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Career Progression and Comparative Advantage

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This paper constructs and structurally estimates a dynamic occupational choice model that has two distinct features. First, an occupation is vertically and horizontally differentiated by a multidimensional task complexity measure. This allows a simultaneous analysis of career progression and comparative advantage. Second, the model includes hundreds of occupations by characterizing all jobs by a multidimensional task complexity vector, thereby avoiding the curse of dimensionality. Estimation results from the Dictionary of Occupational Titles (DOT) and the National Longitudinal Survey of Youth 1979 (NLSY) indicate that wages increase according to task complexity and that individuals climb up the career ladder along the dimension of tasks in which they have a comparative advantage.

1 Introduction

This paper investigates the occupational mobility of male workers during their careers using occupational characteristics from the Dictionary of Occupational Titles (DOT) and career histories from the National Longitudinal Survey of Youth 1979 (NLSY). After providing empirical evidence that characterizes the career dynamics of white male workers, I construct and structurally estimate a dynamic occupational choice model in which occupations are vertically and horizontally differentiated by multidimensional task complexity measures.

A traditional view of labor economists is that human capital can be categorized either as general or firm specific. However, recent empirical papers including Kambourov and Manovskii (2007), Pavan (2006), and Neal (1995, 1999) find that a substantial amount of human capital is associated with occupations, rather than firms. These studies indicate that understanding why individuals choose and change occupations provides implications for the wage structure. In addition, Moscarini and Vella (2003b) point out that worker reallocation across occupations affects business

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cycles and economic growth. Nevertheless, many existing papers examine only separation from the current occupation and ignore the occupation to which individuals move. This paper focuses on the choice of occupations and its relation to wage structure.

In the model, an occupation is viewed as a set of different tasks. Using multidimensional task complexity measures, occupations are both vertically and horizontally differentiated. Wages are determined not only according to individual attributes such as experience and education, but also according to task complexity of the current occupation. Occupations with complex tasks offer higher wages for experienced and/or educated workers. This wage structure sorts workers vertically into occupations with different task complexity. Occupations are also horizontally differentiated: for example, some occupations are characterized by interpersonal-skill intensity, while others are characterized by motor-skill intensity. Heterogeneous individuals choose their occupations depending on their comparative advantages. Some individuals climb the career ladder among interpersonal-skill intensive jobs; others progress through careers that are motor-skill intensive. This multidimensionality of task complexity allows the model to predict rich and realistic career decision patterns.

Individuals' career decisions are formulated as a dynamic discrete choice problem. Similar to the seminal work by Keane and Wolpin (1997), individuals repeatedly choose among work, school, and home alternatives. One limitation of the previous model is that only a few occupations are included, because parameters and state variables increase with occupations, which makes the model computationally intractable. This limitation is quite restrictive for describing upward mobility on the career ladder. This paper overcomes this problem by characterizing all occupations in terms of a four-dimensional task vector. In fact, the model deals with about 350 occupations at three digit classification level. Handling occupations at three digit classification level is important for a precise analysis of occupations, as pointed out by Moscarini and Vella (2003a,b).

The model is numerically solved and estimated by maximum likelihood. Parameter estimates indicate that wages increase according to task complexity and that returns to education and experiences also increase according to task complexity. Other structural parameter estimates such as the cost of switching occupations and the costs of attending school are intuitive. The simulation results, as well as parameter estimates, suggest that permanent unobserved individual heterogeneity strongly influences occupational choices. This has two implications: First, estimates of "skill price" (marginal effects of task complexity on logwage) by OLS are likely to be biased due to endogenous occupational choice. This might explain why Ingram and Neumann (2006) and Bacolod and Blum (2005) estimate some skill prices to be negative.. Second, careers of individuals are distinct between unobserved types; individuals move up the career ladder along the dimension of their comparative advantages. This career progression pattern cannot be predicted without multidimensional task complexity measures.

This paper is related to the career dynamics literature. Miller (1984) shows that the optimal career path for a young worker is to start from a risky job and move to a less risky job if he finds he does not fit. Jovanovic and Nyarko (1997) provide a model in which workers gradually move from low-skill occupations to high-skill occupations, which is consistent with the empirical results of this paper. Sicherman and Galor (1990) show that part of the returns to education is in the form of higher probabilities of occupational upgrading. Gibbons and Waldman (2006) present a model of worker assignment within a firm. In their model, an output of a high-ranking position is sensitive to the ability of a worker. The optimal worker assignment is such that skilled workers occupy high-ranking positions, while less skilled workers hold low-ranking positions. Gibbons, Katz, Lemieux, and Parent (2005) examine the implications of this model combined with learning for the labor market. They claim that workers are gradually sorted into high-skill occupations if they turn out to be skilled, and vice versa. They study the implications for the wage structure, but not for occupational mobility. The present paper departs from these previous contributions in that occupations are characterized by multidimensional tasks, which implies that occupations are not only vertically, but also horizontally, differentiated. This feature of the model allows analysis of career dynamics in greater depth.

The rest of the paper is organized as follows: Section 2 describes the data set including the occupational characteristics in the DOT and occupational histories from the NLSY. The main patterns of the data are also explained in this section. Section 3 describes the model and the estimation strategy. The estimation results are presented in Section 4. Section 5 discusses the extent to which unobserved heterogeneity accounts for labor market outcomes through numerical simulations. Section 6 concludes.

2 Data

2.1 Dictionary of Occupational Titles

The DOT provides variables that characterize occupations. Occupational definitions in the DOT are based on the examination of tasks by expert occupational analysts. The DOT contains the measurements of worker functions and traits required to perform a particular job such as training time, aptitudes, temperaments, interests, physical demand, and environmental conditions. In this paper, the data are taken from the 1991 revised fourth edition for which information was collected between 1978 and 1990. In this edition, 12,099 occupations are studied in terms of 44 characteristics.

Previous studies such as Ingram and Neumann (2006) and Bacolod and Blum (2005) find that many variables in the DOT are highly correlated with one other. Hence, the occupational characteristics featured in the DOT can be aggregated into a small number of categories. Following Bacolod and Blum (2005), I construct a four-dimensional task complexity measure by a principal component analysis: cognitive skills, interpersonal skills, motor skills, and physical demand. The calculated factor scores are rescaled so that the averages are one and the standard deviations are 0.1. The details of the task complexity measure construction are reported in Appendix A.

2.2 National Longitudinal Survey of Youth 1979

The data for career history are taken from the NLSY which includes information on the weekly work history of individuals from 1978. The survey subjects comprise individuals who were between 14 and 21 years old as of January 1, 1979. The NLSY is particularly suitable for this study because it contains a detailed career history of individuals. In addition, the information relating to the transition from school to work is also included in the NLSY, which allows me to assess the relationship between education and career. The DOT variables are added to the NLSY using the 1970 Census three-digit occupation code. Observations from 1979 through 1994 are used in the analysis, because occupation change is not reported on an annual basis in later surveys.[1]

A sample of white males who completed high school or higher is taken in the following way. I start with a sample comprising 1,583 white males who were 18 or younger, because their initial decisions after graduating from high school are observed. I then drop 171 individuals because they did not graduate from high school, using the highest grade completed in the most recent survey year. The sample contains 1,412 individuals at this point. Out of 1,412, I keep 1,188 individuals who graduated from high school between the ages of 18 and 20. Then, I drop 97 from the remaining 1,188 individuals who did not work 1,000 hours or more in any survey year after graduating from high school. Finally, I omit 15 individuals since the occupation code in their first year after graduation is missing. The final sample size is 1,076.

Individuals are assumed to be working, attending school, or staying at home in each year. These alternatives are exhaustive and mutually exclusive. The labor force status of an individual is determined by the following hierarchical rule[2]: (1) If an individual enrolls in a school as of May 1, then he is assumed to be attending a school for the entire year. (2) If an individual does not enroll in a school and works for more than 1,000 hours in a year, he is assumed to be working during the entire year. (3) If neither of the previous conditions apply, the individual is assumed to stay at home during the entire year. The hourly wage and occupation code are taken from the current or most recent job. Hourly wages are deflated by the 2002 CPI. Some recorded hourly wages are extremely high or low. If the recorded hourly wage is greater than \$100 or less than one dollar,

[1] In surveys later than 1994, an occupation change can be identified only when an individual also changes employers.

[2] This is similar to the one used in Lee and Wolpin (2006).

they are regarded as missing.

Previous empirical papers including Neal (1999) and Moscarini and Vella (2003b) report that the occupation codes in the NLSY are contaminated by measurement errors. One possible way to correct these errors is to assume that all occupation changes within the same employer are false. Neal (1999), Pavan (2006), and Yamaguchi (2007) take this approach to identify a broadly defined occupation change.[3] However, many occupation code switches within the same employer are promotions to managers. Thus, this editing is likely to result in a downward bias of the mean task complexity. Another way is to assume that cycles of occupation code within the same employer are caused by measurement errors. Many individuals apparently switch between two occupations while they work for the same employers. If an occupation code changes to a new one, and then comes back to the original one, while an individual stays with the same employer, I edit the code so that he remains in the same occupation. Notice that cycles of occupation code across different employers are left unedited. This correction method reduces the number of occupation changes within the same employer by about 40%.

Occupation codes may still be riddled with measurement errors even after the proposed correction method is applied. When occupation code is misreported, the estimated occupation change rate is biased upwards. However, noisy occupation code is less likely to bias the mean task complexity if the reported occupation is similar to the true occupation.

2.3 Descriptive Analysis

2.3.1 Summary Statistics

Table 1 reports summary statistics of the sample by pooling all observations. The sample mean age is 24.8, while the sample mean years of post-secondary education is 1.5. The sample means of general experience and occupational specific experience at the three-digit level are 3.6 and 0.8 years, respectively. Mean task complexity indexes are 1.0 by construction. The sample mean hourly logwage is 2.5. The annual occupational change rate is 0.47, which is lower than the estimate reported by Moscarini and Vella (2003b), because I edit occupation cycles to address measurement error. Without this correction, the occupation change rate would be 0.61, which is close to the result of Moscarini and Vella (2003b). Task complexity variables are highly correlated with each other, as shown in Table 2. Cognitive skill is strongly and positively correlated with interpersonal skill, while it is strongly and negatively correlated with physical demand. These strong correlations suggest complementarity and substitution between skills. For example, this may reflect that returns to cognitive skills are higher in occupations requiring interpersonal skills, as Bacolod and Blum (2005) find. Another explanation is that learning cognitive skills and interpersonal skills

[3] They call this broadly defined occupation as career.

Table 1: Summary Statistics

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Nobs
Age	18.00	21.00	25.00	24.84	28.00	34.00	13277
Education	0.00	0.00	1.00	1.49	2.00	9.00	13277
General Experience	0.00	0.00	3.00	3.63	6.00	15.00	13277
Occupational Experience	0.00	0.00	0.00	0.84	1.00	14.00	13277
Cognitive Skill	0.85	0.91	0.98	1.00	1.09	1.25	9420
Interpersonal Skill	0.89	0.91	0.96	1.00	1.08	1.28	9420
Motor Skill	0.83	0.91	1.00	1.00	1.08	1.24	9420
Physical Demand	0.84	0.91	1.01	1.00	1.08	1.20	9420
Logwage	0.02	2.16	2.50	2.50	2.83	4.54	9135
Yearly Occupation Change	0.00	0.00	0.00	0.47	1.00	1.00	7933

Note: Wages are deflated by the 2002 CPI.
Source: NLSY and DOT.

Table 2: Correlation Matrix of Task Complexity

	Cognitive	Interpersonal	Motor	Physical
Cognitive	1.000	0.570	−0.193	−0.694
Interpersonal		1.000	−0.603	−0.678
Motor			1.000	0.486
Physical				1.000

Source: NLSY and DOT.

at the same time is easier than improving both cognitive skills and physical strength. The model presented in Section 3 captures such complementarity and substitution between skills.

Task complexity is considerably different within an occupation at the one-digit classification level. Table 3 presents the results of the variance decomposition of task complexity in the pooled sample. Let X be an element of the task complexity vector and I be an index of each one-digit occupation. The variance of X can be decomposed in the following way

$$V(X) \quad = \quad E[V(X|I)] + V[E(X|I)]$$

where the first term captures the variance within one-digit occupations and the second term captures the variance between one-digit occupations. I find that about a third of task complexity variations in interpersonal skill, motor skill, and physical demand remains unexplained by the one-digit occupational classification. The variance of cognitive skill within one-digit occupations is smaller, which accounts for about 15% of the total. The variance decomposition results suggest that occupational tasks can be even more precisely analyzed by using the three-digit occupational classification than the one-digit classification.

Table 4 presents the choice distribution, logwage, occupation change rate by age and two selected education groups. High school graduates are those who did not take any post-secondary education, and college graduates are those who had four years of post-secondary education or more

Table 3: Heterogeneity of Task Complexity Within the One-digit Occupations.

	Cognitive	Interpersonal	Motor	Physical
Within	15.6%	33.5%	37.9%	31.7%
Between	84.4%	66.5%	62.1%	68.3%

Note: The variance of each dimension of task complexity in the pooled white male sample from the NLSY is decomposed into within and between occupations at the one-digit level.

Table 4: Labor Force Status, Logwage, Occupation Changes by Age and Education

	Choice Distribution				Logwage			Occupation Change	
Age	Work	Home	School	Obs	Mean	S.D.	Obs	Prob.	Obs
All									
18-21	0.535	0.159	0.306	3574	2.140	0.419	1851	0.621	1608
22-25	0.786	0.120	0.093	3776	2.437	0.448	2894	0.505	2762
26-29	0.928	0.051	0.021	3306	2.653	0.453	2969	0.399	2824
30-34	0.951	0.036	0.013	1545	2.748	0.488	1421	0.427	951
High School									
18-21	0.639	0.144	0.217	2112	2.156	0.411	1310	0.606	1161
22-25	0.910	0.064	0.026	1392	2.455	0.433	1244	0.485	1201
26-29	0.959	0.036	0.005	1183	2.628	0.414	1110	0.398	1061
30-34	0.974	0.026	0.000	583	2.710	0.411	556	0.430	388
College									
22-25	0.661	0.161	0.178	608	2.612	0.466	395	0.480	377
26-29	0.900	0.052	0.048	709	2.824	0.466	607	0.371	587
30-34	0.950	0.022	0.028	358	2.927	0.520	331	0.352	216

Note: Wages are deflated by the 2002 CPI. High school graduates are those who have not attended a post-secondary school in a given survey year. College graduates are those who have completed four years of post-secondary education or more in a given survey year. Individuals counted as high school graduate in a certain age-education cell may also be counted as college graduate in a later age cell.
Source: NLSY and DOT.

in a given survey year. Individuals counted as high school graduates in a certain age-education cell may also be counted as college graduates in a later age cell. The first three columns report the distributions of career decisions. The fraction of working individuals increases with age. Only about half of the individuals between 18 and 21 are working, while more than 90% of those older than 25 are working in the labor market. The school attendance rate is about 30% for those who are between 18 and 21, but it quickly decreases with age and is as low as 2% for those between 26 and 29. The next two columns report the mean and standard deviation of logwage. Logwage increases with age at a decreasing rate for both education groups. College graduates earn at least 20% higher wages than high school graduates. The last two columns report an annual occupational change rate. The rate is as high as 62% between the ages of 18 and 21, but decreases to 43% between the ages of 30 and 34. High school graduates change occupations more often than college graduates.

To see if the proposed task complexity measures are intuitive, Table 5 presents mean task complexity indexes for each one-digit occupation. Professionals and managers are the most cognitive-

Table 5: Mean and Standard Deviation of Task Complexity Indexes by One-digit Occupation

	Cognitive		Interpersonal		Motor		Physical		
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Obs.
Professional	1.147	0.050	1.059	0.093	0.998	0.112	0.893	0.047	1526
Manager	1.103	0.022	1.091	0.041	0.888	0.016	0.913	0.028	1180
Sales	1.009	0.054	1.188	0.019	0.901	0.024	0.916	0.013	682
Clerical	0.981	0.049	0.981	0.072	0.947	0.059	0.953	0.090	824
Craftsmen	0.993	0.045	0.935	0.052	1.132	0.057	1.067	0.064	1819
Operatives	0.900	0.025	0.909	0.032	1.042	0.042	1.054	0.056	977
Transport	0.894	0.025	0.978	0.078	1.022	0.022	1.067	0.018	476
Laborer	0.876	0.012	0.912	0.013	0.964	0.040	1.126	0.047	756
Farmer	1.059	0.009	0.966	0.032	0.981	0.006	1.166	0.056	71
Farm Laborer	0.887	0.024	0.910	0.022	1.009	0.008	1.152	0.034	134
Service	0.928	0.040	0.989	0.054	0.982	0.063	1.030	0.078	975
ALL	1.000	0.100	1.000	0.100	1.000	0.100	1.000	0.100	9420

Note: The task complexity indexes are constructed using the pooled NLSY sample so that the sample mean and the sample standard deviation are 1.00 and 0.10, respectively. Household service occupations are integrated into service occupation.
Source: NLSY and DOT.

skill intensive and are followed by sales persons, clerical staff, and those with crafts occupations. Tasks of operatives, transport operatives, laborers, and service workers do not require significant cognitive skills. Instead, their tasks are physically demanding. Sales persons are required to have the highest interpersonal skills; they are followed by managers and professionals. The tasks of craftsmen are the most motor-skill intensive, while managers and sales persons require few motor skills. These results are quite intuitive and indicate that the proposed measures are useful in understanding occupational choice patterns.

2.3.2 Evolution of Task Complexity and Occupational Choice

Evolution of mean and standard deviation of task complexity indexes are reported in Table 6. Tasks are more and more cognitive-skill and interpersonal-skill demanding over time, while they are less and less motor-skill demanding and physically demanding. Some of these trends are explained by the fact that educated individuals enter the labor market at older ages, as shown below.

Task complexity difference between education groups is substantially large. College graduates are engaged in more cognitive- and interpersonal-skill intensive tasks than high school graduates, while high school graduates are engaged in tasks that are more motor-skill and physical-strength intensive than college graduates. This is consistent with the occupational choice patterns shown in Table 7. College graduates tend to occupy professional and managerial positions, while high school graduates become craftsmen.

Although tasks differ significantly between education groups, both groups gradually move to occupations with more cognitive- and interpersonal-skill intensive tasks, while they move to less

Table 6: Task Complexity

	Cognitive		Interpersonal		Motor		Physical		
Age	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Obs
All									
18-21	0.946	0.073	0.967	0.085	1.006	0.090	1.037	0.089	1912
22-25	0.995	0.097	0.994	0.099	1.006	0.100	1.003	0.099	2969
26-29	1.023	0.103	1.016	0.103	0.995	0.103	0.983	0.100	3069
30-34	1.031	0.100	1.021	0.102	0.991	0.105	0.982	0.102	1470
High School									
18-21	0.945	0.072	0.963	0.082	1.008	0.090	1.041	0.087	1349
22-25	0.978	0.084	0.974	0.089	1.027	0.103	1.028	0.092	1267
26-29	0.997	0.090	0.991	0.097	1.016	0.105	1.014	0.098	1135
30-34	1.000	0.087	0.995	0.097	1.016	0.104	1.014	0.099	568
College									
22-25	1.079	0.100	1.055	0.099	0.956	0.089	0.922	0.083	402
26-29	1.093	0.095	1.073	0.101	0.954	0.098	0.915	0.075	638
30-34	1.094	0.088	1.078	0.097	0.952	0.102	0.923	0.076	340

Note: High school graduates are those who have not attended a post-secondary educational institute in a given survey year. College graduates are those who have completed four years of post-secondary education or more in a given survey year. Individuals counted as high school graduate in a certain age-education cell may also be counted as college graduate in a later age cell.
Source: NLSY and DOT.

physically demanding occupations. I find that the upward trends of cognitive skill and interpersonal skill indexes are statistically significant for both education groups, by regressing each skill index on age. The downward trend of the physical demand index for high school graduates is also found statistically significant. As Table 7 shows, more and more individuals are promoted to managerial positions as they age. In contrast, the share of low-skill occupations, such as laborers, decreases with age.

Table 7: Distributions of Occupation

Age	PRO	MNG	SLS	CLR	CRF	OPR	TRS	LBR	FMR	FLB	SVC	Obs
All												
18-21	0.04	0.05	0.06	0.12	0.18	0.16	0.06	0.14	0.01	0.03	0.15	1912
22-25	0.16	0.10	0.08	0.09	0.21	0.10	0.06	0.08	0.00	0.01	0.11	2969
26-29	0.21	0.15	0.08	0.07	0.19	0.09	0.04	0.06	0.01	0.01	0.09	3069
30-34	0.22	0.21	0.07	0.06	0.19	0.08	0.04	0.06	0.01	0.01	0.07	1470
High School												
18-21	0.04	0.05	0.05	0.13	0.18	0.16	0.06	0.14	0.01	0.04	0.14	1349
22-25	0.08	0.09	0.06	0.09	0.30	0.11	0.06	0.08	0.01	0.02	0.10	1267
26-29	0.10	0.14	0.07	0.07	0.28	0.10	0.04	0.08	0.01	0.01	0.09	1135
30-34	0.11	0.16	0.06	0.06	0.29	0.10	0.04	0.07	0.02	0.01	0.08	568
College												
22-25	0.46	0.12	0.14	0.10	0.04	0.02	0.00	0.04	0.00	0.00	0.06	402
26-29	0.48	0.16	0.13	0.08	0.04	0.03	0.00	0.01	0.00	0.01	0.06	638
30-34	0.43	0.29	0.09	0.04	0.04	0.04	0.00	0.01	0.01	0.00	0.04	340

Note: PRO: professionals, MNG: managers, SLS: sales persons, CLR: clerical, CRF: craftsmen, OPR: operatives, TRS: transportation equipment operatives, LBR: laborers, FMR: farmer, FLB: farm laborers, SVC: service workers. High school graduates are those who have not attended a post-secondary educational institute in a given survey year. College graduates are those who have completed four years of post-secondary education or more in a given survey year. Individuals counted as high school graduate in a certain age-education cell may also be counted as college graduate in a later age cell.
Source: NLSY

3 Model

This section describes an economic model that fits the main features of the data such as (1) individuals gradually moving to occupations with more complex tasks, (2) educated individuals occupying jobs with more complex tasks, and (3) individuals moving between similar occupations.

After graduating from high school, individuals maximize the present value of their lifetime utility until their retirement age T by choosing one of the following J mutuallyexclusive alternatives: staying at home, attending school, and working in one of $J-2$ occupations. Any work experience before high school graduation does not count for their careers after high school. The population consists of H discrete types of individuals who permanently differ in their ability to learn and earn, and mobility costs as described below.

3.1 Choice Set

Individual i chooses one of J mutually exclusive alternatives. Each alternative is denoted by a dichotomous variable a_{it}^{j} that takes 1 if alternative j is chosen at age t and takes zero otherwise. The alternatives include (a) work in occupation j, a_{it}^{j} $(1 \leq j \leq J-2)$; (b) stay home, a_{it}^{J-1}; and (c) attend school, a_{it}^{J}.

3.2 Preferences

The flow utility for an individual at age t is given by

$$
\begin{aligned}
U_{it} \quad = \quad & (\gamma_{i,0} + \gamma_1 \frac{w_{it}^{\gamma_2}}{\gamma_2}) \sum_{j=1}^{J-2} a_{it}^{j} \\
& + \sum_{j=1}^{J-2} c_{it}(s_j, s_k) \cdot a_{it}^{j}(1 - a_{it-1}^{j}) \\
& + a_{it}^{J}[c_{i,0}^{S} + c_1^{S} I(EDU_{it} \geq 4) + c_2^{S}(1 - a_{it-1}^{J}) + c_3^{S} a_{it-1}^{J} I(EDU_{it} = 4)] \\
& + \sum_{j=1}^{J} a_{it}^{j} \nu_{ijt} \qquad (1)
\end{aligned}
$$

where $EDU_{it} = \sum_{\tau=1}^{t-1} a_{i\tau}^{J}$ denotes years of post-secondary education. The first line is a net utility of work when the wage is w_{it} . It includes a fixed disutility cost of work $\gamma_{i,0}$ and utility from wage which is weakly concave $(\gamma_2 \leq 1)$. No saving or borrowing is considered in the model. Notice that the fixed disutility cost varies across individuals. The second line is the cost of entry to a new occupation. This cost depends on individual type, age t, and task complexities of the new occupation s_j and the current occupation s_k. A worker does not pay this cost, when he stays in the same occupation. The entry cost function $c_{it}(s_j, s_k)$ will be detailed below. The third line is the cost of attending a post-secondary school. I denote by $c^S_{i,0}$ the net utility cost of undergraduate study, which varies across individuals. Individuals pay an additional cost of c^S_1 for graduate study. Because returning to school after a period of non-attendance is rare, a psychic cost of re-entry c^S_2 is included. When an individual attends a graduate school immediately after undergraduate study, a school switching cost c^S_3 is paid. The fourth line includes a choicespecific preference shock ν_{ijt} that is independent and identically distributed and follows type I extreme value distribution.

3.3 Wage Equation

Wage is determined by the attributes of an individual and the complexity of tasks of the current occupation. Specifically, the wage of an individual in occupation j in age t is given by

$$\begin{aligned} \ln w_{ijt} &= \ln w_{ijt}(s_j, EDU_{it}, GX_{it}, \varepsilon_{it}) \\ &= \omega_{i,0} + \omega_1 EDU_{it} + \omega_2 GX_{it} + \omega_3 GX_{it}^2 + \sum_{l=1}^{4} \omega_{i,4,l} s_j + \sum_{l=1}^{4}\sum_{m=1}^{4} \omega_{5,lm} s_{l,j} s_{m,j} \\ &\quad + \sum_{l=1}^{4} \omega_{6,l} s_{l,j} EDU_{it} + \sum_{l=1}^{4} \omega_{7,l} s_{l,j} GX_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

where GX_{it} is general work experience and ε_{it} is a normally distributed measurement error with a zero mean and a variance σ^2_ε. To account for comparative advantages, individual heterogeneity is allowed for the intercept and the coefficients for linear terms of task complexity. Interaction terms between task complexities are included in the wage equation to account for complementarity between tasks, which is consistent with the observed correlations between task complexities (see Table 2). Keane and Wolpin (1997) find that the rates of returns to education and experience vary across white-collar, blue-collar, and military occupations. To capture a possible complementarity between education, experience, and task complexity, the interaction terms are also included.

3.4 Occupation Entry Cost

A worker pays an entry cost when he moves to a different occupation. This entry cost is increasing in task-complexity deficiency and is defined as

$$\begin{aligned} d_l &= s_{l,j} - s_{l,k} \quad \text{if } s_{l,j} > s_{l,k} \\ & \quad\ 0 \quad \text{otherwise} \end{aligned} \tag{3}$$

where subscript l is for task complexity dimension, and s_j and s_k are the task complexity of the new occupation and the current occupation, respectively. The entry cost is given by

$$c_{it}(s_j, s_k) = \alpha_{ij,0} + \alpha_1 t_i + \sum_{l=1}^{4} \alpha_{i,2,l} d_l + \sum_{l=1}^{4} \sum_{m=l}^{4} \alpha_{3,lm} d_l d_m. \quad (4)$$

The first term is a fixed component of occupation entry cost, which varies across individual types. This is common to the same one-digit occupations, but varies across one-digit occupations, to represent the costs not captured by the proposed task-complexity deficiency measures. Age is included in the second term of the cost function to capture decreasing job mobility in advancing age due to changes of family variables such as marital status and children. Interaction terms between different dimensions of task-complexity deficiency are included in the last term to account for complementarity between different task dimensions, which is necessitated by the observed strong correlation between tasks shown in Table 2.

Task complexity of non-working state (either staying home or attending school) is estimated, because it is not in the data. The task complexity of non-working state $s^0_{it,l}$ is given by

$$s^0_{it,l} = (1 - y^0_{it,l}) s^{min}_l + y^0_{it,l} s^{max}_l \quad (5)$$

$$y^0_{it,l} = \frac{\exp(\delta_{0,l} + \delta_{1,l} EDU_{it})}{1 + \exp(\delta_{0,l} + \delta_{1,l} EDU_{it})} \quad (6)$$

where s^{max} (s^{min}) is the highest (lowest) task complexity in the data. Thus, the task complexity of non-working state satisfies $s^{min}_l < s^0_{it,l} < s^{max}_l$. Education affects the task complexity of non-working state, to account for the differences in initial occupations across different education groups. Education increases the likelihood of entering an occupation with complex tasks, as shown in the model by Sicherman and Galor (1990), which also contributes to returns to education.

3.5 Objective Function

Each individual at age t maximizes the expected discounted present value of lifetime utility by choosing among J alternatives. The present value of lifetime utility can be recursively written as

$$V_{it}(\Omega_{it}) = \max_{a_{it}} U_{it} + \rho E V_{it}(\Omega_{it+1} | a_{it}, \Omega_{it}) \quad if\; t^0_i \leq t < T \quad (7)$$

$$V_{iT}(\Omega_{iT}) = \max_{a_{iT}} U_{iT} \quad (8)$$

where Ω_{it} is the state space of individual i at age t, ρ is a discount factor, t^0_i is the age of high school graduation, and T is retirement age. The state space includes education, experience, current occupation (or the choice in the last period), and idiosyncratic choice specific preference shocks.

3.6 Solution and Estimation

The model is numerically solved by backward induction because this is a finite horizon problem. Retirement age is set at 65. Following Keane and Wolpin (1997), the value function is approximated by polynomial regressions to decrease the computational burden. Specifically, the expected value function (sometimes called the Emax function) is first evaluated at some selected points in the dimensions of education and general experience given the current occupation. Then the Emax function is approximated by a second-order polynomial. The discount factor is set to 0.95. The model is estimated for two different utility functions; one is linear in wage level $(\gamma_2 = 1)$ and the other is linear in logwage $(\gamma_2 = 0)$.

The likelihood function is constructed using this numerical solution to the dynamic programming. Denote the vector of parameters by Θ. Because education and experiences are functions of the history of the career choice variable a_{it}, the likelihood of an individual is given by

$$P(\{a_{it}, w_{it}\}_{t=t_i^0}^{\bar{t}_i}|\Theta) = \sum_{h=1}^{H} \pi_h(t_i^0) \prod_{t=t_i^0}^{\bar{t}_i} P_h(a_{it}, w_{it}|\{a_{i\tau}\}_{\tau=t_i^0}^{t-1}; \Theta) \tag{9}$$

where t_i^0 is the age of the individual i's entry into a labor market and $\bar{t}_i$ is the last period in which the individual i is observed in the data, $\pi_h(t_i^0)$ is the probability that an individual is type h, and P_h is the conditional density of wage and occupational choice given individual type and past decisions. The type weight is given by the following logit formula

$$\pi_h(t_i^0) = \frac{\exp(p_h(t_i^0))}{\sum_{r=1}^{4} \exp(p_r(t_i^0))} \tag{10}$$

$$\begin{aligned} p_h(t_i^0) &= 0 \quad \text{if } h = 1 \\ &\quad \pi_{h,0} + \pi_{h,1} t_i^0 \quad \text{if } 2 \leq h \leq 4 \end{aligned} \tag{11}$$

The likelihood of the whole sample is given by

$$P(\{a_i, w_i\}_{i=1}^{N}|\Theta) = \prod_{i=1}^{N} P(\{a_{it}, w_{it}\}_{t=t_i^0}^{\bar{t}_i}|\Theta) \tag{12}$$

where N is the number of individuals in the sample.

4 Estimation Results

I discuss some selected structural parameter estimates and their economic implications for the case where utility is linear in logwage, because this specification fits the data better and the results are not substantially different from the case where utility is linear in wage level. All parameter estimates and their standard errors for both specifications are reported in Appendix B.

Wage Equation To summarize the relationship between task complexity and wages, the marginal effects of task variables on wage are reported in Table 8. The first two columns report the marginal effects at mean task complexity, no experience, and no post-secondary education. For all task dimensions, wages increase in complexity except for type 1. The effects of complexity in cognitive skill and physical demand are stronger than interpersonal skills and motor skills. In particular, the effects of physical demand on wages for inexperienced high school graduates are large. If physical demand factor increases by 0.10, which is by definition the sample standard deviation of task complexity and close to the difference between laborers and the average of occupations, wages increase by about 2-7%.

The effects of task complexity on wages vary with education and experience. The next two columns report the marginal effects of task complexity on logwage at the mean task complexity, 10-year experience, and four-year post-secondary education. The marginal effects of complexities in cognitive skill, interpersonal skill, and motor skill are significantly increased. If the cognitive skill index increases by 0.10, which is close to the difference between managers and the average of occupations, wages increase by about 1-6%. An increase of the interpersonal skill index by 0.10, which is again close to the difference between manager and the average, raises wages by about 1-7%. Similarly, when the motor skill index grows by 0.10, which is close to the difference between craftsmen and the average, wages increase by about 1-5%. In contrast, the return to physical demand is slightly decreased for experienced college graduates. A change in the physical demand index by 0.10 increases wages by 1-6%.

Returns to post-secondary education and experience are reported in Table 9. They are not uniform across occupations, which is consistent with the previous finding by Keane and Wolpin (1997). Returns to education are increasing in task complexity, particularly in cognitive skill and interpersonal skill. For a professional, a year of post-secondary education increases his wage by 1%, while it decreases a laborer's wage by 2%. These estimates are smaller than those previously reported in the structural estimation literature (see Belzil (2007) for a survey), because only this paper takes into account that education directly increases the probability of entering occupations with complex tasks, which are also high-paying occupations. Returns to experience are also different across occupations. They are increasing in task complexity, particularly in the dimensions of cognitive skill and interpersonal skill. In an average occupation (i.e. task complexity is 1.0 in all dimensions), 10-years' experience increases wages by 62%. A professional's wage increases by 64% for 10-years' experience, while a laborer's wage increases by only 59%. Although returns to experience and education are greater in high-skill occupations, the differences are moderate.

Table 8: Marginal Effects of Task Complexity on Logwages

	$GX = EDU = 0$		$GX = 10,\ EDU = 4$	
	Estimates	Std. Dev.	Estimates	Std. Dev.
Cognitive Skill Price (Type 1)	−0.018	0.059	0.269	0.066
——————— (Type 2)	0.119	0.048	0.406	0.058
——————— (Type 3)	0.213	0.048	0.500	0.058
——————— (Type 4)	0.544	0.082	0.831	0.085
Interpersonal Skill Price (Type 1)	−0.102	0.062	0.206	0.060
——————— (Type 2)	0.034	0.092	0.342	0.091
——————— (Type 3)	0.129	0.090	0.437	0.091
——————— (Type 4)	0.460	0.111	0.767	0.116
Motor Skill Price (Type 1)	−0.129	0.049	−0.031	0.047
——————— (Type 2)	0.007	0.072	0.106	0.072
——————— (Type 3)	0.102	0.070	0.200	0.071
——————— (Type 4)	0.432	0.095	0.531	0.100
Physical Strength Price (Type 1)	0.313	0.061	0.207	0.058
——————— (Type 2)	0.449	0.076	0.343	0.071
——————— (Type 3)	0.544	0.077	0.438	0.071
——————— (Type 4)	0.874	0.104	0.768	0.095

Note: Marginal effects of task complexity variables on logwages are reported. In the first two columns, the marginal effects are evaluated at the mean task complexity (1.00), no experience, and no post-secondary education. In the next two columns, the marginal effects are evaluated at the mean task complexity (1.00), 10-year experience, and four-year post-secondary education.

This result suggests that wage structure may not have strong effects on occupational choices of individuals unless mobility cost is small.

Table 9: Returns to Education and Experience

	Estimates	Std. Dev.
Returns to Post-Secondary Education (Professional)	0.008	0.002
——————— (Laborer)	−0.017	0.002
Marginal Returns to Experience (Professional, 10 Years)	0.039	0.001
——————— (Laborer, 10 Years)	0.034	0.001
Cumulative Returns to Experience (Professional, 10 Years)	0.639	0.010
——————— (Laborer, 10 Years)	0.588	0.009

Endogeneity Bias A wage equation comparable to the structural model is estimated by OLS. Parameter estimates are presented in Table 31 in Appendix C with results for other specifications. I find that estimated skill prices and returns would be strongly biased, if choice of occupation is assumed to be exogenous. Marginal effects of task complexity, education, and experience are also constructed for comparison with the corresponding estimates from the structural model. Notice that individual permanent heterogeneity is not considered in OLS. As clearly shown in Table 10, estimated marginal effects of skills are very different from structural parameter estimates in Table 8. According to the OLS estimates, an increase of the cognitive skill index by 0.10 would raise wages by 10% for inexperienced high school graduates, and by 23% for college graduates with 10 years' experience. Both estimates are at least three to four times larger than those of the structural model. Another substantial difference can be found in the prices of physical demand. The OLS estimates indicate that wages would decrease by 2-4% if the physical demand index increased by 0.10, while the structural estimates show that wages would increase by 2-7%. High cognitive skill price and low (and negative) physical strength price from the OLS estimates seem to suffer from endogeneity.

Estimated returns to education and experience from the OLS estimates are reported in Table 11. Returns to education from the OLS estimates are significantly higher than those from the structural estimates. It is also interesting to see that estimated returns to education by OLS vary across specifications. When only education and experience are included in the regressor, the estimated return is 0.087, but it is reduced to 0.058 once occupational variables are included, as shown in Table 31. This suggests that some of the return to education includes a high probability of entering high-skill (and high-wage) occupations. The estimated cumulative returns to experience from OLS are also higher than those from the structural estimates. The difference of the cumulative returns to experience between professionals and laborers is substantially different, which indicates that the return to experience also suffers from endogeneity bias.

Table 10: Marginal Effects of Task Complexity on Logwage (OLS)

	$GX = EDU = 0$		$GX = 10,\ EDU = 4$	
	Estimates	Std. Dev.	Estimates	Std. Dev.
Cognitive	1.130	0.188	2.400	0.239
Interpersonal	−1.215	0.179	−0.255	0.223
Motor	0.315	0.151	−0.172	0.193
Physical	−0.413	0.169	−0.225	0.222

Source: NLSY and DOT
Note: The marginal effects are calculated using the parameter estimates from OLS, which are presented in Table 31. For the corresponding results for structural estimation, see Table 8. Marginal effects of task complexity variables on logwages are reported. In the first two columns, the marginal effects are evaluated at the mean task complexity (1.00), no experience, and no post-secondary education. In the next two columns, the marginal effects are evaluated at the mean task complexity (1.00), 10-year experience, and four-year post-secondary education.

Entry Costs The cost of switching occupations is estimated to be large, regardless of the destination. For example, the constant component of occupational switching cost is equivalent to an hourly logwage loss of between 0.75 and 0.84.[4] Because this cost must be paid even when an individual moves down to a low-skill occupation, this implies that switching occupations costs at least $6.6-$7.1 per hour for those who earn the sample average wage of $12.50 per hour. The cost

[4] This is obtained by dividing the intercept of the cost function by the coefficient of logwage in the utility function γ_1.

Table 11: Returns to Education and Experience (OLS)

	Estimates	Std. Dev.
Returns to Post-Secondary Education (Professional)	0.075	0.005
———————————— (Laborer)	0.029	0.007
Marginal Returns to Experience (Professional, 10 Years)	0.033	0.004
——————————— (Laborer, 10 Years)	0.008	0.004
Cumulative Returns to Experience (Professional, 10 Years)	0.701	0.027
———————————— (Laborer, 10 Years)	0.459	0.026

Source: NLSY and DOT
Note: The returns to education and experience are calculated using the parameter estimates from the OLS, which are presented in Table 31. For the corresponding results for the structural estimation, see Table 9.

of moving to an occupation with more complex tasks increases in the skill deficiency measure. When an individual in an average occupation (task complexity is 1.0 in all dimensions) moves along the cognitive skill dimension by 0.10 (equivalent to the difference from managers), the utility cost equals an hourly logwage loss of between -0.03 and 0.11. The cost of the same move along the interpersonal skill dimension is an hourly logwage loss of between 0.11 and 0.18. A move along the motor skill dimension by 0.1 (equivalent to the difference from craft occupations) equals an hourly logwage loss of between 0.12 and 0.16. Lastly, when an individual moves along the physical demand dimension by 0.10 (equivalent to the difference from laborers), his utility cost equals between 0.08 and 0.17 in hourly logwage. These estimates indicate that individuals pay a substantially large cost to move to an occupation with more complex tasks.

School Attendance Costs The net costs of school attendance vary greatly across individual types. Once an individual has left school, re-entering a school is significantly more costly. There is also a significant cost to entering graduate school, even if an individual enters a graduate school immediately after his undergraduate study, because the institutions are usually different. Finally, studying in graduate school is significantly more costly than undergraduate school.

Initial Locations When individuals are in school or at home, they are assumed to engage in certain tasks performed in other occupations. Task complexity in their home and school activities is reported in Table 13. The estimated task complexity of non-work state in cognitive and interpersonal skill dimensions is increasing in education, but it is decreasing in the other dimensions. Thus, education helps an individual entering occupations which demand cognitive and interpersonal skills occupations, while it prevents the individual from entering occupations that demand motor skills or are physically demanding. High school graduates' task complexity of non-work activity is close to occupations such as stock handlers, vehicle washers, oilers and greasers, where

Table 12: Entry Costs

	Estimates	Std. Dev.
Fixed Component (Type 1)	0.820	0.065
———— (Type 2)	0.775	0.062
———— (Type 3)	0.840	0.067
———— (Type 4)	0.748	0.064
Cognitive Skill (Type 1)	0.106	0.025
———— (Type 2)	0.113	0.017
———— (Type 3)	0.070	0.018
———— (Type 4)	−0.031	0.025
Interpersonal Skill (Type 1)	0.116	0.020
———— (Type 2)	0.123	0.017
———— (Type 3)	0.124	0.018
———— (Type 4)	0.181	0.026
Motor Skill (Type 1)	0.123	0.021
———— (Type 2)	0.130	0.016
———— (Type 3)	0.160	0.018
———— (Type 4)	0.120	0.024
Physical Strength (Type 1)	0.077	0.020
———— (Type 2)	0.103	0.016
———— (Type 3)	0.106	0.018
———— (Type 4)	0.169	0.048

Note: The fixed component is a cost of changing occupations measured by an hourly logwage (denoted by $\alpha_{hj,0}$). The variable component is also measured by an hourly logwage for each task dimension, when a worker moves along each dimension by 0.1 (the sample standard deviation).

similarity is measured by the Mahalanobis distance.[5] The estimated task complexity of college graduates' non-work activity is close to that of clerical workers and mail handlers.

Table 13: Initial Locations

	Estimates	Std. Dev.
Cognitive Skill (High School)	0.888	0.012
———— (College)	0.971	0.019
Interpersonal Skill (High School)	0.916	0.008
———— (College)	0.977	0.013
Motor Skill (High School)	0.929	0.012
———— (College)	0.922	0.016
Physical Strength (High School)	1.054	0.014
———— (College)	0.886	0.011

4.1 Model Fit

To assess the performance of the estimated model, I examine the model fit to the data. Each individual in the data is simulated for 50 times from his first year to the last year in the data.

[5]Using German data, Gathmann and Schönberg (2006) measure the similarity of occupations by the Euclidean distance. It is a special case of the Mahalanobis distance when each dimension of task complexity is uncorrelated with the others. This is clearly not the case in my data.

Because education and labor force status are endogenous in the model, the number of simulations does not equal 50 times the number of observations for some statistics presented in the tables below. It is true that the following discussion of model fit is not a formal statistical testing, but it should provide some sense of the strength and weakness of the model.

Table 15 presents the simulated choice distribution, mean and standard deviation of logwage, and occupation change rate for each age-education group. The results are comparable with the corresponding statistics of the data, which are presented in Table 14.[6] Choice distributions are closely replicated by the model. Logwage profiles are also close to the data; logwage increases with age and the wage gap between high school graduates and college graduates are about 15-20%. The simulated annual occupational change rate decreases with age, which is consistent with the data.

Table 17 reports the simulated distribution of task complexity. The corresponding statistics in the data are also reproduced in Table 16 for readers' convenience.[7] The simulated task complexity is remarkably close to the data in all skill dimensions and in all age groups. Task complexity difference between high school graduates and college graduates is also well replicated.

[6]This table is identical with Table 4, replicated for reader's convenience.

[7]Table 16 is identical with Table 6.

Table 14: Labor Force Status, Logwage, Occupation Changes by Age and Education

	Choice Distribution				Logwage			Occupation Change	
Age	Work	Home	School	Obs	Mean	S.D.	Obs	Prob.	Obs
All									
18-21	0.535	0.159	0.306	3574	2.140	0.419	1851	0.621	1608
22-25	0.786	0.120	0.093	3776	2.437	0.448	2894	0.505	2762
26-29	0.928	0.051	0.021	3306	2.653	0.453	2969	0.399	2824
30-34	0.951	0.036	0.013	1545	2.748	0.488	1421	0.427	951
High School									
18-21	0.639	0.144	0.217	2112	2.156	0.411	1310	0.606	1161
22-25	0.910	0.064	0.026	1392	2.455	0.433	1244	0.485	1201
26-29	0.959	0.036	0.005	1183	2.628	0.414	1110	0.398	1061
30-34	0.974	0.026	0.000	583	2.710	0.411	556	0.430	388
College									
22-25	0.661	0.161	0.178	608	2.612	0.466	395	0.480	377
26-29	0.900	0.052	0.048	709	2.824	0.466	607	0.371	587
30-34	0.950	0.022	0.028	358	2.927	0.520	331	0.352	216

Note: Wages are deflated by 2002 CPI.
Source: NLSY

Table 15: Simulation Results for Labor Force Status, Logwage, Occupation Changes by Age and Education

	Choice Distribution				Logwage			Occupation Change	
Age	Work	Home	School	Obs	Mean	S.D.	Obs	Prob.	Obs
All									
18-21	0.535	0.178	0.287	178700	2.184	0.434	95623	0.614	83818
22-25	0.792	0.115	0.093	188800	2.412	0.450	149536	0.516	136639
26-29	0.909	0.065	0.026	165300	2.633	0.460	150263	0.412	136678
30-34	0.937	0.048	0.015	77250	2.782	0.464	72382	0.396	45820
High School									
18-21	0.608	0.188	0.203	124435	2.169	0.429	75702	0.616	66608
22-25	0.877	0.105	0.017	96762	2.385	0.437	84880	0.522	77698
26-29	0.924	0.065	0.011	79954	2.586	0.439	73896	0.424	67196
30-34	0.943	0.049	0.008	36187	2.710	0.435	34115	0.407	21647
College									
22-25	0.639	0.151	0.210	23823	2.582	0.460	15232	0.483	13959
26-29	0.893	0.062	0.045	29908	2.788	0.477	26705	0.378	24411
30-34	0.949	0.036	0.015	14775	2.973	0.483	14020	0.362	8891

Note: The estimated model is simulated for 50 times for each individual from his first year to the last year in the data. Because education and labor force status are endogenous in the model, the number of simulation does not equal 50 times the number of observations in each cell.

Table 16: Task Complexity

	Cognitive		Interpersonal		Motor		Physical		
Age	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Obs
All									
18-21	0.946	0.073	0.967	0.085	1.006	0.090	1.037	0.089	1912
22-25	0.995	0.097	0.994	0.099	1.006	0.100	1.003	0.099	2969
26-29	1.023	0.103	1.016	0.103	0.995	0.103	0.983	0.100	3069
30-34	1.031	0.100	1.021	0.102	0.991	0.105	0.982	0.102	1470
High School									
18-21	0.945	0.072	0.963	0.082	1.008	0.090	1.041	0.087	1349
22-25	0.978	0.084	0.974	0.089	1.027	0.103	1.028	0.092	1267
26-29	0.997	0.090	0.991	0.097	1.016	0.105	1.014	0.098	1135
30-34	1.000	0.087	0.995	0.097	1.016	0.104	1.014	0.099	568
College									
22-25	1.079	0.100	1.055	0.099	0.956	0.089	0.922	0.083	402
26-29	1.093	0.095	1.073	0.101	0.954	0.098	0.915	0.075	638
30-34	1.094	0.088	1.078	0.097	0.952	0.102	0.923	0.076	340

Source: NLSY

Table 17: Simulation Results for Task Complexity

	Cognitive		Interpersonal		Motor		Physical		
Age	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Obs
All									
18-21	0.948	0.084	0.961	0.082	1.008	0.087	1.039	0.093	95623
22-25	0.983	0.097	0.985	0.095	1.008	0.096	1.014	0.100	149536
26-29	1.013	0.102	1.005	0.101	1.002	0.103	0.994	0.101	150263
30-34	1.035	0.101	1.021	0.103	0.995	0.108	0.979	0.100	72382
High School									
18-21	0.942	0.080	0.956	0.079	1.010	0.085	1.046	0.091	75702
22-25	0.961	0.086	0.966	0.085	1.018	0.091	1.037	0.094	84880
26-29	0.980	0.091	0.977	0.090	1.018	0.096	1.026	0.096	73896
30-34	0.999	0.093	0.991	0.095	1.013	0.103	1.013	0.098	34115
College									
22-25	1.073	0.093	1.054	0.096	0.963	0.100	0.925	0.074	15232
26-29	1.096	0.087	1.069	0.096	0.961	0.105	0.917	0.070	26705
30-34	1.113	0.078	1.083	0.095	0.957	0.108	0.909	0.063	14020

Note: The estimated model is simulated 50 times for each individual from his first year to the last year in the data. Because education and labor force status are endogenous in the model, the number of simulation does not equal 50 times the number of observations in each cell.

5 Discussion

5.1 Unobserved Heterogeneity

Structural parameter estimates indicate that individuals are distinct from each other in their comparative advantages. To see how career paths differ across unobserved individual types, the model is simulated with the estimated parameter values 50 times for each individual in the data. Labor force status in each age group is presented for each individual type in Table 18. Type is ordered by average wage in ascending order, with type 1 being the lowest average wage. Each type is substantially different from the other types in labor force status, logwage, and occupation change rate. Type 1 and type 4 are extreme types among all types. Type 1 is characterized by the weakest labor force attachment, the lowest school attendance rate, and the lowest wage. In contrast, type 4 individuals show the strongest labor force attachment, the highest school attendance rate, and the highest wage.

Evolution of task complexity of each type is presented in Table 19. Again, each type is distinct from the other types in all task dimensions, and type 1 and type 4 are extreme types. Type 1 individuals occupy positions requiring more motor skills and greater physical demand than type 4, while type 4 workers occupy positions with tasks requiring more cognitive and interpersonalskills than those of type 1 workers. Many type 1 individuals start their careers as operatives and laborers. Their tasks become more cognitive-skill and motor-skill intensive and they transition to craftsmen later in their careers. The careers of type 4 individuals are very different. Many of them start their careers as professionals and managers. Type 4 individuals take on tasks that require more and more cognitive and interpersonal skills. All types of individuals improve different dimensions of skills, depending on their comparative advantages. The use of multidimensional skills enables the model to generate this complex and realistic career decision pattern.

Variance Decomposition Unobserved permanent heterogeneity is found to play an important role in explaining differences in labor market outcomes. The variance decomposition is conducted for this simulated data set. Table 20 reports fractions of variances explained by unobserved heterogeneity for some selected labor market outcomes. The first column shows the statistics relating to years of post-secondary education and they are calculated for all individuals. The fraction is stable around 70% after age 25, because most individuals have completed their schooling by this age. The remaining 30% is explained by idiosyncratic shocks.

The next four columns present the statistics relating to task complexity that are calculated for working individuals. Fractions of variance explained by unobserved heterogeneity roughly decrease with age and become stable after age 30. At age 30, about 75% of the variance of cognitive skill is explained by unobserved heterogeneity. Higher fractions of the variance of physical de-

Table 18: Labor Force Status by Unobserved Type

	Choice Distribution				Logwage			Occupation Change	
Age	Work	Home	School	Obs	Mean	S.D.	Obs	Prob.	Obs
Type 1									
18-21	0.644	0.234	0.122	28529	1.780	0.342	18374	0.600	16573
22-25	0.820	0.151	0.029	34500	1.971	0.354	28302	0.517	26401
26-29	0.888	0.097	0.015	34500	2.168	0.356	30624	0.414	29210
30-34	0.919	0.070	0.011	43125	2.333	0.347	39611	0.302	38436
Type 2									
18-21	0.624	0.202	0.174	80515	2.127	0.343	50243	0.644	45234
22-25	0.825	0.128	0.047	93032	2.324	0.356	76776	0.549	71978
26-29	0.899	0.080	0.021	93032	2.521	0.357	83655	0.445	80112
30-34	0.934	0.052	0.015	116290	2.688	0.349	108578	0.331	105728
Type 3									
18-21	0.490	0.149	0.360	56761	2.488	0.345	27840	0.555	24946
22-25	0.804	0.084	0.112	66072	2.656	0.357	53144	0.454	50376
26-29	0.940	0.036	0.024	66072	2.857	0.360	62098	0.343	60274
30-34	0.969	0.019	0.012	82590	3.053	0.345	79992	0.235	78566
Type 4									
18-21	0.167	0.069	0.763	19345	2.811	0.343	3239	0.682	2410
22-25	0.592	0.087	0.321	21596	2.951	0.359	12788	0.519	11821
26-29	0.900	0.035	0.064	21596	3.160	0.365	19443	0.386	18705
30-34	0.962	0.015	0.023	26995	3.402	0.354	25978	0.254	25420

mand are explained by unobserved heterogeneity at 83%. The effect of unobserved heterogeneity is even higher for interpersonal skills and motor skills. The fractions explained by permanent heterogeneity are around 95% for both skill dimensions.

The variance of logwage is examined in the last column. The fraction of the logwage variance explained by unobserved heterogeneity decreases with age. Notice that occupational characteristics and individual attributes such as experience and education are not controlled. Individuals within the same type are engaged in tasks of different complexity due to idiosyncratic shocks. The task complexity differences are accumulated and increase over time, because experiencing complex tasks today helps individuals move to occupations with more complex tasks tomorrow. Consequently, the fraction of the logwage variance due to unobserved heterogeneity quickly decreases over time. At age 25, about 62% of the logwage variance is explained by unobserved heterogeneity, but the fraction decreases to 52% in the next 10 years at age 35.

The results indicate that unobserved permanent individual heterogeneity explains the differences in labor market outcomes to quite a large extent. Although the results in this paper are not directly comparable with those of the previous research by Keane and Wolpin (1997), both find the importance of unobserved heterogeneity in explaining behavioral differences. This implies that individuals' responses to an environmental change (e.g. policy intervention) would be overestimated

Table 19: Task Complexity Evolution by Unobserved Type

	Cognitive		Interpersonal		Motor		Physical		
Age	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Obs
					Type 1				
18-21	0.928	0.073	0.952	0.078	1.002	0.080	1.056	0.088	18374
22-25	0.942	0.079	0.962	0.084	1.008	0.084	1.049	0.090	28302
26-29	0.956	0.084	0.975	0.092	1.008	0.089	1.040	0.093	30624
30-34	0.977	0.090	0.999	0.102	0.995	0.093	1.022	0.096	39611
					Type 2				
18-21	0.941	0.079	0.957	0.080	1.011	0.085	1.044	0.091	50243
22-25	0.966	0.087	0.973	0.090	1.017	0.092	1.029	0.095	76776
26-29	0.989	0.092	0.990	0.098	1.015	0.099	1.014	0.097	83655
30-34	1.019	0.092	1.012	0.103	1.006	0.108	0.993	0.097	108578
					Type 3				
18-21	0.961	0.087	0.968	0.086	1.010	0.090	1.030	0.095	27840
22-25	1.003	0.095	0.997	0.098	1.009	0.101	0.999	0.098	53144
26-29	1.038	0.094	1.022	0.103	1.002	0.110	0.976	0.095	62098
30-34	1.071	0.087	1.045	0.102	0.988	0.116	0.952	0.089	79992
					Type 4				
18-21	1.055	0.101	1.022	0.089	0.974	0.099	0.931	0.076	3239
22-25	1.107	0.083	1.057	0.084	0.949	0.096	0.897	0.049	12788
26-29	1.132	0.070	1.070	0.084	0.940	0.095	0.886	0.041	19443
30-34	1.152	0.058	1.078	0.089	0.928	0.091	0.876	0.034	25978

Table 20: Fractions of Variances Due To Permanent Individual Heterogeneity

	Education	Cognitive	Interpersonal	Motor	Physical	Logwage
20	0.826	0.927	0.977	0.993	0.947	0.623
25	0.685	0.792	0.925	0.959	0.834	0.621
30	0.689	0.762	0.936	0.957	0.826	0.573
35	0.694	0.748	0.960	0.958	0.832	0.521

if unobserved heterogeneity is not accounted for.

6 Conclusion

This paper contributes to the career dynamics literature in two ways. First, I provide empirical evidence to characterize the occupational mobility of male workers over their careers using objective task complexity measures of an occupation from the DOT. Second, I construct and estimate a dynamic occupational choice model where an occupation is vertically and horizontally differentiated by a multidimensional task vector, which makes it tractable to deal with hundreds of occupations at three-digit level.

The estimation results of the structural model indicate that wages largely grow with task complexity and that cognitive-skill intensive occupations offer higher returns to education and experience. This wage structure gradually sorts workers into occupations with different task complexities. The results also suggest that the endogeneity bias of OLS wage regression estimates is substantial, which accounts for the negative skill prices estimated in some previous papers.

I also find the model predicts that individuals move up the career ladder along the dimension of their comparative advantages by a simulation exercise of the estimated model. The multidimensional task complexity vector makes it possible for the model to generate this realistic occupational mobility.

The model can be extended in a couple of ways. First, worker skills can be built through occupational experiences, although this paper considers general work experience. If an individual works in a cognitive-skill intensive job for a long period, he should develop more cognitive skills than other workers, for example. The current model cannot incorporate this skill formation process due to computational burden. Second, learning about workers' comparative advantage would also explain their choices concerning their careers. These extensions would be interesting in studying career dynamics further.

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A Details of the Data

A.1 Dictionary of Occupational Titles

Occupational characteristics are categorized into four types of skills. The first type is cognitive skills. The DOT variables that measure cognitive skills include Data, General Educational Development (reasoning, mathematical, and language), and Intelligence, Verbal, and Numerical aptitude factors. The second type of skill is an interpersonal skill. This is captured by the DOT variables including People, INFLU (adaptability to influencing people), and DEPL (adaptability to dealing with people). The third type of skill is fine motor skill, which is measured by Things and three aptitude variables: Motor Coordination, Finger Dexterity, and Manual Dexterity. The last type of skill is physical demand. The physical demand factor in the DOT is converted into a five-point scale for my measure of physical demand.

The occupational characteristics in the DOT are aggregated to occupations defined by the 1970 Census 3-digit classification system, because the DOT contains more occupations than the Census classification. To construct occupational characteristics for the Census classification, I use the April 1971 Current Population Survey augmented by the fourth edition of the DOT which was compiled by the Committee on Occupational Classification and Analysis at the National Academy of Sciences. Notice that this augmented CPS file contains occupation code for the fourth edition of the DOT, not the revised fourth edition. Some occupations are deleted, or integrated into other occupations, while some are newly added in the revised fourth edition. I update the occupation code in the augmented CPS file using the conversion table in the revised fourth edition. Occupational characteristics for each occupation in the 1970 Census classification are constructed by averaging, using the number of individuals in each DOT occupation as the weighting factor.

The index for each skill type is constructed by a principal component analysis in the following way. First, the DOT variables are converted into percentile scores. Most DOT variables are ordinal, although cardinal numbers are needed to construct a skill index. Following Autor, Levy, and Murnane (2003), I use percentile scores to address this issue. Second, I calculate the first principal component and use it for the skill index for each skill type. When computing percentile scores and the first principal component, all observations in the NLSY are pooled.

Table 21 presents the proportions of variances explained by the first principal components. The constructed cognitive skill index explains 63% of the variation in the seven DOT variables in the pooled white male sample from the NLSY. The interpersonal skill index and the fine motor skill index explain 53% and 59% of the variations, respectively. Tables 22, 23, and 24 show factor loadings for each skill index. The results indicate that each DOT variable loads to each skill index in a similar magnitude.

Table 21: Proportions of Variances

people	influ	depl
0.61	0.53	0.59

Note: Proportions of variances explained by the first principal components are presented. Weights are taken from the pooled white male sample of NLSY.

Table 22: Factor Loadings For Cognitive Skill Index

data	gedr	gedm	gedl	aptgl	aptv	aptn
0.37	0.39	0.37	0.39	0.38	0.38	0.36

Note: Factor loadings for the first principal components are presented. Weights are taken from the pooled white male sample of NLSY.
Legend: data; worker functions related to data, gedr; reasoning development, gedm; mathematical development, gedl; language development, aptgl; aptitude factor for intelligence, aptv; aptitude factor for verbal ability, aptn; aptitude factor for numerical ability.

Table 23: Factor Loadings For Interpersonal Skill Index

people	influ	depl
0.61	0.53	0.59

Note: Factor loadings for the first principal components are presented. Weights are taken from the pooled white male sample of NLSY.
Legend: people; worker functions related to people, influ; adaptability to influencing people, depl; adaptability to dealing with people.

Table 24: Factor Loadings For Fine Motor Skill Index

things	aptmc	aptfd	aptmd	aptehc	aptcd	aptfp	aptcp	sts
0.41	0.40	0.38	0.40	0.20	0.27	0.32	−0.21	0.34

Note: Factor loadings for the first principal components are presented. Weights are taken from the pooled white male sample of NLSY.
Legend: things; worker functions related to objects, aptmc; aptitude factor for motor coordination, aptfd; aptitude factor for finger dexterity, aptmd; aptitude factor for manual dexterity, aptehc; aptitude factor for eye-hand-foot coordination, aptcd; aptitude factor for color discrimination, aptfp; aptitude factor for form perception, aptcp; aptitude factor for clerical perception, sts; adaptability to situations requiring the precise attainment of set limits, tolerance or standards.

B Structural Parameter Estimates

Table 25: Utility Function

	$u(w) = \gamma_0 + \gamma_1 \ln w$		$u(w) = \gamma_0 + \gamma_1 w$	
	Estimates	Std. Dev.	Estimates	Std. Dev.
Utility of Work	−13.342	0.861	−4.932	0.373
Utility of Work (Type 2)	−2.130	0.155	−2.179	0.170
Utility of Work (Type 3)	−3.712	0.280	−4.915	0.379
Utility of Work (Type 4)	−6.141	0.488	−10.330	0.858
Utility from Hourly Wage	5.892	0.393	0.521	0.041

Note 1: The first two columns are parameter estimates for the specification where utility is linear in logwage. The second two columns are for the specification for utility is linear in wage level.
Note 2: The subscript r is for permanent individual type. Type-specific parameters are deviation from Type 1. For example, to recover Type 2 specific constant, "Intercept (Type 2)" has to be added to "Intercept".

Table 26: Cost of Schooling

	$u(w) = \gamma_0 + \gamma_1 \ln w$		$u(w) = \gamma_0 + \gamma_1 w$	
	Estimates	Std. Dev.	Estimates	Std. Dev.
Intercept	1.921	0.201	1.763	0.168
Intercept (Type 2)	−2.130	0.155	−2.179	0.170
Intercept (Type 3)	−3.712	0.280	−4.915	0.379
Intercept (Type 4)	−6.141	0.488	−10.330	0.858
Lagged School Attendance	−1.775	0.090	−1.743	0.090
Graduate School	1.410	0.159	1.319	0.174
Just Graduated 4-year College	0.655	0.215	0.750	0.214

Note 1: The first two columns are parameter estimates for the specification where utility is linear in logwage. The second two columns are for the specification for utility is linear in wage level.
Note 2: The subscript r is for permanent individual type. Type-specific parameters are deviation from Type 1. For example, to recover Type 2 specific constant, "Intercept (Type 2)" has to be added to "Intercept".

Table 27: Task Complexity of Non-work State

	$u(w)=\gamma_0+\gamma_1 \ln w$		$u(w)=\gamma_0+\gamma_1 w$	
	Estimates	Std. Dev.	Estimates	Std. Dev.
Intercept: $S1$	−2.142	0.305	−2.146	0.275
Intercept: $S2$	−2.581	0.304	−2.289	0.315
Intercept: $S3$	−1.116	0.157	−1.113	0.162
Intercept: $S4$	0.383	0.161	0.377	0.136
Education: $S1$	0.336	0.087	0.378	0.080
Education: $S2$	0.337	0.066	−0.066	0.163
Education: $S3$	−0.025	0.065	−0.057	0.069
Education: $S4$	−0.590	0.091	−0.208	0.054

Note 1: The first two columns are parameter estimates for the specification in which utility is linear in logwage. The second two columns are for the specification in which utility is linear in wage level.
Note 2: S1: cognitive skill, S2: interpersonal skill, S3: motor skill, S4: physical demand.

Table 28: Individual Type Distribution

	$u(w)=\gamma_0+\gamma_1 \ln w$		$u(w)=\gamma_0+\gamma_1 w$	
	Estimates	Std. Dev.	Estimates	Std. Dev.
Intercept: Type 2	1.197	0.168	1.181	0.164
Age of High School Graduation: Type 2	−0.340	0.177	−0.344	0.172
Intercept: Type 3	0.840	0.168	0.817	0.166
Age of High School Graduation: Type 3	−0.304	0.171	−0.288	0.169
Intercept: Type 4	−0.112	0.206	−0.136	0.203
Age of High School Graduation: Type 4	−0.691	0.255	−0.741	0.258

Note: The probability that a worker who graduated from high school at age t is type h is given by the logit formula (see Equations 10 and 11).

Table 29: Wage Equation

	$u(w)=\gamma_0+\gamma_1 \ln w$		$u(w)=\gamma_0+\gamma_1 w$	
	Estimates	Std. Dev.	Estimates	Std. Dev.
Intercept	−5.819	0.947	−4.200	0.801
Intercept (Type 2)	0.200	0.099	0.324	0.115
Intercept (Type 3)	0.499	0.095	0.783	0.111
Intercept (Type 4)	1.206	0.179	1.432	0.146
$S1$	6.151	0.717	4.886	0.602
$S1_{h=2}$	0.136	0.049	0.055	0.058
$S1_{h=3}$	0.231	0.048	0.037	0.056
$S1_{h=4}$	0.561	0.082	0.127	0.069
$S2$	3.425	0.774	2.660	0.587
$S2_{h=2}$	−0.030	0.054	−0.010	0.062
$S2_{h=3}$	−0.060	0.053	−0.028	0.060
$S2_{h=4}$	−0.159	0.068	−0.106	0.066
$S3$	−0.820	0.488	−0.177	0.361
$S3_{h=2}$	0.115	0.042	0.077	0.046
$S3_{h=3}$	0.135	0.041	0.064	0.044
$S3_{h=4}$	0.089	0.070	0.005	0.054
$S4$	6.236	0.757	4.142	0.608
$S4_{h=2}$	−0.064	0.047	−0.089	0.054
$S4_{h=3}$	−0.079	0.045	−0.136	0.051
$S4_{h=4}$	−0.669	0.159	−0.355	0.093
$S1^2$	−1.925	0.246	−1.352	0.188
$S2^2$	−0.712	0.222	−0.701	0.157
$S3^2$	0.275	0.169	−0.052	0.122
$S4^2$	−1.417	0.184	−0.911	0.142
$S1S2$	−0.559	0.289	−0.489	0.207
$S1S3$	0.191	0.250	0.363	0.188
$S1S4$	−1.951	0.296	−1.891	0.253
$S2S3$	−0.228	0.278	−0.483	0.197
$S2S4$	−1.315	0.350	−0.382	0.272
$S3S4$	0.177	0.223	0.298	0.168
EDU	−0.128	0.021	−0.086	0.017
$S1EDU$	0.044	0.010	0.030	0.008
$S2EDU$	0.061	0.009	0.046	0.007
$S3EDU$	0.033	0.007	0.031	0.006
$S4EDU$	−0.013	0.010	−0.027	0.009
GX	0.077	0.010	0.086	0.008
$GX^2/100$	−0.244	0.014	−0.278	0.011
$S1GX$	0.011	0.005	−0.004	0.004
$S2GX$	0.006	0.004	0.013	0.004
$S3GX$	−0.003	0.003	0.001	0.003
$S4GX$	−0.005	0.005	−0.007	0.004
Manager	−0.004	0.005	−0.002	0.003
Sales	−0.002	0.007	−0.000	0.005
Clerical	−0.030	0.007	−0.013	0.005
Craftsmen	0.007	0.006	0.015	0.004
Operatives	0.003	0.008	0.006	0.006
Transportation	0.031	0.009	0.013	0.007
Laborer	−0.043	0.009	−0.034	0.008
Service	−0.001	0.007	−0.003	0.005
S.D. of iid Shocks, σ_ε	0.331	0.001	0.331	0.001

Note 1: The first two columns are parameter estimates for the specification in which utility is linear in logwage. The second two columns are for the specification in which utility is linear in wage level.

Note 2: The subscript h is for a permanent individual type. Type specific parameters measure deviations from Type 1. For example, to recover the Type 2 specific constant, "Intercept (Type 2)" has to be added to "Intercept".

Legend: S1: cognitive skill, S2: interpersonal skill, S3: motor skill, S4: physical demand, EDU: years of post-secondary education, GX: general work experience. Dummy variables for one-digit occupation capture the deviation from professional occupation.

Table 30: Mobility Cost Function

	$u(w) = \gamma_0 + \gamma_1 \ln w$		$u(w) = \gamma_0 + \gamma_1 w$	
	Estimates	Std. Dev.	Estimates	Std. Dev.
Intercept	4.830	0.162	4.900	0.159
Intercept (Type 2)	−0.133	0.134	−0.091	0.143
Intercept (Type 3)	−0.732	0.145	−0.405	0.182
Intercept (Type 4)	−1.407	0.227	−0.721	0.333
$d1$	4.481	1.513	4.115	1.460
$d1_{h=2}$	0.389	1.465	−0.143	1.402
$d1_{h=3}$	−2.124	1.489	−3.729	1.451
$d1_{h=4}$	−8.093	1.814	−11.247	1.796
$d2$	6.982	1.270	8.325	1.189
$d2_{h=2}$	0.380	1.116	0.267	1.052
$d2_{h=3}$	0.441	1.187	−0.103	1.128
$d2_{h=4}$	3.788	1.540	0.361	1.419
$d3$	7.757	1.277	9.226	1.234
$d3_{h=2}$	0.435	1.182	−0.083	1.120
$d3_{h=3}$	2.164	1.176	1.365	1.120
$d3_{h=4}$	−0.151	1.524	−0.281	1.486
$d4$	3.661	1.373	2.394	1.419
$d4_{h=2}$	1.574	1.251	1.905	1.298
$d4_{h=3}$	1.748	1.226	2.076	1.302
$d4_{h=4}$	5.416	2.883	7.497	3.198
$d1^2$	17.737	3.946	24.299	3.799
$d2^2$	−1.272	3.416	−4.050	3.054
$d3^2$	−5.232	3.540	−8.910	3.440
$d4^2$	8.627	4.184	15.640	4.538
$d1S2$	−9.306	4.285	−10.583	3.996
$d1S3$	−10.271	4.273	−8.397	4.120
$d1S4$	16.301	8.476	14.351	8.813
$d2S3$	11.992	7.116	−5.171	5.776
$d2S4$	20.793	9.867	51.677	10.918
$d3S4$	−9.976	4.162	−11.296	4.361
Manager	−0.905	0.073	−0.926	0.065
Sales	−1.786	0.099	−1.816	0.092
Clerical	−0.544	0.082	−0.413	0.074
Craftsmen	0.236	0.069	0.251	0.062
Operatives	0.113	0.080	0.084	0.074
Transportation	−0.687	0.104	−0.872	0.096
Laborer	−1.285	0.086	−1.223	0.082
Service	−0.303	0.080	−0.343	0.074
Age	0.100	0.005	0.099	0.005
Lagged Labor Force Participation	−0.790	0.120	−0.853	0.118

Note 1: The first two columns are parameter estimates for the specification in which utility is linear in logwage. The second two columns are for the specification in which utility is linear in wage level.

Note 2: The subscript h is for a permanent individual type. Type specific parameters measure deviations from Type 1. For example, to recover the Type 2 specific constant, "Intercept (Type 2)" has to be added to "Intercept".

Note 3: d1: cognitive skill deficiency, d2: interpersonal skill deficiency, d3: motor skill deficiency, d4: physical demand deficiency.

C Additional Results

Table 31: Wage Regression Results (OLS)

	Estimates	Std. Dev.	Estimates	Std. Dev.	Estimates	Std. Dev.	Estimates	Std. Dev.
Intercept	2.027	0.011	2.229	0.017	2.118	4.032	1.901	4.114
EDU	0.087	0.003	0.068	0.003	0.058	0.003	−0.005	0.097
GX	0.105	0.004	0.095	0.004	0.091	0.004	−0.076	0.043
$GX^2/100$	−0.409	0.034	−0.367	0.033	−0.349	0.033	−0.375	0.033
Manager			−0.117	0.017	0.040	0.025	0.055	0.025
Sales			−0.104	0.020	0.340	0.036	0.359	0.036
Clerical			−0.199	0.019	0.118	0.030	0.126	0.030
Craftsmen			−0.090	0.016	0.173	0.030	0.169	0.030
Operatives			−0.183	0.019	0.181	0.035	0.184	0.035
Transportation			−0.258	0.024	0.165	0.040	0.163	0.040
Laborer			−0.282	0.020	0.113	0.039	0.111	0.039
Service			−0.289	0.019	0.112	0.033	0.109	0.033
$S1$					5.172	2.899	5.580	3.016
$S2$					−3.851	3.664	−3.301	3.708
$S3$					0.063	2.611	0.700	2.654
$S4$					−2.326	3.128	−2.684	3.129
$S1^2$					−0.870	1.067	−1.489	1.113
$S2^2$					−0.421	1.216	−0.904	1.216
$S3^2$					−3.908	0.880	−4.483	0.881
$S4^2$					−0.217	0.871	−0.228	0.875
$S1S2$					2.217	1.451	1.809	1.496
$S1S3$					3.919	1.281	4.877	1.316
$S1S4$					−7.866	1.397	−8.158	1.417
$S2S3$					−2.398	1.434	−2.547	1.453
$S2S4$					4.019	1.643	4.632	1.643
$S3S4$					6.312	1.192	6.253	1.186
$S1EDU$							0.108	0.044
$S2EDU$							0.084	0.041
$S3EDU$							−0.105	0.039
$S4EDU$							−0.032	0.052
$S1GX$							0.084	0.020
$S2GX$							0.062	0.021
$S3GX$							−0.007	0.018
$S4GX$							0.032	0.021
Std. Dev. of Residual	0.435		0.426		0.414		0.412	
Adj. R-squared	0.235		0.267		0.304		0.312	

Source: NLSY and DOT
Legend: S1: cognitive skill, S2: interpersonal skill, S3: motor skill, S4: physical demand, *EDU*: years of post-secondary education, *GX*: general work experience. Dummy variables for one-digit occupation capture the deviation from professional occupation.
Note: Sample size is 9135 for all specifications. Dependent variable is an hourly logwage deflated by the 2002 CPI.