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Task-Specific Human Capital Accumulation and Wage Outcomes Among Young Men: An Empirical Analysis

Morgan Holland
University of South Carolina - Columbia

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Morgan Holland

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Accepted by:

Orgul Ozturk, Director of Thesis

Yi (Crystal) Zhan, Reader

Lacy Ford, Vice Provost and Dean of Graduate Studies

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Abstract

Existing literature suggests that investment in different kinds of task-specific human capital may have significant effects on wage outcomes and overall economic wellbeing of individuals. To examine this claim, the accumulation of task-specific human capital in young male workers with no college education and its effects on wages is measured. Using National Longitudinal Survey of Youth panel data merged with six task-specific human capital measures derived from the Dictionary of Occupational Titles task contents data, fixed effects regression was utilized to measure how workers' task-specific human capital develops over time. This process shows that among the task measures used, accumulation of experience in routine cognitive tasks is the greatest determiner of wage outcomes.

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K	Investment in human capital at each period of a worker's life.
H	Total stock of human capital at each period in a worker's life.
Y	Earnings in each period in a worker's life.
Y_{it}	Wage of worker *i* at time *t* in the fixed effects regression model.
X_n	Task-specific measures used in the fixed effects regression model.
Y_n	Control variables used in the fixed effects regression model.
a_i	The intercept of individual *i* in the fixed effects regression model.
u_{it}	The unmeasured error term of each individual *i* at time *t*.
β_k	The coefficients of the task-specific measures and the control variables

LIST OF ABBREVIATIONS

NRCA	non-routine cognitive abstract
NRCI	non-routine cognitive interpersonal
NRMI	non-routine manual interpersonal
NRMP	non-routine manual physical
OLS	Ordinary Least Squares
RC	routine cognitive
RM	routine manual

CHAPTER 1

INTRODUCTION

The studied concept of task-specific human capital is very new. Its first use in labor economics literature dates to 2003 when Gibbons and Waldman proposed the idea and gave some examples of how it might add to the discussion of occupations, their design, and their effects on wages. Practical acknowledgement of task-specific human capital is quite old. For as long as firms have existed they have chosen to promote their most skilled workers by assigning different levels of merit to different tasks. The integral role that task-specific human capital plays in the labor markets and in individual occupations is evidenced by the large body of research produced in the years since its introduction. It has gained particular prominence as a major explanatory factor in wage disparities brought from technological change, in the mobility of workers between occupations and the occupation matching process, among many other labor topics.

Of interest to this investigation is the research into how investment in particular tasks plays a role in the wage outcomes of workers. Many of the papers on task-specific human capital target the labor market as a whole, examining the effects of investment in specific skills on wage outcomes across all demographics. These investigations have primarily focused on the role of automation in depressing the wages of workers that concentrate on routine tasks. What these papers largely find is that much of the increasing wage gap in the economies of developed nations can be explained by the replacement of workers with computers and robotic equipment (Autor, Levy & Murnane, 2003.

What is lacking from these investigations is a focused look at individual demographic segments of the workforce. As a first step toward reconciling this deficiency, this paper attempts to measure the returns to investment in specific task categories for young men with no college education. The investment in task-specific human capital is estimated using a simple sum of the task categories of each job a worker performs. First, the link between job task contents and wages is explored using OLS and Fixed effects regression. Next, a similar set of regressions is run for the summed task contents variables. These regressions use a number of wage determinants with the addition of the task-specific measures to determine how wages relate to the tasks performed in occupations and how wages grow with the accumulation of task-specific human capital.

The six task categories are those estimated by Acemoglu and Autor (2011) and include non-routine cognitive abstract (NRCA), non-routine cognitive interpersonal (NRCI), routine cognitive (RC), routine manual (RM), non-routine manual physical (NRMP), and non-routine manual interpersonal (NRMI). These categories are derived from the Occupational Information Network (O*NET). For a sample of workers, and data regarding their occupations, wages, and demographic characteristics, this study uses the National Longitudinal Survey of Youth 1997 cohort (NLSY-1997). These two data sources are merged and a fixed effect panel regression is used to estimate worker's wages. It is hypothesized that non-routine abstract and non-routine manual tasks will have a positive effect on wages, while routine tasks will have no effect on wages.

This paper is organized into six sections. Following the introduction is a brief review of papers relevant to task-specific human capital and to this investigation. Next is a short overview of the conceptual framework of the accumulation of task-specific human capital and of human capital in general. Third is a description of the data sources and methods. Fourth, the empirical methods used to estimate the returns to human capital accumulation are presented along with tables of results. The fifth section is a discussion of the results presented in chapter 4 followed by concluding remarks.

CHAPTER 2

LITERATURE REVIEW

Task-specific human capital is a relatively new topic of research interest in the literature. Gibbons and Waldman introduced the theoretical concept in 2003, relating it to job-specific and industry-specific human capital. In their research, they use cohort effects and job design as areas where task-specific human capital can be applied (Gibbons & Waldman, 2003). Following this paper, task-specific human capital quickly gained a footing in both theoretical and empirical work for its ability to explain and refine labor phenomena.

Task-specific human capital has been used to investigate a number of economic trends. Mobility between jobs has been modeled with tasks by using a distance-method to position occupations in relation to their similarity in task contents (2010). It was shown that as workers gain more skill at completing job-specific tasks, their moves between occupations are less frequent. As workers accumulate task-specific human capital, the differences between the jobs they move between become less pronounced as well (Gathman & Schönberg, 2010). Other areas investigated using task-specific human capital include wages and promotion (Gibbons & Waldman, 2006), the offshorability of occupations (Grossman and Rossi-Hansberg), and job training and job rotation (Balmaceda, 2006).

Of specific interest in this investigation is the research of David Autor. Autor et al. (2003) examine the changing wage structure in the United States by relating the tasks done by workers to those that can be handled by robotic equipment and computers. A theoretical model is constructed where the returns to non-routine tasks are complementary with the automation of routine tasks, but the routine tasks are substitutable by automation. This model is verified empirically by merging task contents data from the Dictionary of Occupational Titles (DOT) with workers in the Current Population Survey from 1960 – 1998. They find that routine tasks that are easily automated have experienced the most depression in wages while non-routine tasks have experienced an increase in wages (Autor, Levy, & Murnane, 2003).

Another paper by Autor and Dorn (2013) explores the role of routine tasks in the recent increase in the wage gap. Part of the wage gap is theorized to increase by the falling cost of automating routine tasks and the increase in consumer preferences for variety. A spatial equilibrium model is built to verify the expected outcomes of their theoretical model (Autor & Dorn, 2013).

An interesting addendum to the research on the task component of the growing wage gap is the question of where workers from routine jobs go once wage depression forces them out of routine occupations. Young workers who have spent less time accumulating capital in a particular task have less of an incentive to stay in an occupation when wages fall, so as wages for routine tasks decrease, the average age of the remaining workers in routine jobs increases (Autor & Dorn, 2009).

Autor (2013) provides a foundational model in task-based human capital and summarizes recent research advances regarding task-specific human capital. The advantages and limitations of the task approach to human capital are also explored in this paper (Autor, 2013).

The most influential paper to this analysis creates a set of measures for task categories that can be used to investigate the task requirements of jobs. These task categories are created from the Occupational Information Network (O*Net)'s Work Contents and Work Activities Scales and are used to investigate the role of specific task categories in wage disparities (Acemoglu & Autor, 2011).

Goos and Manning (2007) use a similar approach to examine the polarization of labor markets in the United Kingdom. They conclude that task-specific human capital is the best explanation for the changing wage structure in the UK. Similar to the papers above, automation of routine tasks has been "hollowing out" the middle of the wage spectrum, where routine tasks are commonly performed (Goos & Manning 2007).

CHAPTER 3

CONCEPTUAL FRAMEWORK

To understand the motives of this study, a brief sketch of the main principles of modeling human capital accumulation is presented. This is followed by an explanation of how task-specific human capital can be added to the model of human capital accumulation.

The most important theoretical work on human capital accumulation and its effect on wages is the Ben-Porath (1967) model. This model extends the classic income maximization model to include human capital as a factor of production. Workers may spend time investing in their own human capital in an effort to make themselves more productive, but any effort involved in the production of human capital does not earn them a wage. Under this model, the returns of accumulated human capital are negative until a certain threshold is reached, so individuals spend their early years investing solely in human capital with none of their productive potential going toward earning a wage. These early "unproductive years" are interpreted as time spent being educated.

After a worker's unproductive years, the worker enters a productive period where the worker's main activity is producing output in order to earn a wage. However, the worker continues to invest in human capital in order to increase their productivity. This investment decreases as their life goes on, because the number of years they have left to enjoy the returns to additional investments dwindle. As workers invest in human capital, their wages increase as well, up until the point at which their investment in human capital equals the depreciation of human capital. After this point, wages decrease slowly until the end of a worker's life. A full treatment of the Ben-Porath model can be found in any textbook on labor economics. Figure 3.1 is a visual representation of the path that wages takes at each period of a worker's life.

For many purposes, the classic Ben Porath model is sufficient to explain the behavior of workers in regards to human capital accumulation, but some trends in the labor markets are not so easily accounted for. In the years since the Ben Porath model was first proposed, it has seen many extensions and modifications in efforts to explain different aspects of accumulated experience and its effects on wages.

An important development in the study of human capital is the differentiation of human capital into distinct categories. One of the most recent additions is to view jobs as a bundle of tasks to which workers apply their skills in order to obtain a return (i.e. wage). In this framework, workers improve their skillset by performing tasks, and in this way invest in their own human capital. Therefore, the tasks performed on a job can serve as a measure of the human capital that is produced by a worker performing the job (Yamaguchi, 2012).

For the purposes of this analysis, the incorporation of tasks into human capital accumulation can be thought of as changing the basic Ben-Porath model from one where productivity is based solely on the accumulation of a one-dimensional factor, human capital, to one where human capital accumulation is a multi-dimensional vector composed of accumulated experience in a variety of tasks. A key assumption of this model is that different tasks are rewarded differently in the labor market, so equal investment in different tasks does not yield the same return.

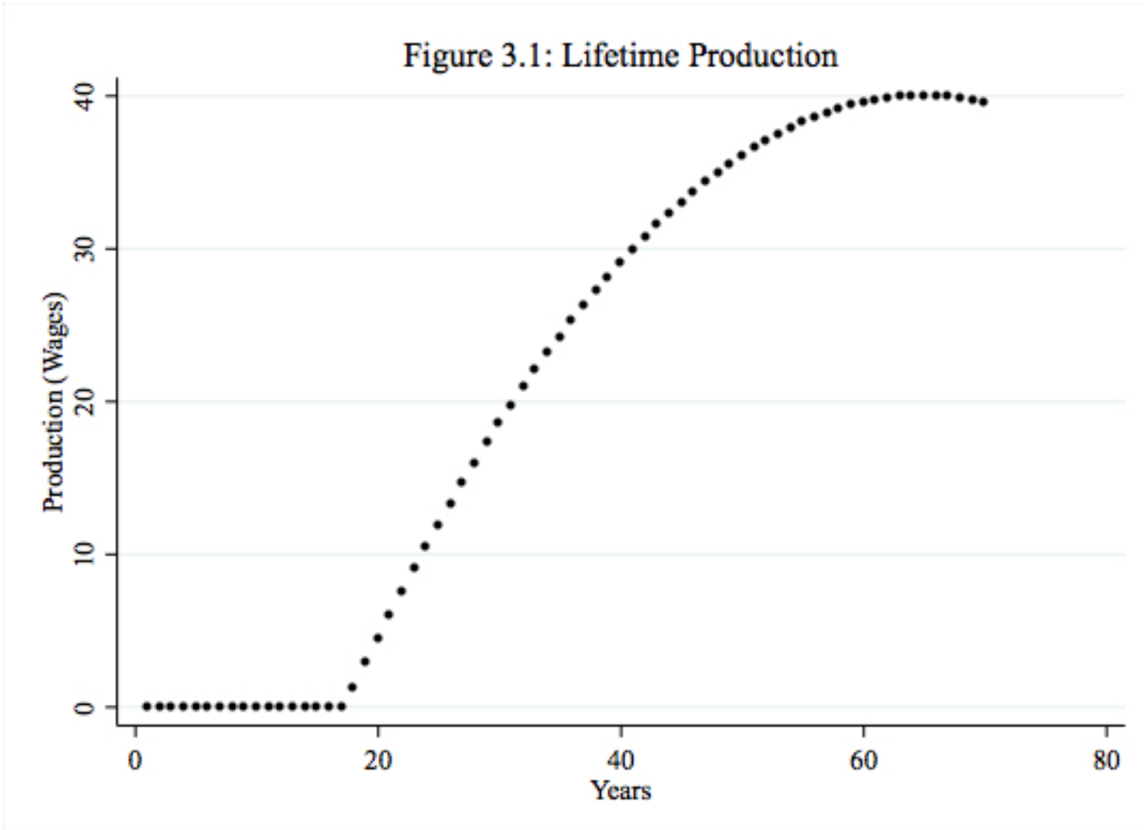

Figure 3.1: This plots a typical Ben-Porath modeling of wages over the life of a worker. The first 18 years show zero wages as the worker accumulates enough human capital to begin earning a wage. After this, wages grow in a parabolic pattern as the worker continues to invest in human capital. The rate of investment approaches zero at age 65, and as human capital depreciates, wages begin to fall in the last portion of the worker's life.

CHAPTER 4

DATA SAMPLE

The data used in this analysis come from two sources. The workers and their occupations come from the NLSY-1997. The NLSY is a longitudinal survey of youth in the United States that asks respondents questions about a variety of topics. It is designed to show a holistic picture of a representative cohort as they age. This data source was selected because it surveys the same respondents over a period of many years, yielding a unique longitudinal look at life experience. There are two cohorts in this study. The first started in 1979 and the second in 1997. The 1997 cohort was utilized in this study because the task-contents of the jobs represented in this cohort would be more applicable to current labor markets. The sample years available for this dataset are 1997 to 2011.

The NLSY-1997 consists of two sample groups, a cross-sectional group and an oversample. The oversample is used to accommodate the changing demographic makeup of the United States and attrition in the core sample as time passes. All respondents were born between January 1, 1980 and December 31, 1984. In order to keep the sample representative, only the original cross-sectional sample was used in this study. The core sample consists of 3,459 males and 3,289 females.

To refine the sample to the desired demographics of this study, females and any male who reported attending college in the survey period were removed. All public sector workers and self-employed respondents were also removed. In order to have a profile of each respondent's employment experience, the survey years were restricted to the first year each respondent reported employment after secondary education and each subsequent year. Note that respondents who did not finish high school but chose to enter the workforce instead remain in the sample. This leaves a total of 770 respondents, covering the years from 1997 – 2011. After reshaping from wide to long the data produces a total of 8364 person-years. The variables of interest in this study include hourly wages, occupational information and demographic characteristics.

The task measures used in this analysis are derived from the Occupational Information Network (O*NET). O*NET is a large database of jobs and their occupational requirements in the United States. The database is produced from a survey of workers who are asked a series of questions about their employment. Two of the measures produced by this survey are the Work Activities and Work Context Importance scales. The Work Activities and Work Context scales were composited to produce six measures of tasks performed in each job: non-routine cognitive: analytical, non-routine cognitive: interpersonal, routine cognitive, routine manual, non-routine manual: physical, and non-routine manual: interpersonal. These task measures are then normalized to mean 0, standard deviation 1 to produce a measure of how much each job requires each task category (Acemoglu & Autor, 2011)

NRCA tasks are tasks that include creative thinking, analytical skill, or interpreting information. Such tasks include complex mathematics, statistically analyzing data, or creating novel solutions to problems (Acemoglu & Autor, 2011). Examples of occupations that have high NRCI scores are financial managers, marketing managers, computer programmers, engineers, or doctors.

NRCI tasks involve interacting with people, especially in guiding or training them. These tasks might include overseeing other employees, developing relationships with others, and teaching (Acemoglu & Autor, 2011). Occupations that score highly in this measure include teachers, most managers and supervisors, clergy, and purchasing specialists.

RC tasks are repetitive cognitive tasks. For instance, data entry, bookkeeping, operating certain machinery, and simple repeated calculations fall into this category (Acemoglu & Autor, 2011). Jobs that score high on this scale are meter readers, surveyors, bank tellers, and telephone operators.

RM tasks include performing repetitive motions, a need to work at a very specific speed, or operating equipment in precise, repetitive ways. Factory work primarily falls into this category (Acemoglu & Autor, 2011). Examples of jobs that score highly on the RM measure are most equipment operators, landscapers, dental laboratory and medical appliance technicians, and locomotive operators.

NRMP tasks are tasks that require manual dexterity, spatial orientation, the ability to operate a variety of equipment, and the manipulation of various tools and objects. These tasks include repairing equipment, operating machinery to perform various tasks, as opposed to repetitive tasks, and assembling unique or novel items (Acemoglu & Autor, 2011). Jobs that score highly on this measure include most mechanics, sailors, bus and truck drivers, plumbers, electricians, carpenters, and other craftsmen.

NRMI tasks require interacting with people, but do not necessarily require any special post-secondary education or training (Acemoglu & Autor, 2011). For instance, salespeople, business promoters, actors, childcare workers, and public transportation attendants all score highly on this measure.

It is important to note that occupations can score highly on more than one measure. For instance, CEOs score highly on both NRCA and NRCI measures, which is intuitive since heads of corporations are often required to be highly creative and analytical while establishing large business relationship networks and effectively guiding subordinates in their decisions. Excavator operators also score highly on more than one measure--RC, RM and NRMP--because they are required to be highly precise in their operation of equipment, may repeat the same operations for long periods of time, and have both manual and cognitive aspects to their work.

The six task measures are merged with the NLSY data to create an unbalanced panel of the occupational task bundles of each worker's jobs. Certain demographic and employment trends become apparent in this dataset after it is cleaned and merged. Table 4.1 presents the summary statistics for each of the job task measures for this dataset. Since the original task measures were standardized, it is easy to see that the task mix of this sample is very different from the average task mix of all the jobs in O*NET. Workers in this sample tend to work in jobs that utilize more than a half standard deviation less NRCA than the average O*NET recorded job, and RM and NRMP tasks are highly overrepresented.

Other key demographics are presented in Tables 4.2, 4.3, and 4.4. Note that because the survey years are restricted to after the respondent finds their first job, the average employment of 73% is not representative since many respondents have a gap between high school and first employment. Also of interest is the average Armed

Services Armed Services Vocational Aptitude Battery (ASVAB) percentile of this demographic, which is almost a full standard deviation below the average for the entire NLSY sample. Interestingly, there are a few outliers who scored very highly on this test and yet chose not to pursue higher education.

In order to get a sense of the kinds of jobs and workers reported in this dataset, Table 4.5 shows the most represented occupations in this dataset along with their task measures. The jobs in table 4.5 represent slightly more than 50% of the person-months in the sample. Cooks are the most represented occupational category in this sample with nearly 420 person-years.

Tables 4.6 and 4.7 present the job and wage outcomes for each year of two similar participants. The cumulative values of each task category are not shown, but can be easily calculated by a simple sum. The first worker presented begins with extremely low reported wages, working as a cook. As the worker continues accumulating experience, his wages rise. The respondent reports working as a retail clerk before a two-year gap in his history during his fifth and sixth year, where he reports no job or income. Gaps in records such as this are common and are caused by either nonresponse in the survey year or unemployment.

The second worker starts his working career as a butcher and earns a small wage. He soon moves to a different job as a cook. Later in his career, this worker switches to a repairer of mechanical controls and valves and he makes a slightly higher salary than he did as a cook. In the final survey year, this worker reported working as a stock clerk making an extraordinary salary.

Several variables had to be created or modified in order to facilitate comparison. The NLSY reports hourly wages for each respondent as a calculated variable based on the respondent's reported income, payment schedule, and weeks worked in each job. These values were converted into 2011 dollars using the Bureau of Labor and Statistics Consumer Price Indices for each survey year. The calculation of hourly wages by the surveyors sometimes results in extreme values. In this sample, there are some respondents with calculated hourly wage values in excess of $1000 per hour. Others appear to make less than $0.25 an hour. While it is possible that some of these extreme values are accurate, most are calculation errors. In order to eliminate the effects of these errors, real hourly wages used are restricted to those between $1.00 and $100 per hour.

Another set of variables was created to track the accumulation of human capital in each task measure. These variables are a simple sum of the current and previous task measures of each year of a worker's life. Since the task contents variables are normalized, the summation process makes the interpretation of the cumulative values somewhat difficult, but is can still be used to measure the process of human capital accumulation over time.

Other calculated variables included in this analysis are average unemployment in the survey year, years of experience, years of tenure, and part-time employment. Average unemployment figures are calculated as the average of the monthly unemployment rate reported by the BLS in the given survey year. Years of experience is a running sum of all the years each respondent has held a job during the survey period. Years of tenure is calculated as the sum of consecutive years each respondent has held the same occupation. Part-time employment is a dummy variable that equals 1 if the respondent reports working less than 30 hours per week at a particular job and 0 if otherwise.

Table 4.1: Task Measure Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
NRCA	-0.532	0.649	-2.271	1.852
NRCI	-0.495	0.577	-2.583	2.338
NRMP	0.922	0.810	-1.587	2.898
NRMI	-0.783	0.741	-3.415	2.235
RC	-0.109	0.813	-4.284	2.929
RM	0.811	0.765	-1.906	2.822

Table 4.2: Demographic Characteristics

Variable	Mean	Std. Dev.	Min	Max
Employment	0.735	0.442	0	1
Number of Children	1.004	0.955	0	5
Birth Year	1981.914	1.395	1980	1984
ASVAB Percentiles	29.676	22.571	0	94.163
NLSY Overall Percentiles	45.317	29.174	0	100

Table 4.3: Marital Status

Marital Status	Percent	Cum.
Never Married	77.89	77.89
Married	18.61	96.5
Separated	2.78	99.28
Divorced	0.69	99.97
Widowed	0.03	100
Total	100	

Table 4.4: Ethnicity of the Sample

Race	Freq.	Percent	Cum.
Non-Black / Non-Hispanic	502	65.19	65.19
Hispanic	138	17.92	83.12
Black	126	16.36	99.48
Mixed Race (Non-Hispanic)	4	0.52	100
Total	770	100	

Table 4.5: The Most Common Occupations

Occupation	Freq.	NRCA	NRCI	RC	RM	NRMP	NRMI
Cooks, variously defined	417	-0.968	-0.431	-0.438	0.881	0.227	-0.351
Construction laborers	399	-0.759	-0.214	0.007	1.038	1.247	-1.672
Laborers outside construction	397	-0.877	-0.530	0.647	1.104	1.174	-1.222
Truck, delivery, and tractor drivers	380	-0.677	-1.017	0.243	1.248	2.261	-0.579
Carpenters	359	-0.003	-0.073	-0.493	0.664	1.579	-0.773
Stock and inventory clerks	209	-1.112	-0.819	0.042	0.394	0.491	-0.701
Gardeners and groundskeepers	185	-0.407	-0.955	-1.960	1.696	1.293	-1.149
Automobile mechanics	166	0.370	-0.276	0.646	0.776	2.002	-0.946
Janitors	150	-1.719	-1.354	-1.124	0.418	0.192	-0.801
Vehicle washers and equipment cleaners	134	-1.114	-1.006	-1.098	0.940	1.054	-1.493
Retail sales clerks	127	0.470	0.323	-0.219	-0.690	-0.487	0.467
Cashiers	125	-1.857	-0.614	1.620	1.136	0.073	-0.018
Machine operators, n.e.c.	115	0.035	-0.011	0.222	0.252	0.095	-1.503
Supervisors and proprietors of	108	0.298	1.425	-0.860	-0.283	-0.365	0.680

sales jobs

Table 4.6: Employment Experience of Respondent # 2854

Occupation	Wages	NRCA	NRCI	NRMP	NRMI	RC	RM
Cooks, variously defined	2000	-1.180	-0.791	0.255	-0.448	-0.486	0.862
Cooks, variously defined	5000	-1.180	-0.791	0.255	-0.448	-0.486	0.862
Stock and inventory clerks	15000	-1.112	-0.819	0.491	-0.701	0.042	0.394
Retail sales clerks	20000	0.470	0.323	-0.487	0.467	-0.219	-0.690
-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-
Cooks, variously defined	27000	-0.198	1.182	0.034	0.275	-0.393	0.721
Cooks, variously defined	30000	-0.198	1.182	0.034	0.275	-0.393	0.721
Cooks, variously defined	30000	-0.198	1.182	0.034	0.275	-0.393	0.721
Cooks, variously defined	35000	-0.198	1.182	0.034	0.275	-0.393	0.721
Cooks, variously defined	38000	-0.198	1.182	0.034	0.275	-0.393	0.721
Cooks, variously defined	40000	-0.198	1.182	0.034	0.275	-0.393	0.721

Table 4.7: Employment Experience of Respondent # 4305

Occupation	Wages	NRCA	NRCI	NRMP	NRMI	RC	RM
Butchers and meat cutters	6000	-1.173	-1.122	0.329	-0.765	0.322	1.495
Cooks, variously defined	15000	-1.180	-0.791	0.255	-0.448	-0.486	0.862
Cooks, variously defined	12000	-1.180	-0.791	0.255	-0.448	-0.486	0.862
Cooks, variously defined	24000	-1.180	-0.791	0.255	-0.448	-0.486	0.862
Cooks, variously defined	35000	-1.180	-0.791	0.255	-0.448	-0.486	0.862
Cooks, variously defined	23000	-1.180	-0.791	0.255	-0.448	-0.486	0.862
Repairers of mechanical controls and valves	56000	-0.435	-0.703	1.281	-1.422	0.970	0.085
Cooks, variously defined	48000	-0.198	1.182	0.034	0.275	-0.393	0.721
Repairers of mechanical controls and valves	50000	-0.435	-0.703	1.281	-1.422	0.970	0.085
Stock and inventory clerks	67000	-1.112	-0.819	0.491	-0.701	0.042	0.394

CHAPTER 5

EMPIRICAL METHODS

The purpose of this empirical section is to investigate the claim that investment in different tasks yields different returns in the specified demographic of young men with no college education. The connection between occupation task contents and wages is first established using a series of Ordinary Least Squares (OLS) and fixed-effects regression. Next, the relationship between task-specific human capital growth and wages is explored using a similar regression analysis. The regressions are performed on a panel of workers that include income, occupation, and a measure of the tasks used in each occupation.

To provide a foundation for the relationship between cumulative task-specific experience and wages, it is necessary to establish a connection between the task mix of individual jobs and the wages of the workers who perform them. Research demonstrates that skill categories command different wage premiums in the workplace. Much of this research has focused on the market as a whole or on the top end of the wage distribution (Autor, Levy & Murnane, 2003). Since this study focuses on a particular demographic, the relationship between tasks and wages may be different.

In order to test this relationship, regressions were run using real hourly wages as the independent variable. First, a set of standard OLS regressions were run followed by fixed effects panel regressions. Walking through the regressions shows the development of the link between the kinds of tasks performed on the job and wages. First, only the task measures are presented, and the results indicate a trend. Next, to account for the effects of experience and underemployment, the years of experience, years of tenure, and a part-time dummy variable are added in as controls. The next regression attempts to control for other firm and occupation-specific wage predictors by including average unemployment, firm size, union status, and broad occupational category. Finally, individual-specific influencers of wages are added in; ASVAB score percentile, number of children in the household, marital status, race, and census region. In the OLS models, NRCA and NRMP are statistically significant predictors of wages with coefficients of 0.101 and 0.836, respectively, once other influencers of wages have been accounted for. The results of the OLS models are presented in table 5.1

Standard OLS regression is indicative of a trend, but it is not the best model to fit to this dataset. Because the data is in a panel form, it is important to account for the time-invariant traits of the individuals that may give some inherent propensity to sort into specific jobs. For example, more dexterous workers may choose to pursue careers that require more manual tasks, especially non-routine ones. However, other workers may be better at relating with people, and so sort themselves into sales or sales management jobs.

In order to account for this individuality, a fixed effects model is fitted to this data:

$$Y_{it} = \beta_1 X_{1,it} + \ldots + \beta_6 X_{6,it} + \beta_7 Z_{1,it} + \ldots + \beta_k Z_{1,it} + a_i + u_{it}$$

Where Y_{it} is the wage for individual i at time t, $X_1 \ldots X_6$ are the task-specific measures for individual i at time t, $Z_1 \ldots Z_6$ are control variables, a_i is the intercept for each individual, controlling for fixed effects, and u_{it} is the unmeasured error term of each individual i at time t.

The control variables are similar to those used in the OLS models, with some differences. The time-invariant control variables of race and ASVAB score percentile are absorbed into the individual intercept of each individual. The results of these regressions are presented in Table 5.2 and are quite different from the OLS estimations. With fixed effects accounted for, the relationship between task-specific human capital and wages changes substantially. The only factors that are significant in the fixed effects models are NRCI and NRMP, which positively affect wages with coefficients of 0608 and 0.0958.

The disconnection between most of the task measures and wages does not necessarily mean that accumulation of task-specific human capital is without worth. Another set of regressions was performed using the cumulative task measures to determine the effect on wages of accumulated experience in the different skill categories.

The regressions follow the same specifications of the ones from Tables 5.1 and 5.2, where log wages is regressed on a number of wage predictors. The first regression uses only the accumulated values of the task measures. The second regression includes the effects of years of experience and years of tenure to account for the accumulation of general and firm-specific human capital. A part-time dummy variable is also added to control for the effects of underemployment. The next three regressions build upon the previous ones, adding in the same control variables as before, excluding time-invariant variables. The results of these regressions are presented in Tables 5.3 and 5.4. They show that most of the accumulated values of tasks are not significant determiners of wages. With all the controlling factors included, only RC is a significant wage determiner at the 95% level, with a coefficient of -0.018.

Table 5.1: OLS Regression Models on Job-Specific Task Measures

Variables	OLS Model 1	OLS Model 2	OLS Model 3	OLS Model 4
NRCA	0.236***	0.195***	0.110***	0.101***
	(0.0290)	(0.0256)	(0.0350)	(0.0336)
NRCI	0.0164	-0.000149	0.0315	0.0257
	(0.0243)	(0.0214)	(0.0230)	(0.0225)
NRMP	0.0802***	0.0605***	0.0785**	0.0836**
	(0.0202)	(0.0185)	(0.0338)	(0.0331)
NRMI	-0.0671***	-0.0658***	-0.0251	-0.0175
	(0.0197)	(0.0179)	(0.0250)	(0.0235)
RC	0.0282	0.0419**	-0.00608	-0.0257
	(0.0190)	(0.0180)	(0.0279)	(0.0260)
RM	0.00585	0.0214	0.00773	0.00780
	(0.0220)	(0.0195)	(0.0288)	(0.0264)
Years of Tenure	No	0.0464***	0.0448***	0.0437***
		(0.00591)	(0.00594)	(0.00575)
Years of Experience	No	0.0387***	0.0307***	0.0247***
		(0.00416)	(0.00492)	(0.00485)
Part-Time (dummy)	No	-0.0711	-0.110**	-0.0616
		(0.0656)	(0.0522)	(0.0533)
Average Unemployment	No	No	Yes	Yes
Firm Size	No	No	Yes	Yes
Union Status	No	No	Yes	Yes
ASVAB Score Percentile	No	No	No	Yes
Number of Children in the Household	No	No	No	Yes
Marital Status	No	No	No	Yes
Race	No	No	No	Yes
Census Region	No	No	No	Yes
Occupational Category	No	No	Yes	Yes
Constant	2.412***	1.996***	1.801***	1.674***
	(0.0228)	(0.0383)	(0.0883)	(0.0975)
Observations	1,083	1,083	1,083	1,083
R-squared	0.134	0.321	0.411	0.468
Number of respondents				

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.2: Fixed-Effects Regression Models on Job-Specific Task Measures

Variables	Fixed Model 1	Fixed Model 2	Fixed Model 3	Fixed Model 4
NRCA	0.0659**	0.0847***	-0.0133	-0.0149
	(0.0320)	(0.0267)	(0.0341)	(0.0343)
NRCI	0.0355	0.00748	0.0606**	0.0608**
	(0.0287)	(0.0241)	(0.0258)	(0.0261)
NRMP	0.0275	0.0308	0.0929**	0.0958**
	(0.0250)	(0.0208)	(0.0380)	(0.0382)
NRMI	-0.00379	-0.0268	-0.0260	-0.0243
	(0.0253)	(0.0211)	(0.0274)	(0.0276)
RC	-0.0200	0.00925	0.0133	0.0186
	(0.0199)	(0.0166)	(0.0245)	(0.0245)
RM	0.0572**	0.0315	0.0120	0.00920
	(0.0262)	(0.0218)	(0.0304)	(0.0306)
Years of Tenure	No	0.0194***	0.0244***	0.0241***
		(0.00591)	(0.00583)	(0.00593)
Years of Experience	No	0.0599***	0.0712***	0.0690***
		(0.00389)	(0.00522)	(0.00571)
Part-Time (dummy)	No	-0.000524	-0.0439	-0.0442
		(0.0398)	(0.0394)	(0.0396)
Average Unemployment	No	No	Yes	Yes
Firm Size	No	No	Yes	Yes
Union Status	No	No	Yes	Yes
ASVAB Score Percentile	No	No	No	No
Number of Children in the Household	No	No	No	Yes
Marital Status	No	No	No	Yes
Race	No	No	No	No
Census Region	No	No	No	Yes
Occupational Category	No	No	Yes	Yes
Constant	2.395***	1.918***	2.054***	2.356***
	(0.0214)	(0.0308)	(0.0799)	(0.249)
Observations	1,083	1,083	1,083	1,083
R-squared	0.032	0.337	0.413	0.421
Number of respondents	288	288	288	288

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3: OLS Regression Models on Accumulated Task Measures

Variables	OLS Model 1	OLS Model 2	OLS Model 3	OLS Model 4
Accumulated NRCA	0.0275***	0.0321***	0.0203***	0.0160***
	(0.00530)	(0.00511)	(0.00536)	(0.00513)
Accumulated NRCI	0.0164***	0.00522	0.0119***	0.0113***
	(0.00482)	(0.00450)	(0.00408)	(0.00401)
Accumulated RC	-0.00125	0.00763*	-0.00169	-0.00514
	(0.00428)	(0.00419)	(0.00441)	(0.00398)
Accumulated RC	-0.00123	-0.00218	-0.00446	-0.00452
	(0.00479)	(0.00429)	(0.00478)	(0.00432)
Accumulated NRMP	0.0219***	0.00719*	0.00689	0.00726
	(0.00382)	(0.00377)	(0.00458)	(0.00465)
Accumulated NRMI	-0.0324***	-0.0247***	-0.0153***	-0.0141***
	(0.00393)	(0.00362)	(0.00393)	(0.00389)
Years of Tenure	No	0.0394***	0.0411***	0.0410***
		(0.00605)	(0.00601)	(0.00590)
Years of Experience	No	0.0362***	0.0335***	0.0259***
		(0.00544)	(0.00625)	(0.00592)
Part Time (Dummy)	No	-0.114*	-0.125**	-0.0862
		(0.0672)	(0.0541)	(0.0555)
Average Unemployment	No	No	Yes	Yes
Firm Size	No	No	Yes	Yes
Union Status	No	No	Yes	Yes
ASVAB Score Percentile	No	No	No	Yes
Number of Children in the Household	No	No	No	Yes
Marital Status	No	No	No	Yes
Race	No	No	No	Yes
Occupational Category	No	No	Yes	Yes
Census Region	No	No	No	Yes
Constant	2.268***	2.035***	1.802***	1.716***
	(0.0253)	(0.0320)	(0.0853)	(0.0948)
Observations	1,083	1,083	1,083	1,083
R-squared	0.212	0.327	0.427	0.473
Number of pubid_1997				

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.4: Fixed Effects Regression Models on Accumulated Task Measures

Variables	Fixed Model 1	Fixed Model 2	Fixed Model 3	Fixed Model 4
Accumulated NRCA	-0.0208**	0.0197*	0.00950	0.00970
	(0.00973)	(0.0105)	(0.0104)	(0.0105)
Accumulated NRCI	0.0324***	-0.000425	0.00700	0.00661
	(0.00751)	(0.00809)	(0.00817)	(0.00818)
Accumulated RC	-0.0368***	-0.0200***	-0.0172**	-0.0179***
	(0.00676)	(0.00673)	(0.00672)	(0.00672)
Accumulated RC	0.00492	0.000409	-0.000263	-0.000513
	(0.00848)	(0.00810)	(0.00787)	(0.00789)
Accumulated NRMP	0.0272***	-0.00557	-0.00228	-0.000568
	(0.00723)	(0.00784)	(0.00776)	(0.00787)
Accumulated NRMI	-0.0247***	-0.0178**	-0.0124*	-0.0116
	(0.00747)	(0.00717)	(0.00702)	(0.00713)
Years of Tenure	No	0.0158***	0.0218***	0.0209***
		(0.00591)	(0.00591)	(0.00599)
Years of Experience	No	0.0581***	0.0694***	0.0661***
		(0.00728)	(0.00832)	(0.00860)
Part Time (Dummy)	No	-0.0116	-0.0404	-0.0437
		(0.0401)	(0.0396)	(0.0397)
Average Unemployment	No	No	Yes	Yes
Firm Size	No	No	Yes	Yes
Union Status	No	No	Yes	Yes
ASVAB Score Percentile	No	No	No	No
Number of Children in the Household	No	No	No	Yes
Marital Status	No	No	No	Yes
Race	No	No	No	No
Occupational Category	No	No	Yes	Yes
Census Region	No	No	No	Yes
Constant	2.085***	1.958***	1.986***	2.229***
	(0.0244)	(0.0274)	(0.0763)	(0.250)
Observations	1,083	1,083	1,083	1,083
R-squared	0.257	0.327	0.408	0.414
Number of pubid_1997	288	288	288	288

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

CHAPTER 6

DISCUSSION

The lack of explanatory power of the task measures and their accumulated value makes it difficult to be certain about the effect of task-based human capital accumulation on this demographic. However, the effects that are significant are in line with what other literature suggests, especially the research on tasks and automation presented in the literature review. These papers find that the growing automation of tasks has pushed wages for routine tasks down, while increasing the demand for non-routine tasks (Autor, Levy & Murnane, 2003).

A number of factors, both empiric and economic, may contribute to why most of the cumulative measures are not significant. The sample is limited to a maximum of twelve years of employment, so the distribution of wages may not have had enough time to fully develop in the workers sampled. Also, limiting the sample to young men without a college degree restricts the number of occupations represented to a point where the effect on wage growth by investment in these task measures is relatively narrowly distributed. Figure 6.1 shows the wage distribution for each year respondents spent in the labor market in real dollars. The lower three wage quartiles remain below $20 per hour for every survey year, with outliers as high as $100 per hour. Figure 5.1 shows the effect of additional experience remains relatively low for most of the sampled jobs. Another contributor to the lack of explanatory power is the inconsistency of many of the responses. The high number of missing values in the reported data leads to mismatches that cause the regression process to lose usable observations. This can be seen by the low number of responses used in all the regressions of tables 5.1 – 5.4. It is possible that more exact statistical methods could be used to increase the predictive power of the cumulative measures. However, with such a small sample size, and with such a large number of missing responses it is not practical to investigate them fully in this paper.

In spite of the limitations of the data, the results are not out of line with other studies. Other investigations found that non-routine tasks are associated with higher wages, while routine tasks should have lower wages, with NRCA having the greatest effect on wages. In this sample, not many workers are afforded the opportunity to work in occupations that have high NRCA, and workers have not had enough time to earn promotions into occupations that require high NRCI, however, even with these limitations, our data shows that workers who invest in non-routine human capital produce higher returns than those who do not.

Non-routine cumulative RC remains a strong negative influencer of wages, even in the small sample used in this investigation. This implies that workers with no college education might be better off investing in other skill types, if possible. Table 5.1 presents the occupations with one standard deviation above normal RC involvement. The most frequent occupation among these is cashier, a job not known for its high compensation. Other common jobs with high RC, like billing clerks, customer service representatives, and meter readers are also low paying. This finding is in line with the broader literature on the effects of automation and computerization on the wages of workers. However, according to other studies, RM tasks should be equally predictive of low compensation but are not significant in this investigation.

Table 6.1: Occupations with RC More than 1 Standard Deviation Above the Mean

1990 Census Occupation Code	Freq.	Percent	Cum.
Cashiers	125	35.51	35.51
Customer Service Reps and Investigators	37	10.51	46.02
Grinding, abrading, buffing, and polish	20	5.68	51.7
Dispatchers	14	3.98	55.68
Electric Power Installers and Repairers	13	3.69	59.37
Crane, Derrick, Winch, and Hoist Operators	13	3.69	63.07
Assemblers of Electrical Equipment	12	3.41	66.48
Musician or Composer	10	2.84	69.32
Billing Clerks and Related Financial Occupations	10	2.84	72.16
Meter Readers	10	2.84	75
Others	88	25	100
Total	352	100	100

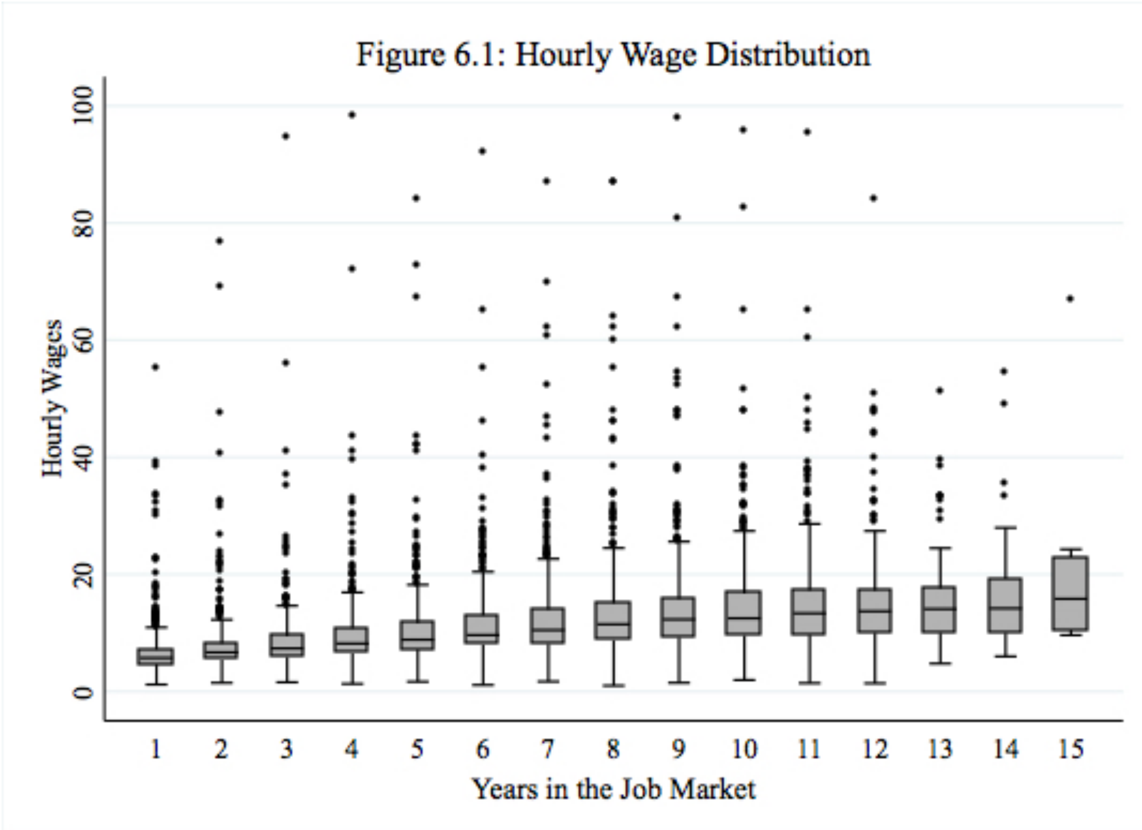

Figure 5.1 shows the distribution of hourly wages for each year respondents spent in the job market. Boxes show the inner two quartiles of the wage distribution. Tales show the outer two quartiles, with more distant outliers plotted as points. While the average compensation does rise as workers spend more time employed, relatively few respondents made more than $20 per hour over the entire survey period.

CHAPTER 7

CONCLUSION

In this study, the influence of task-specific human capital on wages is explored for young men with no college education. A brief framework of how the empirical results fit into the theoretical model of human capital accumulation is presented, followed by an empirical analysis of the chosen demographic. OLS and fixed effects regressions were used to determine the effect of the task mix of jobs and cumulative task-specific human capital on wages. The results of these regressions are inconclusive for all the cumulative measures except RC. However, our conclusions cannot be confirmed to be robust when controlling for other factors, as the sample size is relatively small. Economically, these results indicate that RC tasks are not valued in the labor markets, and investment in other skills is more beneficial even for male workers with no college education. This is in line with what other research suggests, especially the literature on task-specific human capital and the automation of tasks.

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