of regular drinking	0.0854***	0.0826***	0.00283
at current employer	(0.00583)	(0.00601)	(0.00837)
Years of regular drinking	0.0367***	0.0129**	0.0238***
before current employer	(0.00537)	(0.00566)	(0.00780)
(c) Individual fixed effects			
Years of regular drinking	0.0854***	0.0308***	0.0546***
at current employer	(0.0106)	(0.00842)	(0.0135)
Years of regular drinking	0.0408***	0.00760	0.0332**
before current employer	(0.0102)	(0.00952)	(0.0140)
(d) Individual fixed effects - No Job Type Changers			
Years of regular drinking	0.105***	0.00950	0.0952***
at current employer	(0.0152)	(0.0101)	(0.0182)
Years of regular drinking	0.102***	0.00301	0.0994***
before current employer	(0.0166)	(0.0134)	(0.0213)

The same controls as Table 2 are used. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: Returns to drinking and binge drinking at the current employer and before the current employer

The pattern of results in Table 2.8 suggests several important points. First, there are clearly returns to both the specific and general portions of social capital associated with drinking. Thus, in every specification the years spent drinking prior to the current employer increase earnings in

social jobs. These returns cannot be associated with building specific relationships with colleagues and supervisors at the current job and likely reflect the building of otherwise unmeasured general social skills, the improvement of networks and the resulting acquisition of valuable information.

Second, the returns to drinking at the current employer are typically larger. In part, this may reflect that the returns are a combination of those to general and specific social capital. One might assume that the returns to previous employers represent the general portion of the current employer's return. If correct, the difference between the current employer and previous employer returns would be the return to specific social capital. Table 2.8 makes clear that this remains large, perhaps even larger than the return to general social capital.[14] This represents the improved relationships, trust and communication at the current job that will not transfer to a future employer. As with all specific capital, it would serve to bind the worker and employer.

Third, the results show that both general and specific returns are larger when current employment is in a social job. This reflects the major point of the paper and argues that those who invest in social skills in a current social job have a strong incentive to capture a larger portion of that investment by moving to another social job. Indeed, the returns to years of drinking prior to the current employer are remarkably small (and essentially zero in some estimations) when the current job is non-social. This fits with Glaeser et al. (2002) arguing that those who anticipate a career in social jobs have a greater incentive to invest heavily and early in social capital.

2.6 Conclusion

Economists have examined the returns to drinking for several decades. While the association between drinking and income has been found consistently, less agreed on is the mechanism through which drinking affects income. Worker and job characteristics have been examined as part of the search for this mechanism. I show the returns to drinking are larger for workers in social jobs. These jobs provide a greater opportunity to build social capital and a higher return to that social capital.

This role persists when trying to account for the obvious sorting. Workers with greater measured social skills are more likely to be in social jobs and that these social skills are better

[14]As an illustration in Table 8, the return to specific social capital would be 0.0854-0.0367 or 0.0487.

rewarded in social jobs. If the larger returns to alcohol use in social jobs reflected only these skills, accounting for them should eliminate the difference in returns. It does not. Individual fixed effect estimates that control for time invariant worker characteristics show the return to alcohol use persists and only increases the disparity between workers in social and non-social jobs. This would also be unanticipated if the return to alcohol reflected sorting on stable worker characteristics.

A series of robustness checks show the results do not vary greatly by gender and are not driven by a specific definition of alcohol use. The estimates are also robust to including hours worked as an independent variable and using hourly wage as the dependent variable in place of annual earnings. Excluding occupations such as bartenders and sales workers who might drive the result through a more direct mechanism. The pattern of results is consistent across all these variations, workers in social jobs experience larger returns to drinking than workers in non-social jobs. This argues for the importance of drinking as a method of developing otherwise unmeasured social capital.

The developed social capital may include improved social skills, improved trust, expanded work related networks and the resulting information about other actors in the industry. This long list of suggests potential differences in returns to general and specific social capital. Efforts to examine this suggests there are important elements of both types of social capital in the return to alcohol use. I found a persistent return to drinking while working for previous employers, for workers in social jobs. Thus, some of the overall return reflects transferable skills such as improved social awareness and ability to work and communicate well with others. Included among this would be those parts of an expanded network that profitably transfer between employers. Returns to drinking while with the current employer are persistent for workers in both social and non-social occupations. These returns appear larger as they also include investment in the specific social capital associated with current colleagues, supervisors, suppliers and competitors.

Remaining open questions include the exact kind of social capital associated with drinking. A direct measure of the size of one's social network might be useful in showing some of the specific linkages. Measures of mutual trust and productivity within a company could provide another another way to directly test social capital formation. Differentiating between social and non-social drinking as well as identifying drinking with co-workers could offer further evidence

of the importance of work networks versus broader social skill building. While these avenues for future improvement require alternative data, identifying the important role of social jobs and the pattern of general and specific returns stand as notable advancements.

Chapter 3

CHANGING PATTERNS IN THE JOBS OF COLLEGE GRADUATES

3.1 Introduction

The relationship between skills, education and technology has been the focus of a vast literature. Autor et al. (1998) use Census and CPS data to show a steady increase in demand for skilled workers between 1940 and 1996, this increase in demand is larger in computer-intensive industries. They argue that the skill biased technical change, i.e. a technological change that is a complement to high skilled labor and increases their productivity, due to the adoption of computers has led to the increase in demand for these skilled workers. Goldin and Katz (2009) update this data to show the demand for skilled workers continues at least until 2005.

Autor et al. (2003) use the Dictionary of Occupational Titles (DOT), the precursor to the O*NET, matched with the CPS to study the mechanism behind these changes. They confirm that changes to the tasks required by occupations have played a role in increasing the demand for skilled labor. Specifically they suggest that computers reduce the need for routine tasks, but they complement workers performing non-routine cognitive tasks. Beaudry et al. (2016) use data from the CPS from 1980 to 2013 to show a change in the pattern of demand for skills. They show that the demand for cognitive skills steadily increased from 1980 to 2000, but remains relatively flat after 2000. They suggest this has resulted in the growth of low-skilled manual jobs, with workers outside the top of the distribution "downskilling" and pushing low skilled workers out of the labor force. Castex and Dechter (2014); Ashworth and Ransom (2019); Ashworth et al. (2017, 2020); Venkatesh (2019) show that the returns to cognitive ability has reduced between the two NLSY cohorts providing further evidence to support Beaudry et al. (2016).

The importance of cognitive or non-routine analytical tasks has increased until 2000, but it

has not been a driver in the US labor market since. The question of what may be important in the market was not explored by those paper. However, Deming (2017) shifts the focus to non-cognitive ability and examines the importance of social skills in the labor market. He combines NLSY and ACS data with the O*NET to add social skills to the Autor et al. (2003) framework of task intensity. He shows that jobs requiring social skills have seen wage and employment growth since 1980, this is irrespective of the importance of non-routine analytical task intensity. He also shows a 24% increase in social skill task inputs between 1980 and 2012, compared to an 11% increase for non-routine analytical task inputs in the same period. The non-routine task inputs have declined for the period between 2000 and 2012, while the social task intensity has grown in the same period. This suggests a shift in importance toward social tasks and away from non-routine analytic tasks since 2000.

Left un-answered is how the changes in task inputs have affected workers with different levels of education. In this paper I use two cohorts of the National Longitudinal Survey of Youth (NLSY) and two waves of the Occupational Information Network (O*NET) to uniquely document the pattern of changes in the task characteristics for college graduates. In the NLSY79 college graduates are more likely than high school graduates to be employed in jobs where social skills are important, jobs where math/cognitive ability is important and jobs where both social skills and math/cognitive ability are important. This is no longer the case in the NLSY97, college graduates are more likely than high school graduates to be employed only in jobs where both social skills and math/cognitive ability are important.

This pattern is important as it suggests that the change in employment shares and wages described in Deming (2017) is not applicable to the entire labor market. Instead, the shift in the importance of social tasks may not be entirely universal across education levels. For college graduates, the increase in importance of social tasks is only due to employment in occupations both social tasks and cognitive/math ability are important, but not when only social tasks are important.

The rest of the paper is structured as follows. Section 2 explores describes the data from both the NLSY and O*NET. Section 3 presents the results. Section 4 concludes.

3.2 Data

My primary data sources are two cohorts of the National Longitudinal Survey of Youth (NLSY) and two versions of the Occupational Information Network data (O*NET). The two NLSY cohorts, the NLSY79 and NLSY97 uniquely allow me to control for cognitive ability and social skills, while the O*NET provides detailed data about the importance of tasks and skills in occupations.

The NLSY79 follows 12,686 individuals who were between the ages of 14 and 22 at the time of the first interview in 1979. The NLSY97 follows 8,984 individuals who were between the ages of 12 and 28 at the time of the first interview in 1997. In the latest wave of the NLSY97, from 2017, respondents were between 31 and 37. I therefore limit my sample of workers from the NLSY79 to match this age range. The last survey wave I include in the NLSY79 is from 2000 so the final sample includes 17 survey waves each from the NLSY79 and NLSY97. I limit the sample to workers between the ages of 18 and 37, and exclude all observations of individuals if they are enrolled in school or are in the military.

Both cohorts of the NLSY provide detailed data on occupation. The primary occupation for workers in the NLSY79 is reported in Census 1970 occupation codes while the primary occupations for workers in the NLSY97 are reported in Census 2000 codes. I use the aggregated Census 1990 occupation codes developed by David and Dorn (2013) to generate a consistent set of occupation codes across the NLSY79 and NLSY97. I create an identical set of controls in both cohorts. First, educational attainment is the highest degree attained at the time of observation. For individuals with no reported degree I use years of education. So I use education dummies for not completing high school (no High School diploma or fewer than 12 years of education), completing some college (an associates degree or between 13 and 16 years of education), college completion (a college degree or 16 or 17 years of education) and graduate degree completion (masters degrees, doctoral degrees, professional degrees or more than 17 years of education). This follows Castex and Dechter (2014). All estimated values are compared to high school graduates.

I control for cognitive ability using the Armed Forces Qualification Test (AFQT) scores and control for social skills using a measure of "Extraversion".[1] This is important as cognitive ability

[1]The AFQT scores in the NLSY79 and NLSY97 have been adjusted to account for type of test and age at testing using the procedures suggested by Altonji et al. (2012) as used in Castex and Dechter (2014), and all test scores are

plays a large role in college completion affecting labor market decisions indirectly, if not directly (Caviglia-Harris and Maier, 2020). I also control for race, region, residence in an Metropolitan statistical area (MSA), age, year, birth year and marital status. All estimates apply traditional individual sampling weights.

The Occupational Information Network (O*NET) is a database containing information about occupational requirements, experience requirements, workers requirements, workforce characteristics, worker characteristics and occupation-specific information for each occupation included in the Standard Occupational Classification (SOC) occupation taxonomy. The database is based on responses from individuals employed in the occupation to a survey asking about the importance and level of each of the requirements, characteristics and skills in each SOC occupation. I use a survey of workers in 2003, the O*NET 5.0 for occupations in the NLSY79 and a survey of workers in 2017, O*NET 22.0 for occupations in the NLSY97. The O*NET 5.0 is the earliest version of the O*NET available that is based on survey responses from workers. Earlier versions of the O*NET between 1998 and 2001 were based on survey responses from analysts. Using an earlier version of the O*NET (O*NET 3.0 (2000)) does not change the pattern of results.

Following Deming (2017) I normalize the importance of "social perceptiveness", "coordination", "persuasion" and "negotiation" in each occupation, add the four measures and re-normalize the sum to create a measure for the importance of social skills in each occupation. Occupations for whom the measure is above the mean are classified as "Social" occupations and the rest are classified as "Non-social" occupations. Again following Deming (2017) I normalize the importance of "Using mathematics to solve problems", "Mathematical Reasoning" and "Mathematical Knowledge" in each occupation, add the three measures and re-normalize the sum to create a measure for the importance of math in each occupation. Occupations for whom the measure is above the mean are classified as "High Math" occupations and the rest are classified as "Low Math" occupations.

In addition two the classifications based on the above measures I create alternate methods of classifying occupations. The first is an alternate to the "Math" classification based on Deming

scaled to have a mean of zero and a standard deviation of one. The AFQT scores do not account for cognitive ability completely but is the only available measure.

(2017) to include the the data on the importance of cognitive ability to each occupation available in both versions of the O*NET. Specifically, I normalize the importance of "Category Flexibility ", "Flexibility of Closure", "Inductive Reasoning", "Information Ordering", "Mathematical Reasoning", "Memorization", "Selective Attention", "Speed of Closure", and "Time Sharing" in each occupation, add the four measures and re-normalize the sum to create a measure for the importance of cognitive ability in each occupation. Occupations for whom the measure is above the mean are classified as "High Cognitive" occupations and the rest are classified as "Low Cognitive" occupations.

The above methods only use a small portion of the information available in the O*NET. All available scores related to cognition and social interaction for each occupation are used. Categorizing occupations this way also does not force each measure to have an equal value in the classification. Each measure is standardized and k-means clustering is used to group the occupations into four categories in each O*NET version. But, the measures used for classification in the O*NET 5 and O*NET 22 are different and the role they play in classifying occupations into each of the categories is also different. The groups created in each O*NET version may there also not be directly comparable in the same way as those created using the previous methods.

For the final analysis workers in the NLSY are matched to the O*NET using SOC - Census occupation crosswalks. Occupations are defined at a much finer level in the SOC than the Census codes, so the mean of the corresponding occupations are used for the aggregated Census occupation.

Table 3.1 shows the descriptive statistics for workers in the NLSY79 split by the importance of Math and Social Skills in their occupation. Low Math Non-social jobs make up 40% of the sample in the NLSY79 and 9% of the sample in the NLSY97, High Math Non-social jobs make up 16% of the NLSY79 and only 0.5% of the NLSY97, Low Math Social jobs make up 11% of jobs in the NLSY79 and 37% of jobs in the NLSY97, and finally High Math Social jobs make up 33% of the sample in the NLSY79 and 53% of the sample in the NLSY97. The mean level of cognitive ability and social skills (extraversion) for workers in the four categories align with what might be expected from selection into those occupation groups.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low Math Non-social		High Math Non-social		Low Math Social		High Math Social	
	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
High School	0.554	0.784	0.464	0.701	0.422	0.711	0.326	0.577
Some College	0.203	0.037	0.249	0.042	0.296	0.05	0.251	0.067
College Degree	0.059	0.039	0.153	0.104	0.157	0.114	0.241	0.244
Graduate Degree	0.017	0.003	0.054	0.009	0.064	0.018	0.132	0.067
Male	0.624	0.768	0.436	0.712	0.161	0.442	0.494	0.55
Black	0.175	0.219	0.127	0.141	0.142	0.151	0.103	0.117
Other	0.024	0.100	0.023	0.240	0.022	0.103	0.023	0.117
Msa	0.748	0.879	0.803	0.916	0.801	0.902	0.834	0.941
Age	26.81	24.06	27.23	24.88	27.69	24.22	28.63	25.92
Cognitive Ab.	-0.244	-0.369	0.186	0.016	0.113	-0.043	0.394	0.266
Social Skills	-0.017	-0.166	0.015	-0.131	0.151	0.069	0.192	0.108
Annual Income	29,140	31,134	32,508	31,018	25,630	20,674	47,896	39,969
N	34,057	3,508	12,442	169	8,368	13,318	23,259	17,588

Table 3.1: Descriptive statistics for workers in the NLSY79 and NLSY97 split by importance of math and social skills.

Table 3.2 provides a list of five occupations in each cohort of the NLSY that appear most frequently in each occupation group. The workers in some of these groups may go against common wisdom in terms of where you may expect them to appear, for example construction laborers may not be expected to be in the Low Math Social job group as they do in the NLSY97 in the table. This is a reflection of the imperfect nature of these measures in classifying occupations. I make use of the other data available in the O*NET to classify occupations into groups in two additional ways.

Non-Social Low Math	Non-Social High Math	Social Low Math	Social High Math
NLSY79			
Waiter/waitress	Cashiers	Secretaries	Postmasters
Typists	Accounting clerks	Health aides	Salespersons
Cooks	Machine operators	Child care workers	Primary school teachers
Truck drivers	Inventory clerks	Social workers	Accountants and auditors
Janitors	Customer service reps	Hairdressers	Managers in marketing
NLSY97			
Laborers and freight	Payroll clerks	Waiters and waitresses	Retail salespersons
Janitors	Grinding setters, etc.	Childcare workers	Customer service reps
Vehicle cleaners	Cutting setters, etc.	Stock clerks	Supervisors of retail workers
Packers	Extruding setters, etc.	Receptionists	Managers, all other
Maintenance workers	Biological technicians	Construction laborers	Carpenters

Table 3.2: List of occupations grouped by math and social skills.

3.3 Results

Table 3.3 reports the results of the bi-variate probit estimation of the likelihood of working in social and math jobs for the two NLSY cohorts. Columns 1 and 2 of Row 1 show that the marginal effect of a college degree on working in a job where Math is important increases to 0.219 in the NLSY97 from 0.141 in the NLSY79. Columns 3 and 4 of Row 1 show that the marginal effect of a college degree on working in a job where Math is important increases to 0.178 in the NLSY97 from 0.093 in the NLSY79 when controlling for cognitive ability and social skills (extraversion).

Columns 3 and 4 of Row 2 show that the marginal effect of cognitive ability on working in a job where Math is important is 0.056 in the NLSY97 and 0.052 in the NLSY79. Columns 3 and 4 of Row 3 show that the marginal effect of social skills on working in a job where Math is important is 0.0095 in the NLSY97 and -0.0017 in the NLSY79.

	(1)	(2)	(3)	(4)
	NLSY79	NLSY97	NLSY79	NLSY97
Marginal effect on working in Math Jobs				
Undergraduate	0.141***	0.219***	0.0934***	0.178***
Degree	(0.00620)	(0.00873)	(0.00662)	(0.00910)
Cognitive			0.0517***	0.0563***
Skill			(0.00259)	(0.00327)
Social			-0.00175	0.00952***
Skill			(0.00186)	(0.00278)
Marginal effect on working in Social Jobs				
Undergraduate	0.211***	0.0415***	0.204***	0.0331***
Degree	(0.00741)	(0.00378)	(0.00798)	(0.00385)
Cognitive			0.00506	0.0106***
Skill			(0.00323)	(0.00119)
Social			0.0300***	0.0115***
Skill			(0.00239)	(0.00102)
ρ	0.69	0.45	0.69	0.44

Table 3.3: Results of a Bivariate probit on Social and Math Jobs in the NLSY79 and NLSY97

Columns 1 and 2 of Table 3.4 Row 4 show that the marginal effect of a college degree on working in a job where Social Skills are important decreases to 0.042 in the NLSY97 from 0.211 in the NLSY79. Columns 3 and 4 of Row 4 show that the marginal effect of a college degree on working in a job where Social Skills are important decreases to 0.0331 in the NLSY97 from 0.204 in the NLSY79 when controlling for cognitive ability and social skills (extraversion).

Columns 3 and 4 of Row 5 show that the marginal effect of cognitive ability on working in a job where Social Skills are important is 0.011 in the NLSY97 and 0.005 in the NLSY79. Columns

3 and 4 of Row 6 show that the marginal effect of social skills on working in a job where Social Skills are important is 0.03 in the NLSY97 and 0.012 in the NLSY79. The final line in Table 3.3, ρ presents the correlation coefficient between the importance of math and social skills in the sample.

The results in this table show that the marginal effect of a college degree on the likelihood of working in a math job increases between the two NLSY cohorts, whereas its marginal effect on working in social jobs declines between the two cohorts. The marginal effect of Cognitive ability on working in a math job is steady across the two cohorts, but the marginal effect of cognitive ability on working in a social job is higher in the NLSY97 than the NLSY79. The marginal effect of social skills on working in a math job is statistically significant only in the NLSY97, but the marginal effect of social skills on working in a social job is lower in the NLSY97 than the NLSY79.

Table 3.4 reports the results of the multinomial probit estimation of the likelihood of working in jobs classified on importance of social skills and math. Columns 1 and 2 of Row 1 show that the marginal effect of a college degree on working in a High Math Non-Social job decreases to 0.003 in the NLSY97 from 0.037 in the NLSY79. Columns 3 and 4 of Row 1 show that the marginal effect of a college degree on working in a High Math Non-Social job decreases to 0.003 in the NLSY97 from 0.016 in the NLSY79 when controlling for cognitive ability and social skills (extraversion).

Columns 3 and 4 of Row 2 show that the marginal effect of cognitive ability on on working in a High Math Non-Social job is 0.001 in the NLSY97 and 0.022 in the NLSY79. Columns 3 and 4 of Row 3 show that the marginal effect of social skills on working in a High Math Non-Social job is -0.003 in the NLSY97 and -0.012 in the NLSY79.

Columns 1 and 2 of Row 4 show that the marginal effect of a college degree on working in a Low Math Social job decreases to -0.107 in the NLSY97 from 0.034 in the NLSY79. Columns 3 and 4 of Row 4 show that the marginal effect of a college degree on working in a Low Math Social job decreases to -0.087 in the NLSY97 from 0.046 in the NLSY79 when controlling for cognitive ability and social skills (extraversion).

	NLSY79	NLSY97	NLSY79	NLSY97
High Math Non-Social				
Undergraduate	0.0372***	0.00316	0.0159***	0.00250
Degree	(0.00476)	(0.00249)	(0.00523)	(0.00259)
Cognitive			0.0224***	0.000724
Skill			(0.00223)	(0.00105)
Social			-0.0119***	-0.00322***
Skill			(0.00160)	(0.000891)
Low Math Social				
Undergraduate	0.0339***	-0.107***	0.0456***	-0.0872***
Degree	(0.00338)	(0.00823)	(0.00381)	(0.00862)
Cognitive			-0.0130***	-0.0272***
Skill			(0.00160)	(0.00296)
Social			0.00316***	0.00533**
Skill			(0.00117)	(0.00253)
High Math Social				
Undergraduate	0.270***	0.242***	0.220***	0.196***
Degree	(0.00545)	(0.00785)	(0.00608)	(0.00822)
Cognitive			0.0480***	0.0562***
Skill			(0.00271)	(0.00298)
Social			0.0253***	0.0176***
Skill			(0.00196)	(0.00255)

Table 3.4: Results of a Multinomial probit on Social and Math Jobs in the NLSY79 and NLSY97

Columns 3 and 4 of Row 5 show that the marginal effect of cognitive ability on on working in a Low Math Social job is -0.027 in the NLSY97 and -0.013 in the NLSY79. Columns 3 and 4 of Row 6 show that the marginal effect of social skills on working in a Low Math Social job is 0.005 in the NLSY97 and 0.003 in the NLSY79.

Columns 1 and 2 of Row 7 show that the marginal effect of a college degree on working in a High Math Social job decreases to 0.242 in the NLSY97 from 0.270 in the NLSY79. Columns 3 and 4 of Row 7 show that the marginal effect of a college degree on working in a High Math Social job decreases to 0.196 in the NLSY97 from 0.220 in the NLSY79 when controlling for cognitive ability and social skills (extraversion).

Columns 3 and 4 of Row 8 show that the marginal effect of cognitive ability on on working in a High Math Social job is 0.056 in the NLSY97 and 0.048 in the NLSY79. Columns 3 and 4 of Row 9 show that the marginal effect of social skills on working in a High Math Social job is 0.018 in the NLSY97 and 0.025 in the NLSY79.

The results in Table 3.4 show more evidence that the pattern of job sorting for college graduates having changed between the two cohorts. Importantly, college graduates are less likely to work in Low Math Social jobs in the NLSY97 than high school graduates. The education based differences in job sorting was not considered in earlier research and may suggest a more complex pattern than a simple increase in the demand for social skills.

3.3.1 Robustness Checks

I re-estimate Tables 3.3 and 3.4 using alternate measures to classify occupations. First, I use the O*NET measures of the importance of cognitive ability for the job in the place of the importance of math. The math variable was used initially by Autor et al. (2003) is an attempt to non-routine analytical task intensity, the cognitive ability measure may do a better job of capturing that than the math measure. I also use k-means clustering to create apriori grouping using all available information related to social skills and critical reasoning/cognition.

First, Table 3.5 reports the results of the bi-variate probit estimation of the likelihood of working in social and cognitive jobs for the two NLSY cohorts. Columns 1 and 2 of Row 1 show that the marginal effect of a college degree on working in a job where cognitive ability is

important increases to 0.134 in the NLSY97 from 0.121 in the NLSY79. Columns 3 and 4 of Row 1 show that the marginal effect of a college degree on working in a job where cognitive ability is important increases to 0.111 in the NLSY97 from 0.079 in the NLSY79 when controlling for cognitive ability and social skills (extraversion).

Columns 3 and 4 of Row 2 show that the marginal effect of cognitive ability on working in a job where cognitive ability is important is 0.028 in the NLSY97 and 0.045 in the NLSY79. Columns 3 and 4 of Row 3 show that the marginal effect of social skills on working in a job where cognitive ability is important is 0.014 in the NLSY97 and 0.002 in the NLSY79.

	(1)	(2)	(3)	(4)
	NLSY79	NLSY97	NLSY79	NLSY97
Marginal effect on working in Cognitive Jobs				
Undergraduate	0.121***	0.134***	0.0786***	0.111***
Degree	(0.00703)	(0.00664)	(0.00756)	(0.00686)
Cognitive			0.0450***	0.0284***
Skill			(0.00298)	(0.00198)
Social			0.00230	0.0137***
Skill			(0.00219)	(0.00175)
Marginal effect on working in Social Jobs				
Undergraduate	0.315***	0.0531***	0.282***	0.0419***
Degree	(0.00716)	(0.00469)	(0.00776)	(0.00479)
Cognitive			0.0330***	0.0140***
Skill			(0.00321)	(0.00145)
Social			0.0329***	0.0130***
Skill			(0.00236)	(0.00124)
ρ	0.26	0.59	0.25	0.58

Table 3.5: Results of a Bivariate probit on Social and Cognitive Jobs in the NLSY79 and NLSY97

Columns 1 and 2 of Table 3.5 Row 4 show that the marginal effect of a college degree on working in a job where Social Skills are important decreases to 0.053 in the NLSY97 from 0.315 in the NLSY79. Columns 3 and 4 of Row 4 show that the marginal effect of a college degree on working in a job where Social Skills are important decreases to 0.042 in the NLSY97 from 0.282 in the NLSY79 when controlling for cognitive ability and social skills (extraversion).

Columns 3 and 4 of Row 5 show that the marginal effect of cognitive ability on working in a job where Social Skills are important is 0.014 in the NLSY97 and 0.033 in the NLSY79. Columns

3 and 4 of Row 6 show that the marginal effect of social skills on working in a job where Social Skills are important is 0.013 in the NLSY97 and 0.033 in the NLSY79.

The results in this table show that the marginal effect of a college degree on the likelihood of working in a cognitive job increases between the two NLSY cohorts, whereas its marginal effect on working in social jobs once again declines between the two cohorts. The marginal effect of cognitive ability on working in a cognitive job declines between the two cohorts, as does the marginal effect of cognitive ability on working in a social job. The marginal effect of social skills on working in a cognitive job is statistically significant only in the NLSY97, but the marginal effect of social skills on working in a social job is lower in the NLSY97 than the NLSY79. Based on the vales of the ρ the correlation of the errors between the importance of math and social skills is higher in the NLSY79. However, correlation of the errors between the importance of cognitive ability and social skills is higher in the NLSY97.

Table 3.6 reports the results of the multinomial probit estimation of the likelihood of working in jobs classified on importance of social skills and cognitive ability. Columns 1 and 2 of Row 1 show that the marginal effect of a college degree on working in a High Cognitive Non-Social job increases to -0.025 in the NLSY97 from -0.042 in the NLSY79. Columns 3 and 4 of Row 1 show that the marginal effect of a college degree on working in a High Cognitive Non-Social job increases to -0.021 in the NLSY97 from -0.055 in the NLSY79 when controlling for cognitive ability and social skills (extraversion).

Columns 3 and 4 of Row 2 show that the marginal effect of cognitive ability on on working in a High Cognitive Non-Social job is -0.005 in the NLSY97 and 0.013 in the NLSY79. Columns 3 and 4 of Row 3 show that the marginal effect of social skills on working in a High Cognitive Non-Social job is -0.008 in the NLSY97 and -0.011 in the NLSY79.

	NLSY79	NLSY97	NLSY79	NLSY97
High Cognitive Non-Social				
Undergraduate	-0.0419***	-0.0251***	-0.0549***	-0.0205***
Degree	(0.00591)	(0.00424)	(0.00642)	(0.00436)
Cognitive			0.0133***	-0.00524***
Skill			(0.00255)	(0.00148)
Social			-0.0105***	-0.00811***
Skill			(0.00188)	(0.00122)
Low Cognitive Social				
Undergraduate	0.0813***	-0.0928***	0.0814***	-0.0789***
Degree	(0.00443)	(0.00672)	(0.00489)	(0.00693)
Cognitive			-0.00237	-0.0167***
Skill			(0.00211)	(0.00195)
Social			0.0109***	-0.00740***
Skill			(0.00156)	(0.00173)
High Cognitive Social				
Undergraduate	0.215***	0.218***	0.177***	0.178***
Degree	(0.00503)	(0.00824)	(0.00564)	(0.00844)
Cognitive			0.0379***	0.0459***
Skill			(0.00257)	(0.00256)
Social			0.0178***	0.0304***
Skill			(0.00185)	(0.00223)

Table 3.6: Results of a Multinomial probit on Social and Cognitive Jobs in the NLSY79 and NLSY97

Columns 1 and 2 of Row 4 show that the marginal effect of a college degree on working in a Low Cognitive Social job decreases to -0.093 in the NLSY97 from 0.081 in the NLSY79. Columns 3 and 4 of Row 4 show that the marginal effect of a college degree on working in a Low Cognitive Social job decreases to -0.079 in the NLSY97 from 0.081 in the NLSY79 when controlling for cognitive ability and social skills (extraversion).

Columns 3 and 4 of Row 5 show that the marginal effect of cognitive ability on on working in a Low Cognitive Social job is -0.017 in the NLSY97 and -0.002 in the NLSY79. Columns 3 and 4 of Row 6 show that the marginal effect of social skills on working in a Low Cognitive Social job is -0.007 in the NLSY97 and 0.011 in the NLSY79.

Columns 1 and 2 of Row 7 show that the marginal effect of a college degree on working in a High Cognitive Social job is 0.218 in the NLSY97 from 0.215 in the NLSY79. Columns 3 and 4 of Row 7 show that the marginal effect of a college degree on working in a High Cognitive Social job is 0.178 in the NLSY97 and 0.177 in the NLSY79 when controlling for cognitive ability and social skills (extraversion).

Columns 3 and 4 of Row 8 show that the marginal effect of cognitive ability on on working in a High Cognitive Social job is 0.046 in the NLSY97 and 0.038 in the NLSY79. Columns 3 and 4 of Row 9 show that the marginal effect of social skills on working in a High Cognitive Social job is 0.030 in the NLSY97 and 0.018 in the NLSY79.

I name the four categories obtained from clustering "Non-Technical", "Service", "Management", and "Technical". For example the occupation Janitor would be in the category "Non-Technical", the occupation Health Aides would be in "Service", managers would be in "Management" and accountants would be in "Technical".

"Non Technical" jobs make up 58% of the sample in the NLSY79 and 23% of the sample in the NLSY97, "Service" jobs make up 5% of the NLSY79 and only 42% of the NLSY97, "Management" jobs make up 11% of jobs in the NLSY79 and 8% of jobs in the NLSY97, and finally "Technical" jobs make up 25% of the sample in the NLSY79 and 27% of the sample in the NLSY97. The mean level of cognitive ability and social skills (extraversion) for workers in most of the four categories align with what might be expected from selection into those occupation groups.

Table 3.7 reports the results of the multinomial probit estimation of the likelihood of working in jobs classified by clustering. Columns 1 and 2 of Row 1 show that the marginal effect of a

college degree on working in a “Service job” decreases to -0.049 in the NLSY97 from 0.011 in the NLSY79. Columns 3 and 4 of Row 1 show that the marginal effect of a college degree on working in a “Service job” decreases to -0.057 in the NLSY97 from 0.006 in the NLSY79 when controlling for cognitive ability and social skills (extraversion).

Columns 3 and 4 of Row 2 show that the marginal effect of cognitive ability on on working in a “Service job” job is 0.009 in the NLSY97 and 0.005 in the NLSY79. Columns 3 and 4 of Row 3 show that the marginal effect of social skills on working in a “Service job” is -0.007 in the NLSY97 and -0.001 in the NLSY79.

	NLSY79	NLSY97	NLSY79	NLSY97
Service Jobs				
Undergraduate	0.0111***	-0.0491***	0.00610**	-0.0572***
Degree	(0.00273)	(0.00751)	(0.00310)	(0.00787)
Cognitive			0.00513***	0.00865***
Skill			(0.00128)	(0.00283)
Social			-0.000873	-0.00649***
Skill			(0.000915)	(0.00241)
Management Jobs				
Undergraduate	0.125***	0.102***	0.0899***	0.0877***
Degree	(0.00341)	(0.00317)	(0.00378)	(0.00335)
Cognitive			0.0369***	0.0189***
Skill			(0.00200)	(0.00179)
Social			-0.00294**	-0.00327**
Skill			(0.00132)	(0.00133)
Technical Jobs				
Undergraduate	0.191***	0.163***	0.164***	0.132***
Degree	(0.00509)	(0.00599)	(0.00568)	(0.00638)
Cognitive			0.0236***	0.0347***
Skill			(0.00252)	(0.00273)
Social			0.0263***	0.0250***
Skill			(0.00183)	(0.00222)

Table 3.7: Results of a Multinomial probit on Jobs grouped by clustering in the NLSY79 and NLSY97

Columns 1 and 2 of Row 4 show that the marginal effect of a college degree on working in a "Management job" decreases to 0.102 in the NLSY97 from 0.125 in the NLSY79. Columns 3 and 4 of Row 4 show that the marginal effect of a college degree on working in a "Management job" decreases to 0.088 in the NLSY97 from 0.0899 in the NLSY79 when controlling for cognitive ability and social skills (extraversion).

Columns 3 and 4 of Row 5 show that the marginal effect of cognitive ability on on working in a "Management job" is 0.19 in the NLSY97 and 0.037 in the NLSY79. Columns 3 and 4 of Row 6 show that the marginal effect of social skills on working in a "Management job" is -0.003 in the NLSY97 and -0.003 in the NLSY79.

Columns 1 and 2 of Row 7 show that the marginal effect of a college degree on working in a "Technical job" decreases to 0.163 in the NLSY97 from 0.191 in the NLSY79. Columns 3 and 4 of Row 7 show that the marginal effect of a college degree on working in a "Technical job" decreases to 0.132 in the NLSY97 from 0.164 in the NLSY79 when controlling for cognitive ability and social skills (extraversion).

Columns 3 and 4 of Row 8 show that the marginal effect of cognitive ability on on working in a "Technical job" is 0.035 in the NLSY97 and 0.024 in the NLSY79. Columns 3 and 4 of Row 9 show that the marginal effect of social skills on working in a "Technical job" is 0.025 in the NLSY97 and 0.026 in the NLSY79.

Using the alternate classification systems does not change the broad pattern of results that were seen in the initial specification, college graduates did not become more likely to work in all types of social jobs between the NLSY79 and NLSY97.

3.4 Conclusion

The literature examining the changes in job sorting in the US labor market has primarily focused on education and cognitive ability. The growth in the demand for jobs requiring cognitive tasks has slowed down if not reversed. More recently the literature has shifted it's focus to non-cognitive abilities. As the demand for cognitive ability has declined, the demand for non-cognitive ability, specifically social skills have increased. Deming (2017) shows a clear trend of increasing employment in social jobs, both routine analytical social jobs and non-routine analytical social

jobs. However none of this research has examined the role of education in this process.

I show that there exists a robust relationship between college and job sorting that has also changed over time. In the NLSY79 College graduates were more likely than high school graduates to work in occupations that require high levels of skill, either social skill, math or both social skills and math. This general relationship has become more specific in the NLSY97, college graduates are more likely than high school graduates to work in jobs that require high levels of both social skill and math, but not the jobs that require either one individually. In fact, unlike in the NLSY79 college graduates are significantly less likely than high school graduates to work in jobs that require social skills alone.

As robustness checks I use an alternate measure of task required by jobs. I use the O*NET's importance of cognitive ability for jobs particularly as it is one of the major changes to tasks demanded in the labor market. The NLSY also uniquely has a measure of cognitive ability allowing better control for selection. Once again the results are consistent with the primary results. In the NLSY97 college graduates are more likely than high school graduates to work only in occupations that require both social skills and cognitive ability. I also use clustering to create an apriori way of classifying occupations. This separated occupations in a unique way but college graduates were still less likely than high school graduates to be employed in one group in the NLSY97. This group, that I call "service jobs" once again seem to generally be related to higher levels of social skills required based on the earlier measures.

There are several questions yet to find resolution in this work. A more granular way of splitting occupations would allow a better understanding of the mechanism of the sorting. Attempting to estimate if the relationship between education and job sorting is causal would also have value.

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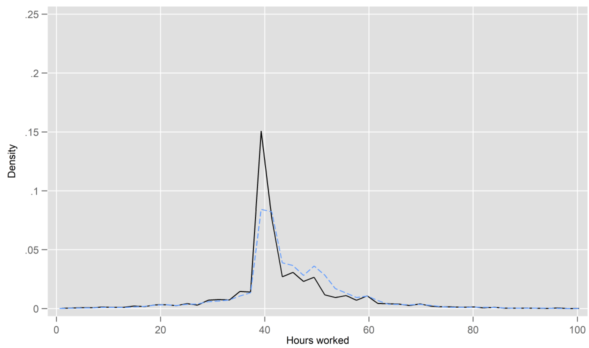
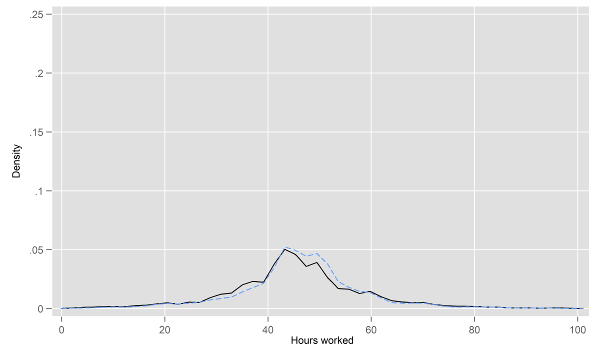
Appendix A: Chapter 1 Appendix

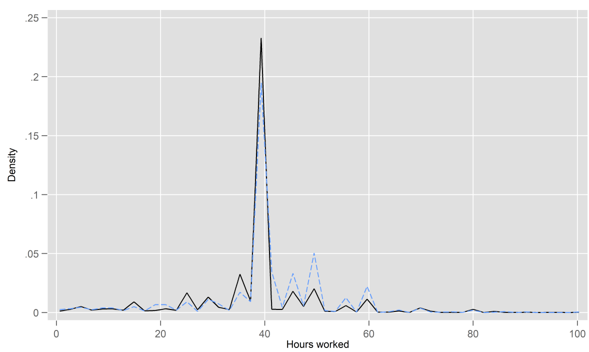
A.1 Appendix I - Figures



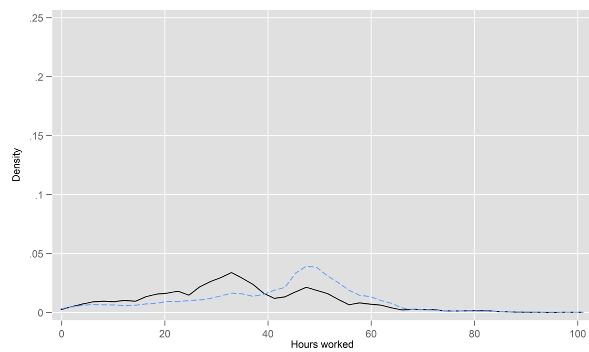
(a) NLSY79 with 40 hours



(c) NLSY79 without 40 hours

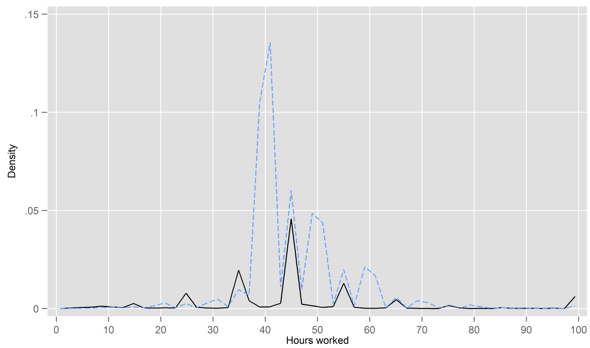


(b) NLSY97 with 40 hours

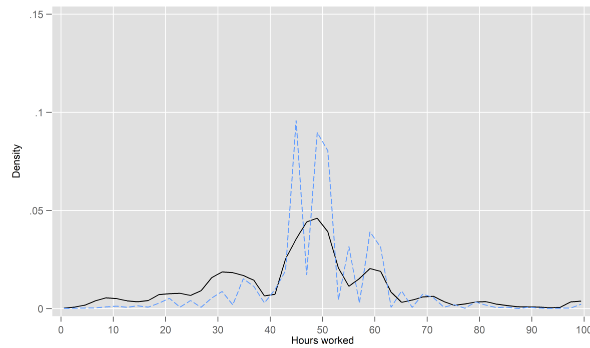


(d) NLSY97 without 40 hours

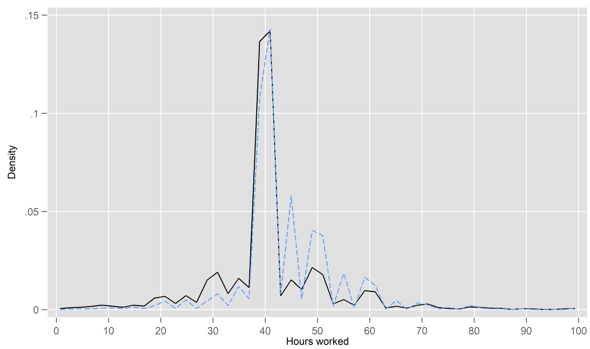
Figure A1: Distribution of hours worked in the NLSY79 and NLSY97 for male workers with a high school education and college education.



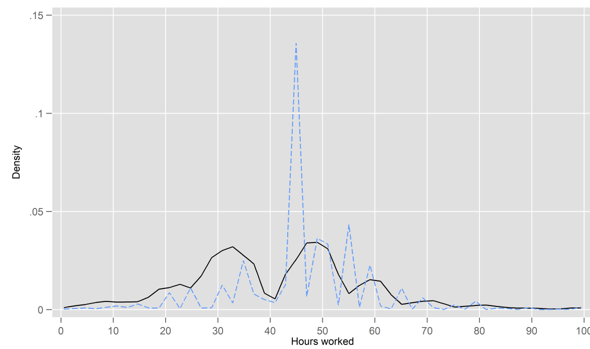
(a) NLSY79 with 40 hours



(c) NLSY79 without 40 hours

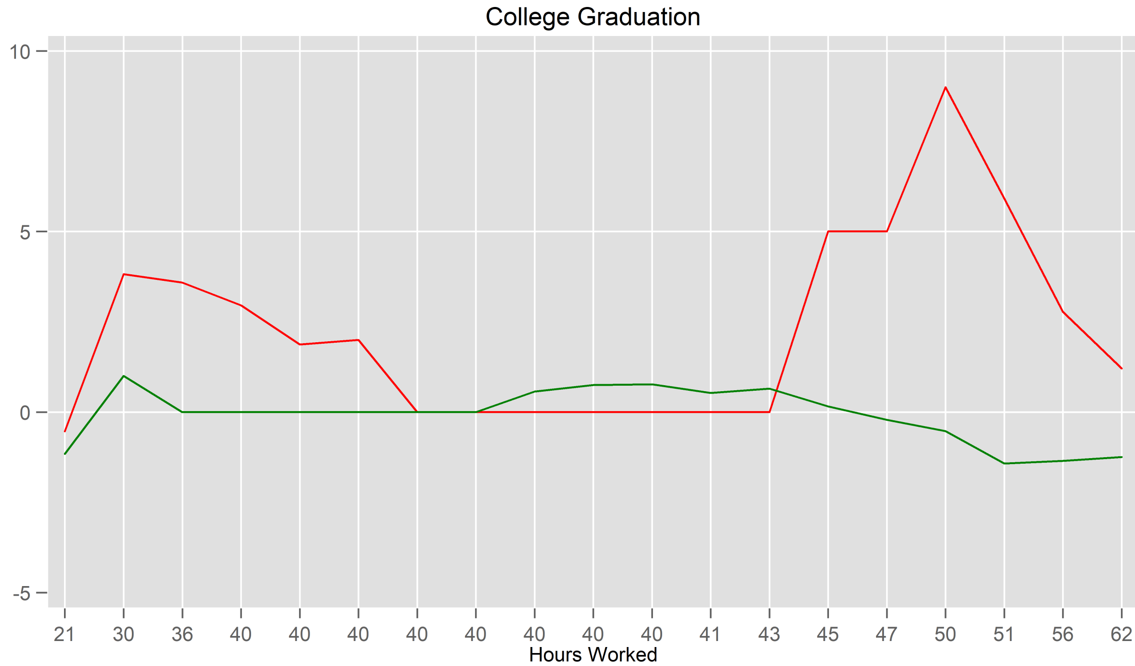


(b) NLSY97 with 40 hours



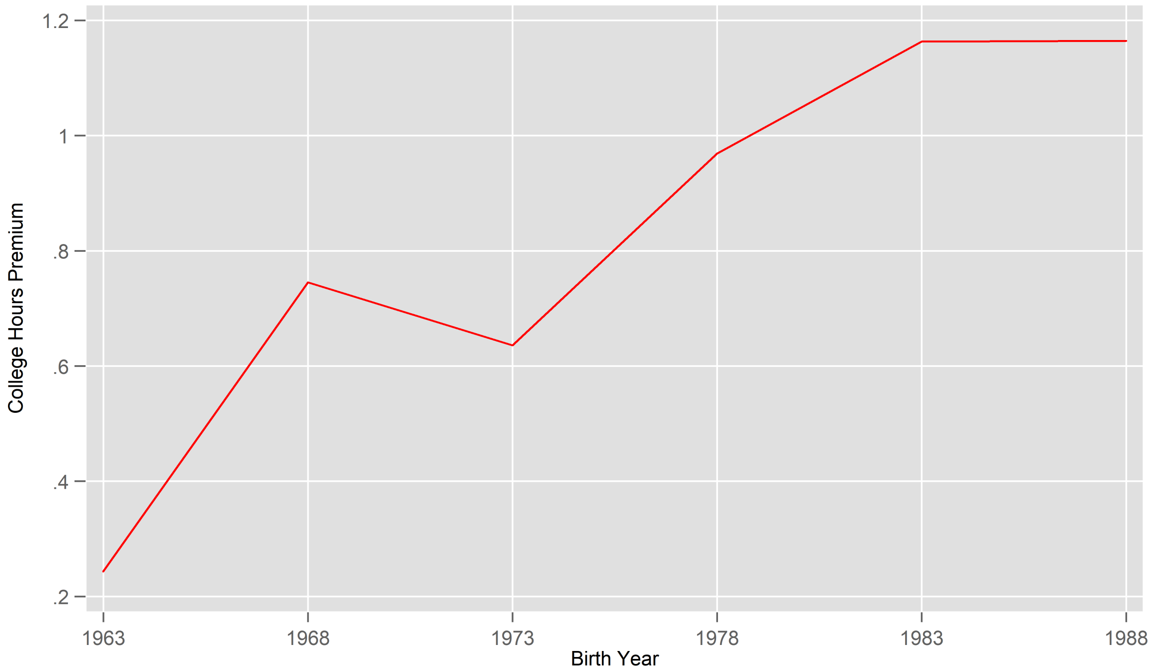
(d) NLSY97 without 40 hours

Figure A3: Distribution of hours worked in the NLSY79 and NLSY97 equivalent cohorts created from the ACS for male workers with a high school education and college education.



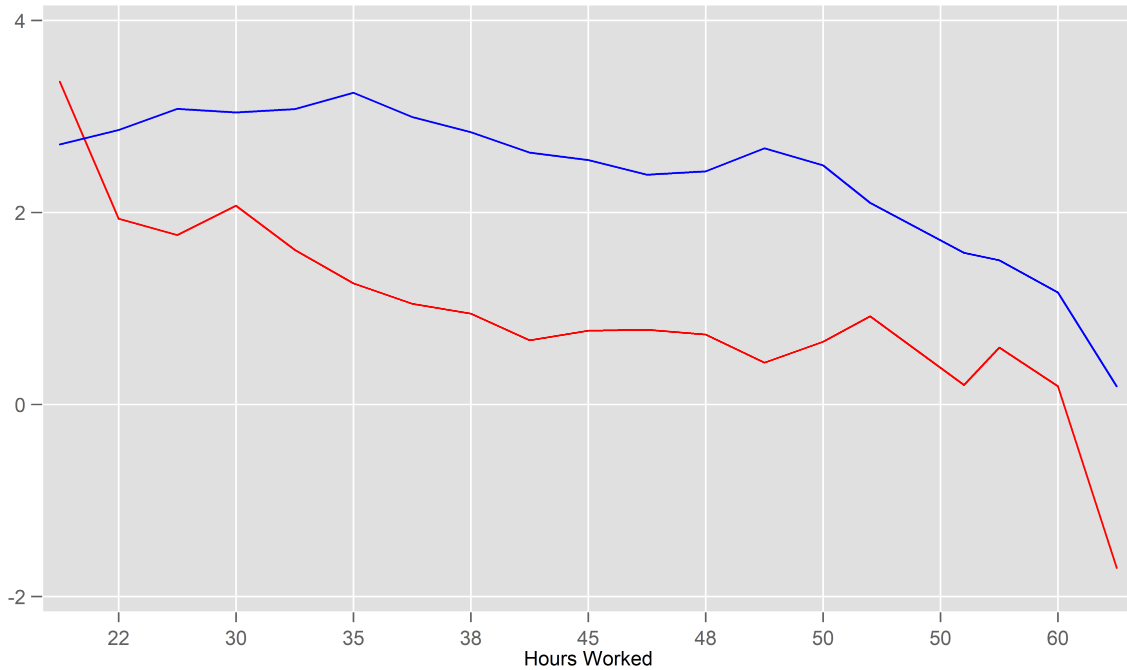
The vertical axis represents the college hours premium. The horizontal axis logs hours associated with each 5th quantile of the hours distribution. Since a large number of workers report working 40 hours a week, it represents a large portion of the distribution in both cohorts. The difference between the two cohorts is statistically significant for the entire distribution. The difference is calculated by a stacked equation with a dummy variable for a cohort and interaction term between the dummy variable and all the dependent variables.

Figure A5: Estimates of the quantile regression of college graduation on hours worked by men in the NLSY79 and NLSY97.



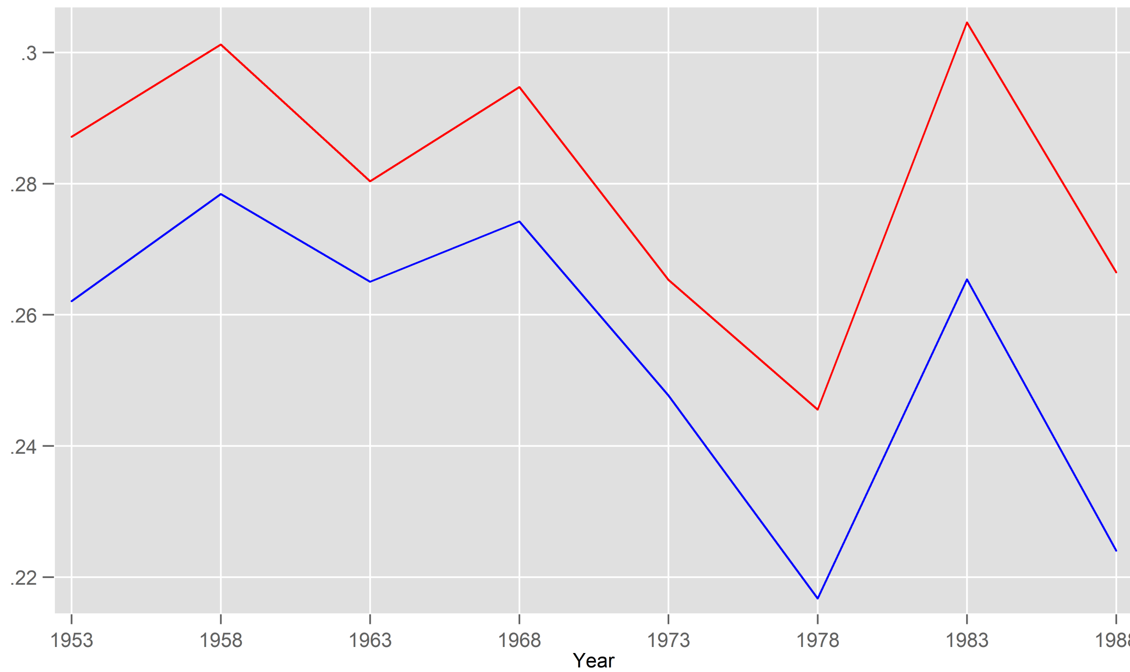
The vertical axis represents the college hours premium. The horizontal axis logs the birth year with each 5 year birth cohort plotted at the middle year.

Figure A7: Estimates of the college hours premium for 5 year birth cohorts of men in the CPS.



The vertical axis represents the college hours premium. The horizontal axis logs the number of hours associated with quantiles of the hours distribution. Workers who work exactly 40 hours are excluded from this distribution. The difference between the two cohorts is statistically significant for the entire distribution. The difference is calculated by a stacked equation with a dummy variable for a cohort and interaction term between the dummy variable and all the dependent variables.

Figure A9: Estimates of the quantile regression of college graduation on hours worked by men in the CPS.



The vertical axis represents the college aggregate labor income premium. The horizontal axis logs the birth year with each 5 year birth cohort plotted at the middle year. The thin lines to either side of the main lines in the legend represent the 95% confidence interval for the estimate.

Figure A11: Estimates of the college aggregate labor income premium for men for each 5 year cohort in the CPS with and without a control for hours worked.

A.2 Appendix II - Tables

	(1) NLSY79	(2) NLSY97	(3) NLSY79	(4) NLSY97
No diploma	-0.497	-0.578	-0.150	-0.284
	(0.342)	(0.484)	(0.372)	(0.523)
Some College	-0.0901	0.0481	-0.306	-0.0146
	(0.334)	(0.775)	(0.342)	(0.772)
College Degree	-0.0958	2.215***	-0.506	1.898***
	(0.365)	(0.460)	(0.401)	(0.480)
Graduate Degree	0.784	4.292***	0.275	3.919***
	(0.550)	(1.043)	(0.577)	(1.049)
Race - Black	-2.386***	-1.516***	-2.010***	-1.265***
	(0.248)	(0.368)	(0.303)	(0.389)
Race - Other	-0.768	-0.512	-0.573	-0.420
	(0.718)	(0.487)	(0.726)	(0.490)
MSA	-1.008***	-1.003*	-1.034***	-1.071*
	(0.302)	(0.571)	(0.303)	(0.579)
North Central	-0.320	-0.125	-0.345	-0.101
	(0.367)	(0.564)	(0.368)	(0.564)
South	0.313	1.150**	0.363	1.210**
	(0.340)	(0.509)	(0.338)	(0.508)
West	-0.625	-0.197	-0.636	-0.158
	(0.389)	(0.575)	(0.389)	(0.573)
Married	1.777***	2.397***	1.750***	2.390***
	(0.226)	(0.355)	(0.224)	(0.354)
Cognitive Ability			0.434**	0.383*
			(0.181)	(0.214)
N	49058	19425	49058	19425

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A1: Coefficients for demographic controls not provided in table 3 of the paper.

Hours Worked/Week in the	(1) NLSY79	(2) NLSY97	(3) NLSY79	(4) NLSY97
No diploma	-0.449	-0.388	-0.186	-0.0489
	(0.388)	(0.478)	(0.414)	(0.516)
Some College	0.0659	0.299	-0.0898	0.266
	(0.369)	(0.742)	(0.378)	(0.740)
College Degree	-0.148	2.025***	-0.419	1.725***
	(0.467)	(0.511)	(0.500)	(0.524)
Graduate Degree	1.646**	5.141***	1.319*	4.800***
	(0.658)	(1.123)	(0.682)	(1.123)
Cognitive Ability			0.342*	0.466**
			(0.194)	(0.199)
Individual Fixed Effects				
N	16556	19219	16556	19219

All estimates include controls for race, birth year, year, region, msa status and marital status.

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Estimates of the college hours premium for male workers in the NLSY79 and NLSY97 with industry and occupation controls.

Hours Worked/Week in the	(1) NLSY79	(2) NLSY97	(3) NLSY79	(4) NLSY97
No diploma	0.0681	1.962**	0.114	-0.293
	(0.481)	(0.763)	(0.396)	(0.936)
Some College	-1.902***	1.981*	-0.789**	-1.478
	(0.500)	(1.084)	(0.379)	(1.537)
College Degree	-1.686*	3.738***	-0.718	2.181**
	(0.889)	(1.010)	(0.555)	(1.063)
Graduate Degree	1.662	6.221***	-0.269	2.983
	(1.106)	(1.319)	(0.797)	(1.822)
Cognitive Ability			1.417***	-0.948**
			(0.247)	(0.436)
Sibling Fixed Effects			x	x
Individual Fixed Effects	x	x		
N	49058	19425	16615	4413

All estimates include controls for race, birth year, year, region, msa status and marital status.

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Estimates of the college hours premium for male workers in the NLSY79 and NLSY97 with individual fixed effects and sibling fixed effects.

Hours Worked/Week in the	(1) NLSY79	(2) NLSY97	(3) NLSY79	(4) NLSY97
No diploma	-0.125***	-0.123***	-0.0696***	-0.129***
	(0.0229)	(0.0338)	(0.0247)	(0.0352)
Some College	-0.148***	-0.0764*	-0.184***	-0.0749
	(0.0244)	(0.0459)	(0.0251)	(0.0459)
College Degree	-0.150***	0.171***	-0.221***	0.178***
	(0.0283)	(0.0303)	(0.0305)	(0.0323)
Graduate Degree	-0.220***	0.202***	-0.305***	0.210***
	(0.0425)	(0.0643)	(0.0448)	(0.0659)
Cognitive Ability			0.0715***	-0.00865
			(0.0119)	(0.0127)
N	49940	19687	49940	19687

All estimates include controls for race, birth year, year, region, msa status and marital status.

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Marginal effects from probit estimates for male workers working more than 40 hours a week in the NLSY79 and NLSY97.

Hours Worked/Week in the	(1) NLSY79	(2) NLSY97	(3) NLSY79	(4) NLSY97
No diploma	0.0598***	-0.0330	-0.0109	-0.0951**
	(0.0194)	(0.0395)	(0.0209)	(0.0409)
Some College	-0.0634***	-0.0642	-0.0197	-0.0515
	(0.0200)	(0.0508)	(0.0206)	(0.0509)
College Degree	-0.176***	-0.492***	-0.0925***	-0.429***
	(0.0231)	(0.0292)	(0.0250)	(0.0312)
Graduate Degree	-0.276***	-0.741***	-0.173***	-0.667***
	(0.0347)	(0.0543)	(0.0365)	(0.0558)
Cognitive Ability			-0.0879***	-0.0780***
			(0.00966)	(0.0138)
N	49940	19687	49940	19687

All estimates include controls for race, birth year, year, region, msa status and marital status.

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Marginal effects from probit estimates for male workers working fewer than 40 hours a week in the NLSY79 and NLSY97.

	(1) NLSY79	(2) NLSY97	(3) NLSY79	(4) NLSY97
Hours<40				
No diploma	0.0170***	0.0179**	0.00271	0.0110
	(0.00391)	(0.00891)	(0.00421)	(0.00919)
Some College	0.000970	0.00464	0.00999**	0.00614
	(0.00416)	(0.0119)	(0.00428)	(0.0119)
College Degree	-0.0172***	-0.105***	0.0000824	-0.0981***
	(0.00496)	(0.00764)	(0.00533)	(0.00812)
Graduate Degree	-0.0302***	-0.166***	-0.00904	-0.157***
	(0.00772)	(0.0167)	(0.00806)	(0.0170)
Cognitive Abitlity			-0.0180***	-0.00896***
			(0.00199)	(0.00314)
Hours=40				
No Diploma	0.0118***	-0.00181*	0.00188	-0.00111
	(0.00271)	(0.000925)	(0.00292)	(0.000941)
Some College	0.000672	-0.000470	0.00692**	-0.000621
	(0.00288)	(0.00121)	(0.00296)	(0.00121)
College Degree	-0.0119***	0.0107***	0.0000571	0.00992***
	(0.00346)	(0.00140)	(0.00369)	(0.00137)
Graduate Degree	-0.0210***	0.0168***	-0.00627	0.0159***
	(0.00538)	(0.00254)	(0.00559)	(0.00251)
Cognitive Ability			-0.0125***	0.000906***
			(0.00139)	(0.000326)
Hours>40				
No Diploma	-0.0288***	-0.0161**	-0.00459	-0.00987
	(0.00661)	(0.00800)	(0.00713)	(0.00826)
Some COllege	-0.00164	-0.00417	-0.0169**	-0.00552
	(0.00704)	(0.0107)	(0.00724)	(0.0107)
College Degree	0.0292***	0.0948***	-0.000140	0.0881***
	(0.00841)	(0.00696)	(0.00902)	(0.00735)
Graduate Degree	0.0512***	0.149***	0.0153	0.141***
	(0.0131)	(0.0150)	(0.0137)	(0.0153)
Cognitive Ability			0.0304***	0.00805***
			(0.00337)	(0.00283)
N	49940	19687	49940	19687

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Estimated marginal effects using an ordered probit to examine the effect of a college education on working fewer than 40 hours, 40 hours and more than 40 hours a week for male workers in the NLSY79 and NLSY97.

Hours Worked/Week in the	(1) NLSY79	(2) NLSY97	(3) NLSY79	(4) NLSY97
No diploma	-0.532	-0.655	-0.485	-0.199
	(0.427)	(0.487)	(0.433)	(0.498)
Some College	0.419	-0.665	0.388	-0.949
	(0.293)	(0.783)	(0.300)	(0.798)
College Degree	1.159***	3.003***	1.098***	2.523***
	(0.361)	(0.464)	(0.387)	(0.515)
Graduate Degree	2.565***	5.649***	2.496***	5.032***
	(0.527)	(0.986)	(0.551)	(0.990)
Cognitive Ability			0.0610	0.573***
			(0.157)	(0.219)
N	44313	19577	44313	19577

All estimates include controls for race, birth year, year, region, msa status and marital status.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Estimates of the college hours premium for female workers in the NLSY79 and NLSY97.

Hours Worked/Week in the	(1) NLSY79	(2) NLSY97	(3) NLSY79	(4) NLSY97
No diploma	-3.624***	-5.153***	-2.840***	-4.671***
	(0.345)	(0.671)	(0.362)	(0.678)
Some College	0.576**	2.431***	0.0899	2.327***
	(0.253)	(0.490)	(0.261)	(0.495)
College Degree	1.174***	2.153***	0.250	1.636***
	(0.231)	(0.290)	(0.257)	(0.327)
Graduate Degree	-0.329	0.647	-1.478***	0.0413
	(0.346)	(0.512)	(0.376)	(0.547)
Cognitive Ability			0.977***	0.625***
			(0.143)	(0.199)
N	49940	19687	49940	19687

All estimates include controls for race, birth year, year, region, msa status and marital status.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Association between college and weeks employed for male workers in the NLSY79 and NLSY97.

Number of jobs worked in the	(1) NLSY79	(2) NLSY97	(3) NLSY79	(4) NLSY97
No diploma	0.000426	-0.0645**	0.00654	-0.0558*
	(0.0173)	(0.0316)	(0.0181)	(0.0319)
Some College	0.0583***	0.0242	0.0545***	0.0224
	(0.0161)	(0.0461)	(0.0166)	(0.0462)
College Degree	0.00717	0.0521*	-0.0000371	0.0427
	(0.0158)	(0.0285)	(0.0176)	(0.0307)
Graduate Degree	-0.0297	-0.0141	-0.0386	-0.0251
	(0.0219)	(0.0435)	(0.0240)	(0.0457)
Cognitive Ability			0.00763	0.0113
			(0.00763)	(0.0133)
N	48899	19071	48899	19071

All estimates include controls for race, birth year, year, region, msa status and marital status.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Association between college and number of jobs worked for male workers in the NLSY79 and NLSY97.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Salaried workers				Hourly Workers		
	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
No diploma	-1.142**	-1.004	-0.867	-0.569	0.210	0.205	0.447	0.114
	(0.492)	(0.711)	(0.535)	(0.753)	(0.322)	(0.400)	(0.345)	(0.432)
Some College	-0.420	-0.284	-0.578	-0.367	-0.536	0.931	-0.690*	0.959
	(0.426)	(0.904)	(0.432)	(0.900)	(0.344)	(0.751)	(0.356)	(0.748)
College Degree	-0.954**	2.382***	-1.259***	1.921***	-2.083***	-0.946*	-2.368***	-0.840
	(0.423)	(0.516)	(0.464)	(0.549)	(0.556)	(0.533)	(0.588)	(0.544)
Graduate Degree	0.218	4.896***	-0.164	4.342***	-4.541***	-7.997***	-4.888***	-7.888***
	(0.600)	(1.087)	(0.635)	(1.100)	(0.988)	(1.888)	(1.004)	(1.896)
Cognitive Ability			0.337	0.569**			0.302*	-0.120
			(0.239)	(0.258)			(0.180)	(0.205)
N	27766	13842	27766	13842	21292	5583	21292	5583

All estimates include controls for race, birth year, year, region, msa status and marital status.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Estimates of the college hours premium for male workers in the NLSY79 and NLSY97 grouped by pay rate.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Union Workers				Non-union Workers			
	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
No diploma	-1.113*	0.544	-0.985	1.010	-0.510	-0.224	-0.412	0.0575
	(0.592)	(1.076)	(0.639)	(1.088)	(0.711)	(0.548)	(0.749)	(0.587)
Some College	-0.513	-0.0771	-0.571	-0.215	-0.639	0.00881	-0.695	-0.0337
	(0.531)	(0.898)	(0.545)	(0.916)	(0.659)	(0.885)	(0.670)	(0.882)
College Degree	0.121	0.431	0.00908	-0.00888	1.048	2.727***	0.938	2.412***
	(1.117)	(0.849)	(1.111)	(0.912)	(0.689)	(0.480)	(0.749)	(0.515)
Graduate Degree	0.514	5.636***	0.373	4.976***	1.598	4.330***	1.466	3.963***
	(1.148)	(1.592)	(1.170)	(1.660)	(0.984)	(1.275)	(1.049)	(1.272)
Cognitive Ability			0.151	0.609*			0.117	0.377*
			(0.297)	(0.336)			(0.333)	(0.221)
N	4833	2059	4833	2059	6829	12909	6829	12909

All estimates include controls for race, birth year, year, region, msa status and marital status.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Estimates of the college hours premium for male workers in the NLSY79 and NLSY97 grouped by union status.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Government Workers				Non-government Workers			
	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
No diploma	-1.209	-4.031	-0.355	-3.143	-0.487	-0.563	-0.146	-0.335
	(1.596)	(3.162)	(1.432)	(3.129)	(0.342)	(0.493)	(0.373)	(0.535)
Some College	0.636	0.856	-0.338	0.611	-0.0794	-0.244	-0.291	-0.286
	(1.139)	(1.371)	(1.194)	(1.356)	(0.337)	(0.759)	(0.344)	(0.758)
College Degree	-0.400	2.003*	-1.706	1.422	-0.0746	2.322***	-0.478	2.070***
	(1.339)	(1.136)	(1.506)	(1.153)	(0.367)	(0.486)	(0.404)	(0.507)
Graduate Degree	3.387	4.432***	1.590	3.659***	0.795	4.170***	0.294	3.881***
	(2.071)	(1.243)	(1.924)	(1.321)	(0.554)	(1.329)	(0.581)	(1.327)
Cognitive Ability			1.640***	0.753			0.426**	0.302
			(0.552)	(0.525)			(0.182)	(0.225)
N	417	1511	417	1511	48636	17746	48636	17746

All estimates include controls for race, birth year, year, region, msa status and marital status.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Estimates of the college hours premium for male government and non-government workers in the NLSY79 and NLSY97.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Industry Group	IND-A				IND-B				IND-C			
Cohort	79	97	79	97	79	97	79	97	79	97	79	97
No diploma	-0.0397	0.0464	0.471	0.148	-5.250***	1.285	-5.324***	1.435	-0.532	-4.571***	-0.483	-3.296**
	(0.502)	(0.515)	(0.537)	(0.533)	(1.461)	(0.885)	(1.553)	(0.902)	(1.026)	(1.366)	(1.041)	(1.541)
Some College	0.340	0.657	0.0553	0.634	-1.687	-2.239	-1.630	-2.283	0.104	1.512	0.0714	1.501
	(0.477)	(1.097)	(0.483)	(1.092)	(1.180)	(1.485)	(1.216)	(1.490)	(0.828)	(1.085)	(0.864)	(1.096)
College Degree	0.782	1.647**	0.192	1.539**	-1.162	1.982**	-1.093	1.833*	0.310	4.867***	0.247	3.509***
	(0.565)	(0.639)	(0.615)	(0.668)	(1.281)	(0.900)	(1.345)	(0.941)	(0.781)	(0.870)	(0.878)	(0.889)
Graduate Degree	0.758	-0.167	0.0914	-0.283	-5.557***	5.757***	-5.468***	5.570***	4.037***	8.252***	3.963***	6.611***
	(0.861)	(1.438)	(0.909)	(1.458)	(1.603)	(1.744)	(1.690)	(1.734)	(1.081)	(1.747)	(1.143)	(1.751)
Cognitive Ability			0.626**	0.134			-0.0777	0.209			0.0618	1.582***
			(0.253)	(0.227)			(0.555)	(0.398)			(0.400)	(0.473)
N	9197	10116	9197	10116	1270	4592	1270	4592	3380	4511	3380	4511

Agriculture, forestry, fisheries, mining, construction, manufacturing, utilities, transportation and public services make up industry group IND-A, education, health, social services, public administration, entertainment and recreation make up industry group IND-B and finance, insurance, real estate, business and professional services make up industry group IND-C.
All estimates include controls for race, birth year, year, region, msa status and marital status. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A13: Estimates of the college hours premium for male workers in the NLSY79 and NLSY97 grouped by industry.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Occupation Group	OCC-A				OCC-B				OCC-C			
Cohort	79	97	79	97	79	97	79	97	79	97	79	97
No diploma	-1.676*	-4.022*	-2.169**	-3.197	-0.506	-0.589	0.428	0.0273	-0.369	-0.705	-0.177	-0.731
	(0.965)	(2.255)	(1.001)	(2.516)	(0.486)	(0.716)	(0.543)	(0.757)	(0.393)	(0.604)	(0.428)	(0.651)
Some College	-1.154*	-0.861	-0.940	-0.881	-0.224	0.236	-0.874*	0.139	0.336	0.869	0.220	0.874
	(0.614)	(1.716)	(0.632)	(1.728)	(0.488)	(0.784)	(0.502)	(0.790)	(0.422)	(1.325)	(0.426)	(1.326)
College Degree	-2.046***	2.661***	-1.574**	2.198**	0.889	2.301***	-0.282	1.685***	-0.145	-0.506	-0.357	-0.478
	(0.540)	(1.014)	(0.619)	(1.060)	(0.541)	(0.652)	(0.585)	(0.652)	(0.905)	(1.239)	(0.921)	(1.273)
Graduate Degree	-0.729	4.671***	-0.0930	4.105***	-0.394	-0.487	-1.731*	-0.966	-3.248***	-1.100	-3.472***	-1.066
	(0.725)	(1.450)	(0.793)	(1.475)	(0.865)	(2.243)	(0.908)	(2.216)	(1.149)	(3.399)	(1.164)	(3.407)
Cognitive Ability			-0.667*	0.799			1.252***	0.873***			0.247	-0.0374
			(0.371)	(0.552)			(0.297)	(0.338)			(0.207)	(0.241)
N	9982	4086	9982	4086	11968	7696	11968	7696	27108	7643	27108	7643

Group OCC-A consists of professional workers, technical workers, manager, officers and proprietors, OCC-B consists of clerical, sales and service workers and OCC-C consists of farmers, laborers, craftsmen and operatives. All estimates include controls for race, birth year, year, region, msa status and marital status. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A14: Estimates of the college hours premium for male workers in the NLSY79 and NLSY97 grouped by occupation.

Annual labor earnings in	(1) NLSY79	(2) NLSY97	(3) NLSY79	(4) NLSY97	(5) NLSY79	(6) NLSY97
No diploma	-0.311***	-0.353***	-0.188***	-0.262***	-0.182***	-0.241***
	(0.0262)	(0.0507)	(0.0284)	(0.0531)	(0.0265)	(0.0475)
Some College	0.117***	0.186***	0.0412	0.168***	0.0504**	0.175***
	(0.0242)	(0.0525)	(0.0250)	(0.0525)	(0.0242)	(0.0514)
College Degree	0.305***	0.177***	0.160***	0.0798**	0.169***	0.0479
	(0.0257)	(0.0336)	(0.0274)	(0.0344)	(0.0261)	(0.0311)
Graduate Degree	0.354***	0.253***	0.174***	0.139**	0.172***	0.0716
	(0.0338)	(0.0618)	(0.0355)	(0.0624)	(0.0334)	(0.0569)
Cognitive Ability			0.154***	0.119***	0.146***	0.110***
			(0.0139)	(0.0203)	(0.0129)	(0.0180)
Hours Worked					0.0206***	0.0203***
					(0.000842)	(0.00114)
N	46431	17581	46431	17581	46431	17581

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable is labor income. All other controls are identical to previous analysis.

These results replicate the ACS results in Figure 5.

Table A15: Education aggregate labor earnings premium for male workers in two cohorts of the NLSY.

Appendix B: Chapter 2 Appendix

B.1 Appendix I - Tables

	(1) Full sample	(2) Social Jobs	(3) Non-Social Jobs
High school	-0.313***	-0.279***	-0.325***
	(0.0213)	(0.0412)	(0.0248)
Some college	0.162***	0.166***	0.135***
	(0.0210)	(0.0297)	(0.0291)
Undergraduate degree	0.223***	0.204***	0.146***
	(0.0149)	(0.0190)	(0.0264)
Graduate degree	0.458***	0.393***	0.360***
	(0.0277)	(0.0322)	(0.0659)
North Central	-0.0987***	-0.118***	-0.0872***
	(0.0161)	(0.0225)	(0.0229)
South	-0.0769***	-0.0893***	-0.0748***
	(0.0151)	(0.0207)	(0.0219)
West	-0.0380**	-0.0472**	-0.0392
	(0.0166)	(0.0226)	(0.0241)
Urban	0.0295**	0.0395**	0.0146
	(0.0131)	(0.0197)	(0.0174)
Black	-0.136***	-0.0616***	-0.196***
	(0.0137)	(0.0195)	(0.0191)
Native American	-0.144***	0.0570	-0.288***
	(0.0506)	(0.0649)	(0.0690)
Asian	0.173***	0.220***	0.0412
	(0.0400)	(0.0455)	(0.0770)
Other	0.0272	0.0523**	-0.00799
	(0.0184)	(0.0266)	(0.0253)
AFQT	0.0943***	0.0896***	0.0857***
	(0.00646)	(0.00970)	(0.00861)
Women	-0.380***	-0.327***	-0.489***
	(0.0105)	(0.0144)	(0.0159)
N	38535	18766	19769

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B1: Coefficients of controls other than years of binge drinking and standard errors of controls not listed in Table 2

	(1) Full sample	(2) Social Jobs	(3) Non-Social Jobs
Years of regular Drinking	0.0530***	0.0588***	0.0425***
	(0.00296)	(0.00415)	(0.00419)
Years of Binge Drinking	0.0163***	0.00233	0.0309***
	(0.00452)	(0.00698)	(0.00591)
Social Skills	0.0734***	0.0803***	0.0544***
	(0.00536)	(0.00770)	(0.00758)
N	38535	18766	19769

Regular drinking is defined as drinking fewer than 5 drinks and binge drinking as drinking 5 or more drinks in each instance. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2: Returns to drinking and a continuous measure of Social skills

	(1) Full sample	(2) Social Jobs	(3) Non-Social Jobs
Years of regular Drinking	0.0526***	0.0577***	0.0424***
	(0.00296)	(0.00414)	(0.00424)
Years of Binge Drinking	0.0190***	0.00280	0.0348***
	(0.00464)	(0.00712)	(0.00612)
Extraversion	0.0697***	0.0782***	0.0491***
	(0.00536)	(0.00770)	(0.00758)
Agreeableness	-0.0595***	-0.0742***	-0.0472***
	(0.00577)	(0.00808)	(0.00809)
Conscientiousness	0.0871***	0.0780***	0.0944***
	(0.00587)	(0.00819)	(0.00827)
Neuroticism	0.0272***	0.0284***	0.0289***
	(0.00613)	(0.00867)	(0.00859)
Openness	-0.0208***	-0.0186**	-0.0232***
	(0.00592)	(0.00870)	(0.00796)
N	37148	18301	18847

Regular drinking is defined as drinking fewer than 5 drinks and binge drinking as drinking 5 or more drinks in each instance. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B3: Returns to drinking and all non-cognitive abilities

Appendix C: Chapter 3 Appendix

C.1 Appendix I - Tables

	(1) NLSY79	(2) NLSY97
High School	0.450	0.646
Some College	0.236	0.057
College Degree	0.145	0.176
Graduate Degree	0.066	0.043
Annual Income	35,540	31,134
Male	0.501	0.531
Black	0.14	0.139
Other	0.023	0.110
Msa	0.791	0.921
Age	27.58	25.12
Cognitive Ab.	0.074	0.015
Social Skills (Extraversion)	0.075	0.015
N	78,126	34,583

Table C1: Descriptive statistics for men in the NLSY79 and NLSY97

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low Cog, Non-social		High Cog, Non-social		Low Cog, Non-social		High Cog, Social	
	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
High School	0.546	0.784	0.500	0.767	0.401	0.729	0.324	0.62
Some College	0.201	0.023	0.241	0.082	0.235	0.045	0.276	0.062
College Degree	0.072	0.038	0.107	0.055	0.194	0.067	0.234	0.209
Graduate Degree	0.022	0.002	0.037	0.006	0.091	0.007	0.128	0.053
Male	0.615	0.787	0.499	0.695	0.383	0.450	0.427	0.514
Black	0.175	0.219	0.127	0.141	0.131	0.215	0.103	0.118
Other	0.024	0.100	0.023	0.240	0.023	0.099	0.023	0.113
Msa	0.748	0.879	0.803	0.916	0.827	0.901	0.825	0.929
Age	26.81	24.06	27.23	24.88	27.43	24.204	28.88	25.41
Cognitive Ab.	-0.196	-0.434	-0.002	0.016	0.186	-0.227	0.395	0.195
Social Skills	-0.014	-0.193	0.003	-0.131	0.166	-0.026	0.190	0.11
Annual Income	29,288	17,007	31,378	28,070	35,972	15,830	45,567	34,813
N	29,025	2,834	17,474	843	11,180	4,594	20,477	26,312

Table C2: Descriptive statistics for workers in the NLSY79 and NLSY97 split by importance of cognitive ability and social skills.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	“Non Technical”		“Service”		“Management”		“Technical”	
	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
High School	0.545	0.773	0.326	0.721	0.265	0.32	0.336	0.511
Some College	0.212	0.040	0.363	0.055	0.227	0.068	0.271	0.074
College Degree	0.074	0.048	0.133	0.125	0.326	0.462	0.232	0.286
Graduate Degree	0.021	0.004	0.129	0.016	0.148	0.130	0.123	0.094
Male	0.552	0.861	0.163	0.332	0.592	0.675	0.412	0.518
Black	0.162	0.159	0.155	0.155	0.084	0.069	0.109	0.117
Other	0.025	0.085	0.020	0.116	0.019	0.107	0.023	0.127
Msa	0.762	0.867	0.801	0.920	0.852	0.968	0.829	0.957
Age	26.84	24.63	28.67	23.93	29.06	27.29	28.39	26.8
Cognitive Ab.	-0.162	-0.264	0.257	0.045	0.581	0.602	0.361	0.329
Social Skills	-0.002	-0.084	0.128	0.088	0.091	-0.013	0.236	0.190
Annual Income	29,124	25,874	39,787	19,368	51,853	57,371	42,105	44,037
Imp. of S. Skills	-0.908	0.095	0.644	0.721	0.484	0.849	0.895	1.349
Imp. of Math	-0.424	-0.215	0.343	-0.122	1.851	1.409	0.505	0.670
Imp. of Cog. Ab.	-0.480	0.275	0.727	0.204	0.821	1.227	0.327	0.944
N	48,682	7,955	3,975	15,821	7,251	2,202	18,218	8,605

Table C3: Descriptive statistics for workers in the NLSY79 and NLSY97 split by clustering.

Most Social	Least Social
NLSY79	
Financial services sales	Packers
Salespersons	Shoemaking operators
Managers of medicine	Mixing operatives
Marketing managers	Butchers
Social workers	Office operators
NLSY97	
Agents and managers of performers	Pressers, textile, etc.
Clergy	Shoe machine operators
Lodging managers	Mine shuttle car operators
Sales engineers	Proofreaders
Supervisors of correctional officers	Woodworking machine operators

Table C4: List of occupations by importance of social skills.

Most Critical Thinking	Least Critical Thinking
NLSY79	
Veterinarians	Waiter's assistant
Judges	Motion picture projectionists
Other therapists	Bartenders
Podiatrists	Butchers
Engineers, n.e.c	Truck drivers
NLSY97	
Lawyers	Vehicle Cleaners
Actuaries	Graders and sorters
Biomedical engineers	Pressers, textile, etc.
Chief executives	Dining room attendants
Aerospace engineers	Machine feeders

Table C5: List of occupations by importance of critical thinking.

Most Math	Least Math	Most Cognitive	Least Cognitive
NLSY79			
Subject instructors	Garbage Collectors	Chemical engineers	Garbage Collectors
Mathematicians	Performers	Registered nurses	Machine operators
Statistical clerks	Housekeepers	Librarians	Butchers
Economists	Crossing guards	Airplane pilots	Meter readers
Bookkeepers	Janitors	Engineering technicians	Construction laborers
NLSY97			
Operations researchers	Actors	Fire station supervisors	Telemarketeters
Actuaries	Janitors	Civil engineers	Graders and sorters
Statisticians	Barbers	Nuclear technicians	Pressers, textile, etc.
Chemical engineers	Crossing guards	Chemical engineers	Mine car operators
Cost estimators	Vehicles Cleaners	Geological engineers	Barbers

Table C6: List of occupations by importance of math or cognitive ability.

High Math		Low Math	
Most Social	Least Social	Most Social	Least Social
NLSY79			
Financial sales jobs	Statistical clerks	Social workers	Packers
Salespersons, n.e.c.	Lathe operatives	Vocational counselors	Shoemaking operators
Administrators	Tool and die makers	Child care workers	Mixing operatives
Marketing Managers	Cutting operators	Therapists, n.e.c.	Butchers
Managers in education	Punching press operatives	Judges	Dressmakers
NLSY97			
Lodging managers	Lathe operators	Agents of performers	Pressers, textile, etc.
Sales engineers	Cutting operators	Clergy	Shoe machine operators
Chief executives	Tool operators	Correctional supervisors	Mine car operators
Purchasing managers	Heat treaters	Lawyers	Woodworking operators
Office supervisors	Metal fabricators	Residential advisors	Proofreaders
Social		Non-Social	
Most Math	Least Math	Most Math	Least Math
NLSY79			
Subject instructors	Other law enforcement	Mathematicians	Garbage collectors
Economist	Personal service jobs	Statistical clerks	Performers
Operations researchers	Child care workers	Bookkeepers	Housekeepers
Financial managers	Clergy	Actuaries	Crossing guards
Aerospace engineer	Actors, directors	Physicists	Butchers
NLSY97			
Actuaries	Telemarketers	Operations researchers	Actors
Chemical engineers	Animal control	Statisticians	Janitors
Cost estimators	Writers and authors	Economists	Barbers
Civil engineers	Door-to-door sellers	Statistical assistants	Crossing guards
Aerospace engineers	Ushers	Financial analysts	Vehicles Cleaners

Table C7: List of occupations grouped by math and social skills.

High Cognitive		Low Cognitive	
Most Social	Least Social	Most Social	Least Social
NLSY79			
Financial services sales	Packers	Vocational counselors	Mixing operatives
Salespersons, n.e.c.	Statistical clerks	Child care workers	Shoemaking operators
Managers and administrators	Drillers	Advertising	Butchers
Marketing Managers	Janitors	Designers	Office operators
Managers in education	Automobile mechanics	Administrators	Dressmakers
NLSY97			
Lodging managers	Woodworking operators	Agents of performers	Pressers, etc.
Clergy	Cutting operators	Property managers	Shoe operators
Sales engineers	Tool and die operators	Retail salespersons	Mine car operators
Correctional supervisors	Heat treating operators	Door-to-door sellers	Proofreaders
Chief executives	Milling operators	Telemarketers	Graders and sorters

Social		Non-Social	
Most Cognitive	Least Cognitive	Most Cognitive	Least Cognitive
NLSY79			
Chemical engineers	Personal service jobs	Mechanical engineers	Garbage collectors
Registered nurses	Clergy	Bookkeepers	Machine operators
Judges	Optical goods workers	Explosives workers	Butchers
Airplane pilots	Sales demonstrator	Photographers	Meter readers
Engineering technicians	Child care workers	Clinical technicians	Construction workers
NLSY97			
Fire station supervisors	Telemarketers	Nuclear technicians	Graders and sorters
Civil engineers	Sales workers	Geological engineers	Pressers, etc.
Chemical engineers	Ushers	Physical scientists	Mine car operators
EMTs and paramedics	Hosts and hostesses	Statistical assistants	Barbers
Actuaries	Housekeeping supervisors	Statisticians	Vehicles Cleaners

Table C8: List of occupations grouped by cognitive and social skills.

Low Social Low Cognitive	Low Social High Cognitive	High Social Low Cognitive	High Social High Cognitive
NLSY79			
Typists	Cashiers	Salespersons	Postmasters
Cooks	Waiter/waitress	Health aides	Secretaries
Assemblers	Bookkeepers	Accountants and auditors	Primary school teacher
Construction laborers	Truck drivers	Child care workers	Managers in marketing
Carpenters	Janitors	Shipping Clerks	Production supervisors
NLSY97			
Laborers and freight	Maintenance workers	Stock clerks	Retail salespersons
Janitors	Typists	Food prep workers	Waiters and waitresses
Vehicle cleaners	Industrial mechanics	Personal care aides	Customer service reps
Packers	Couriers	Housekeeping cleaners	Retail supervisors
Food servers	Mail clerks	Food prep. & serving	Childcare workers

Table C9: List of occupations grouped by cognitive and social skills.

Less-Technical Jobs	Service Jobs	Management Jobs	Technical Jobs
NLSY79			
Cashiers	Health aides	Postmasters	Accountants
Postal clerks	Registered nurses	Salespersons	Foremen
Waiter/waitress	Health technologists	Secretaries	Managers of service orgs
Cooks	Licensed nurses	School teachers	Software developers
Bookkeepers	Dental assistants	Marketing Managers	Financial managers
NLSY97			
Laborers and freight	Retail salespersons	Customer service reps	Accountants
Construction laborers	Waiters and waitresses	Retail supervisors	Software developers
Janitors	Childcare workers	Managers, all other	Construction managers
Carpenters	Stock clerks	Food supervisors	Sales representatives
Automotive mechanics	Receptionists	Office supervisors	Production clerks

Table C10: List of occupations grouped by clustering

Shrathinth Venkatesh

Curriculum Vitae

Education

- Ph.D. Economics, University of Wisconsin - Milwaukee, 2021.
- B.E. Mechanical Engineering, PES Institute of Technology, India, 2013.

Teaching Experience

Lecturer, Department of Economics, University of Wisconsin - Whitewater

-
  - ECON 245 - Business Statistics (HyFlex) — Spring 2021, Fall 2020
  - ECON 201 - Principles of Microeconomics (HyFlex) — Fall 2020

Graduate Teaching, Department of Economics, University of Wisconsin - Milwaukee

- **Instructor** (Full responsibility for the class)
  - ECON 210 - Economic Statistics — Spring 2017
  - ECON 104 - Principles of Macroeconomics — Fall 2017, Fall 2016, Spring 2016, Fall 2015
  - ECON 103 - Principles of Microeconomics — Summer 2017, Summer 2016
  - ECON 110 - Personal Finance (Online and in person) — Spring 2016
- **Teaching assistant - Graduate courses** (Responsibilty for applying empirical methods and data)
  - ECON 734 - Foundation Econometric methods — Spring 2018
  - ECON 710 - Applied Econometrics — Spring 2017

Research Assistantship

Department of Economics and School of Nursing, University of Wisconsin - Milwaukee

- Assessed the impact of the PERISCOPE perinatal health intervention using claims data from Medicaid and private insurance providers in Wisconsin.

Research Papers

"The Emerging College Hours Premium for Men" *(accepted by Education Economics)*

Working Papers

"The Returns to Drinking: Social Workers or Social Jobs?" *with SJ Adams, JS Heywood & D Ullman*

"Are the Returns to Education Still Rising?"

"Changes in the Returns to Education : Evidence from Three Cohorts of the NLSY"

In Progress

"Estimating the Effects of the Periscope Project" *with SJ Adams & JJ Doering*

"Changes in education's effect on job sorting"

Presentations

"Changes in the returns to education : Evidence from 3 cohorts of the NLSY"

- Midwest Economic Association Annual Meeting, St.Louis, MO, 2019
- Wisconsin Economics Association Annual Meeting, Stevens Point, WI, 2019
- UWM Economics Labor Lunch, 2019
- UWM Applied Microeconomics group, 2019

Honours and Awards

- Richard Perlman Prize for Outstanding Paper in Labor Economics, 2018
- University of Wisconsin - Milwaukee Chancellors Graduate student award, 2014 and 2015

Software

- STATA, R, Matlab, LaTeX

Professional Service

- Discussant - Midwest Economic Association Annual Meeting, St.Louis, MO, 2019
- Co-organiser - Graduate Student Applied Micro Economics Group

Professional Associations

American Economic Association, Midwest Economic Association