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Career and Skill Formation:

A Dynamic Occupational Choice Model with Multidimensional Skills

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VERY PRELIMINARY AND INCOMPLETE
Comments/Corrections Welcome.

Abstract

The objective of the paper is to construct and estimate a dynamic structural model of schooling and occupational choice at the three-digit classification level, in which different occupations involve different mix of tasks. In the model, occupations are characterized by complexity of various tasks. Unlike occupational specific human capital, skills used in one occupation help a worker to enter a new occupation, depending on the similarity of the tasks of the two. Individuals build up their skills in low-paying occupations that provide relevant experience before they enter a high-paying occupation. Hence, low skill occupations can be viewed as "stepping stone" to better occupations. The structural parameters of the model are estimated using the occupational characteristics in the Dictionary of Occupational Titles and the work history in the National Longitudinal Survey of Youth 79. I find that the model does a good job of fitting the data on occupational choices: individuals gradually move from low-skill occupations to high-skill occupations.

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1 Introduction

The importance of post-schooling human capital investment as well as education has been widely recognized among labor economists. Numerous empirical papers find that wages greatly increase over the career, and the consensus in the literature is that human capital accumulation is the main source of the wage growth.[1] However, the contents of skills and the skill acquisition process in a labor market are not well understood. What are the skill differences between occupations? Why don't people immediately enter the best-paying occupations instead of starting with worse-paying ones? How does educational attainment help an individual enter an occupation? These questions are relevant for many labor market policies including job training programs, the Earned Income Tax Credit, and the design of income tax.

The objective of the paper is to construct and estimate a dynamic structural model of schooling and occupational choice at the three-digit classification level, in which different occupations involve different mix of tasks. In the model, occupations are characterized by the complexity of tasks in terms of cognitive skill, interpersonal skill, motor skill, and physical demand using the data from the Dictionary of Occupational Titles (DOT.) To enter an occupation, workers must pay an entry cost to learn skills to be able to take on tasks. If the tasks of a new occupation are similar to those of the current occupation, they already have a relevant occupational experience and pay fewer costs. Thus, an individual acquires needed skill by experiencing an occupation that involves a similar, but less complex task, before he enters high-paying occupations. In other words, a low-paying occupation serves as a "stepping stone" to a high-paying occupation by providing a training opportunity[2]. Educational attainment reduces this skill learning cost of some skill dimensions.

One of the earliest theory of human capital formation is developed by Ben-Porath (1967) to understand the age-earnings profiles. A number of papers extend the theory and they mainly focus on schooling decision as human capital investment. Keane and Wolpin (1997) construct a model where work experience, as well as educational attainment, is endogenously accumulated. In their model, individuals choose among white-collar, blue-collar, and military occupations and the productivity of a worker in a given occupation is enhanced by occupational experiences. This paper departs from the previous contributions by providing more detailed analysis for post-schooling human capital formation by considering choices among hundreds of occupations where various tasks are involved.

A methodological contribution of the paper is to develop an occupational choice model using occupational characteristics from the DOT.[3] Recent empirical papers including Neal (1999), Kam-

[1] Topel and Ward (1992) find that only about 30% of the wage growth is explained by search.

[2] Jovanovic and Nyarko (1997) constructs a stepping stone mobility model in which high-paying occupations are characterized by high risk. Job experience in a related occupation reduces this risk, which prompts upward movement in a career ladder.

[3] Ingram and Neumann (2006) and Bacolod and Blum (2005) construct similar skill measures to estimate a wage

bourov and Manovskii (2005), and Pavan (2006) find evidence that a substantial amount of human capital can be associated with occupations. The results are usually interpreted as the evidence of occupational specific human capital. However, specific human capital is not most useful for understanding "stepping stone" mobility of workers, because it does not explain the relationship of skills between occupations. In the model, occupational mobility depends on similarity of task complexity between occupations. In addition, the skill measures are more interpretable than years of occupation specific experience. Yet another advantage is that the model is able to deal with occupations at three digit classification level. Skills are even more precisely measured at the three-digit level than the one-digit level. Using the occupational characteristics from the DOT, I find that about 30-70% of the skill variances are explained by within one-digit occupation skill variances. This result suggests that skills within one-digit occupations are considerably heterogeneous. Previous structural dynamic occupational choice models rely on occupational specific experience, and thus, they cannot handle more than a few occupations due to the curse of dimensionality. This paper avoids the limitation by characterizing all occupations in terms of four dimensions of tasks.

The structural parameters are estimated by the maximum likelihood and the model fits the basic features of the data. In particular, the model replicates the "stepping stone" occupational mobility over the careers. The model is then used for a counterfactual simulation of a tuition subsidy.

The rest of the paper is organized as follows. Section 2 describes the data set including the occupational characteristics in the DOT and the occupational histories from the NLSY 79. Section 3 presents main patterns of the data. Section 4 describes the model and the estimation strategy. The estimation results are presented in section 5. The estimated parameters are used for a counterfactual simulation to evaluate the effect of a tuition subsidy on college attendance and occupational choice in a later life stage in section 6. Section 7 summarizes the current progress of the research.

2 Data

2.1 Dictionary of Occupational Titles

The Dictionary of Occupational Titles provides skill information for characterizing occupations. Occupational definitions in the DOT are based on the examination of tasks by expert occupational analysts. The DOT contains the measurements of worker function 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 of which information was collected between 1978 and 1990. In the fourth edition, 12,099 occupations are studied in terms of 44 characteristics.

equation for explaining wage inequality.

Table 1: Skill Heterogeneity Within the One-digit Occupations.

	Cognitive	Interpersonal	Motor	Physical
Within	0.0035	0.0053	0.0071	0.0049
Between	0.0065	0.0047	0.0029	0.0051
Total	0.0100	0.0100	0.0100	0.0100

Note: The variance of each dimension of the skill measure in the April 1971 CPS is decomposed into within and between the one-digit occupations. Factor scores are constructed so that the total variance is 0.01 (the standard deviation is 0.1.)

2.2 Constructing Skill Measures

Previous studies such as Ingram and Neumann (2006) and Bacolod and Blum (2005) find that many variables in the DOT are highly correlated with each other. Hence, the occupational characteristics in the DOT can be aggregated into a small number of skill categories. Following Bacolod and Blum (2005), I construct a four dimensional skill measure by a principal component analysis: cognitive skills, interpersonal skills, motor skills, and physical demand.

Because the DOT job classification is much finer than the 1970 Census three-digit classification that contains 574 occupations, the DOT occupations have to be aggregated into the Census classification. For this purpose, I use April 1971 Current Population Survey augmented with DOT characteristics which is constructed by the Committee on Occupational Classification and Analysis of the National Academy of Sciences. In this augmented CPS file, both the DOT occupation code and the 1970 Census three-digit code are recorded. The DOT characteristics for the 1970 Census three-digit occupation can be constructed by averaging the DOT indices over workers in a given census occupation. After aggregating the DOT occupations into the 1970 census occupations, a four dimensional skill measure is constructed by a principal component analysis using the occupational characteristics in the augmented CPS file. The calculated factor scores are rescaled so that the averages are one and the standard deviations are 0.1. The details of the skill measure construction are reported in the appendix A.

Skills are considerably heterogeneous within the one-digit occupations. Table 1 presents the results of the variance decomposition of the skill measures in the April 1971 CPS. Let X be an element of the skill vector and I be an index of the 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. Remember that the total variance is constructed to be 0.01 (the standard deviation is 0.1.) The results indicate that about 30-70% of the total variance is due to the variation within the same one-digit occupations. Thus, the skill structure can be much more precisely analyzed by using the three-digit occupational classification than the one-digit classification.

Table 2: Top 10 and Bottom 10 Occupations

Cognitive Skills		Interpersonal Skills	
Top 10	Bottom 10	Top 10	Bottom 10
Geologists	Garbage Collectors	Clergymen	Bookbinders
Physicists	Dishwashers	Lawyers	Brickmasons
Petroleum Engineers	Clothing Ironers	Biology Teachers	Printing Trades Apprentices
Biological Scientists	Oilers	Mathematics Teachers	Engravers
Architects	Cleaners	Economics Teachers	Furniture Finishers
Mining Engineer	Busboys	Education Teachers	Lumber Inspectors
Chemical Engineers	Produce Packers	Social Workers	Plumber Apprentices
Lawyers	Fork Lift Operatives	Elementary School Teachers	Shipfitters
Dentists	Warehousemen	Secondary School Teachers	Sign Painters
Material Engineers	Childcare Workers	Religious Workers	Upholsterers

Motor Skills		Physical Strength	
Top 10	Bottom 10	Top 10	Bottom 10
Dentists	Credit men	Garbage Collctors	Actuaries
Painters	Household Childcare Workers	Firemen	Statisticians
Sign Painters	Meter Readers	Construction Laborer	Physical Scientists
Machinists	Bill Collectors	Brickmasons	Legal Secretaries
Tool and Die Makers	Insurance Agents	Plumber Apprentices	Secretaries, Misc.
Electrical Technicians	Stock Salesmen	Millwrights	Computer System Analysts
Draftsmen	Childcare Workers	Cement Finishers	Computer Programmers
Decorators	Clergymen	Carpenters' Helpers	Payroll Clerks
Physicists	Lawyers	Farmers	Lawyers
Aircraft	Economists	Farm Laborers	Accountants

Source: NLSY 79 and DOT.

The top ten and bottom ten occupations in terms of each of four skill measures are listed in table 2. The list confirms that the DOT characteristics provide reasonable measures of skills required for occupations. The top 10 occupations for cognitive skills are all professionals, while many of bottom 10 are laborers. Teachers, lawyers, and clergymen are required to effectively communicate with people. They are listed as top 10 occupations for interpersonal skills. Occupations of which tasks include little communication with people are bookbinders, and brickmasons, for example. Many craftsmen and technicians are listed as top 10 occupations for motor skills. These are occupations in which individuals need to have high levels of motor coordination and finger dexterity. Examples of low motor skill occupations are credit men, clergymen, and lawyers. Physically demanding occupations are laborers and craftsmen, while professional occupations are less physically demanding.

Table 3: Summary Statistics

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Nobs
Age	19.00	22.00	25.00	25.19	29.00	35.00	31682
Education	0.00	0.00	1.00	1.69	3.00	9.00	31682
General Experience	0.00	0.00	3.00	3.74	6.00	16.00	31682
Occupational Experience	0.00	0.00	0.00	0.41	0.00	15.00	31682
Cognitive Skill	0.83	0.93	1.00	1.01	1.09	1.25	19678
Interpersonal Skill	0.90	0.92	0.95	0.99	1.06	1.28	19678
Motor Skill	0.81	0.94	1.00	1.01	1.06	1.31	19678
Physical Demand	0.85	0.95	1.02	1.01	1.07	1.22	19678
Logwage	0.02	2.23	2.55	2.54	2.87	4.59	19002
Yearly Occupation Change	0.00	0.00	1.00	0.61	1.00	1.00	16224

Note: Wages are deflated by 2002 CPI.
Source: NLSY 1979

2.3 NLSY

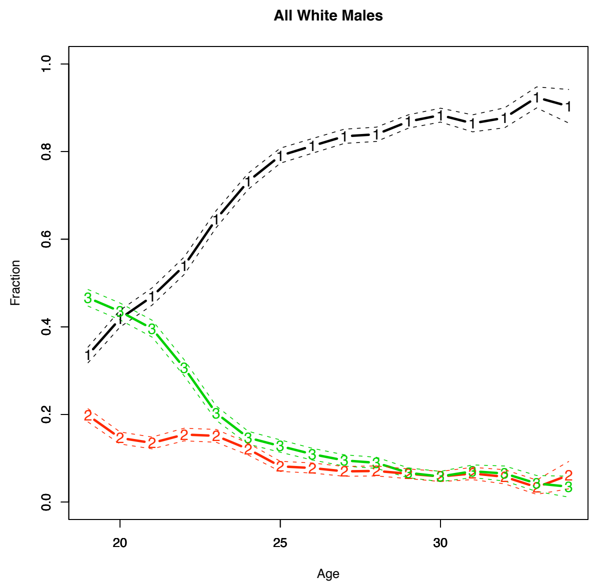
The data for career history are taken from the National Longitudinal Survey of Youth 1979 which includes information on the weekly work history of individuals from 1978. The survey consists of individuals who were from 14 to 21 years old as of January 1, 1979. The DOT variables are added to the NLSY 79 using the 1970 Census three-digit occupation code. I take a sample of white males who completed high school in age 18. Individuals are followed annually until the year of 1994. In each year, individuals are assumed to be working, attending school, or staying home. These alternatives are exhaustive and mutually exclusive. The labor force status of an individual is determined by the following hierarchical rule[4]: (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 one thousand hours in a year, he is assumed to be working during the entire year. (3) If neither of the previous conditions apply, he is assumed to stay home during the entire year. The hourly wage and the occupation code are taken from the current or the most recent job. Hourly wages are deflated by 2002 CPI. Some recorded hourly wages are extremely high or low. If the recorded hourly wage is greater than one hundred dollars or less than one dollar, they are regarded as missing.

3 Descriptive Analysis

3.1 Summary Statistics

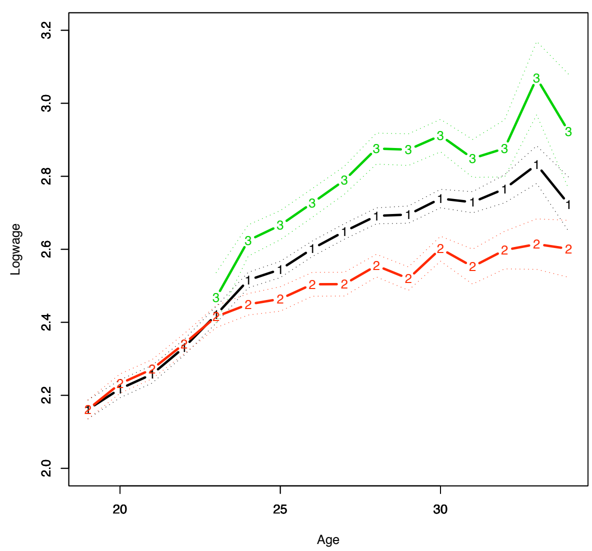
The summary statistics of the sample are presented in table 3. These statistics are calculated by pooling all observations. The average wage of the sample is 25.19 years old. The sample average years of post-secondary education is 1.69. The sample averages of general experience and occupational specific experience (at three digit level) are 3.74 and 0.41 years, respectively. Because of the normalization described above, the averages of all complexity variables are close to one. The sample mean logwage is 2.54. The annual occupational change rate is 0.61, which may seem to be high, but this estimate is very close to the one reported by Moscarini and Vella (2003) who also use a sample from the NLSY 79. The average labor force status by age is plotted in figure 1. About 30% of individual at age 19 work full-time. The proportion of full-time workers steadily increases over time. At age 30, more than 80% of white males work full-time. At age 19, about half of the sample white males enroll in a post-secondary educational institution. The school attendance rate quickly decreases around age 21 and it continues to decrease. About 10% of the sample individuals enroll in a school at age 30. Individuals are considered to stay home if they are not enrolled in school or do not work full-time. At age 19, about 20% of the sample individuals stay home (or work part-time.) The proportion of staying home steadily decreases with age. At age of 30, about 10% of the population is regarded as staying home. The sample wage profiles are shown in 2. Wages are rapidly increase when workers are young. The average logwage at age 20 is about 2.2, and it grows to about 2.7 at age 30, which implies that average annual wage growth rate is about 5%. Wage profiles are substantially different between educational groups. High school graduates are defined as those who do not take any post-secondary education, while college graduates are defined as those who enrolled in a post-secondary school for four years or more. Many of college graduates first enter a full-time labor market at age 23. At this age, average wages between high school graduates and college graduates are as small as about 5%. However, the gap quickly increases with age and the logwage difference grows to about 0.4 at age 30. Annual occupational change rate is shown in figure 3. It is as high as around 70% at age 20. The occupational change rate gradually decrease to about 50% at age 30, and then it quickly decreases to about 30% at age 34. The difference of occupational change rate between educational groups are small. Although the occupational change rates of college graduates are lower than those of high school graduates during age twenties, the differences in each year are not statistically significant.

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



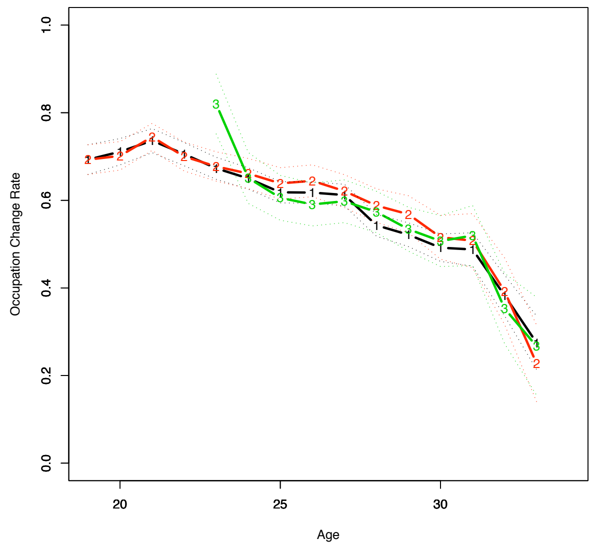
Legend: (1) work, (2) home, (3) school
Note: The dotted lines show 95% confidence intervals.

Figure 1: Labor Force Status



Legend: (1) All individuals (2) High school graduates, (3) College graduates.
Note: The dotted lines show 95% confidence intervals. Hourly logwages are deflated by 2002 CPI. High school graduates are those who do not take any post-secondary education. College graduates are those who enrolled in a post-secondary school for four years or more.

Figure 2: Hourly Logwage



Legend: (1) All individuals (2) High school graduates, (3) College graduates.
Note: The dotted lines show 95% confidence intervals. High school graduates are those who do not take any post-secondary education. College graduates are those who enrolled in a post-secondary school for four years or more.

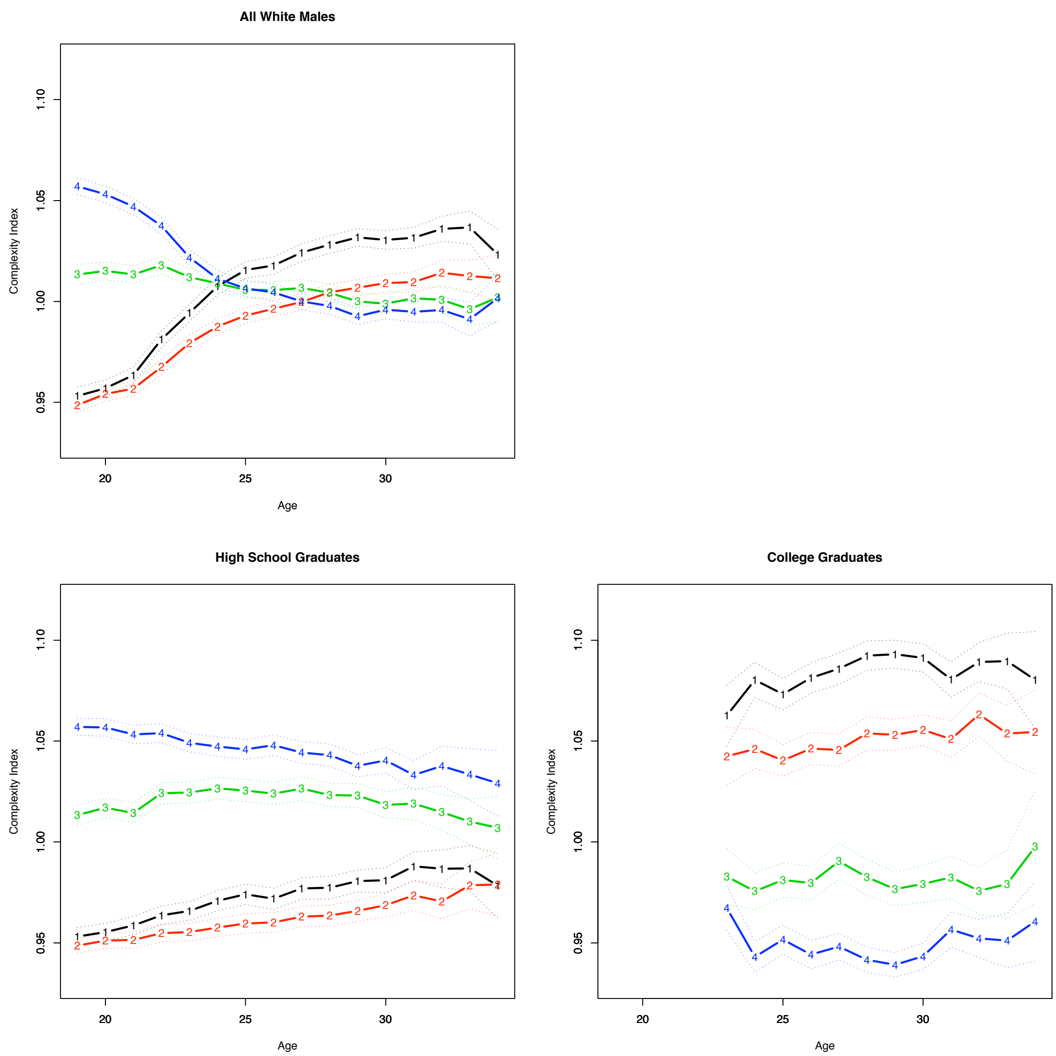
Figure 3: Yearly Occupational Change Rate (3 digit level)

3.2 Time Evolution of Task Complexities

Time evolution of task complexity is shown in figure 4. Task complexities of occupations in terms of cognitive skills and interpersonal skills are increasing in age, while those in terms of motor skills and physical demand decrease with age. Average task complexities quickly change in age of early twenties, because college graduates begin to enter the labor market. The task complexities are very different between high school graduates and college graduates. College graduates work in occupations where cognitive skills and interpersonal skills are more important, while high school graduates take more physically and motor-skill-demanding tasks compared with the other education group. Although the composition effect explains a large part of the time evolution for the all white males, individuals gradually take on more complex and less physically demanding tasks over time.

3.3 Distance of Occupations and Transition Patterns

The relationship between occupational characteristics and mobility patterns is analyzed in this subsection. Gathmann and Schönberg (2006) find that individuals move to occupations with similar task requirements using German Qualification and Career Survey. The following shows that a very



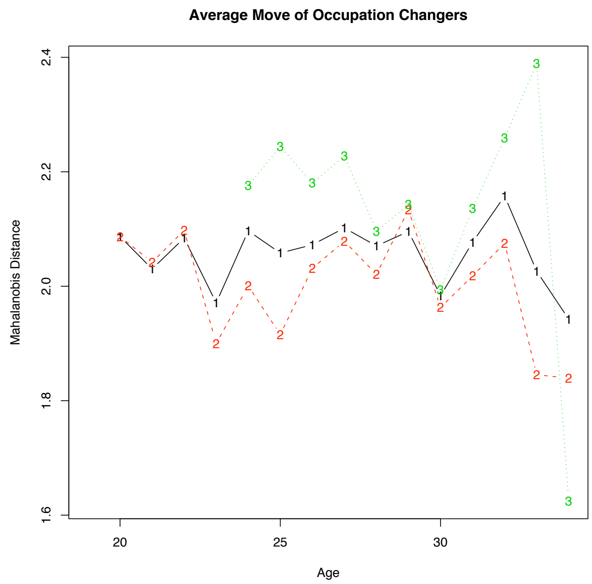
Legend: (1) Cognitive Skills, (2) Interpersonal Skills, (3) Motor Skills, (4) Physical Demand.
Note: The dotted lines show 95% confidence intervals.

Figure 4: Complexity of Tasks

Table 4: Occupational Choice Probability Decreases With Distance

	Estimates	Std. Dev.	Nobs.
All Individuals	−0.7906	0.0112	9870
High School	−0.7493	0.0156	5458
College	−0.8725	0.0255	1700

Note: A multinomial logit model is estimated for a subsample of occupational changers of while males in the NLSY. The only independent variable is Mahalanobis distance between occupations.



Legend: (1) All individuals (2) High school graduates, (3) College graduates.

Figure 5: Average Distance (Occupational Changers Only)

similar pattern is also found in the NLSY 79 and the DOT. Let x_A be a four dimensional vector of task complexity of occupation A. The distance between occupation A and occupation B is given by the Mahalanobis distance

$$d(A, B) = \sqrt{(x_A - x_B)^T \Sigma^{-1} (x_A - x_B)} \tag{1}$$

where Σ is the covariance matrix of the four dimensional skill vector. When the covariance matrix Σ is the identity matrix, the Mahalanobis distance reduces to the Euclidean distance. The advantage of the Mahalanobis distance is that it takes into account the correlation of the variables and it is scale-invariant. The covariance matrix Σ is estimated by pooling all observations.

The occupational choice probabilities are estimated by a multinomial logit model. The distance defined above is the only covariate and the subsample of occupational changers is used. The estimation results are summarized in table 4. The coefficient for the distance is significantly negative for both educational groups, which implies that the occupational choice probability of occupation changers is decreasing in the distance.

The average moves of occupation changers are calculated and plotted by age in figure 5. I excluded occupation stayers because the occupational change rate decreases with age, which certainly generate the negative correlation of age and the distance in the pooled sample. Gathmann and Schönberg (2006) find that the Euclidean distance of moves declines with time in the labor market in Germany. However, a clear relationship between age and the distance is not found in the white male sample of the NLSY 79. I also estimated a linear regression model in which the distance is the dependent variable and the age is the only independent variable. Although the coefficients are negative for both high school graduates and college graduates, they are both statistically insignificant. For the pooled sample, the age is positively correlated with the distance, but it is insignificant. I also used Euclidean distance for the analysis, but no clear downward trend is found in the sample.

4 The Model

The objective of individual i is to maximize the present value of utility by making decisions on school attendance, labor force participation, and occupational choices. Individuals graduate from high-school at age 18 and make the first decision, which is the labor force status and occupations in age 19. These choices are mutually exclusive. The timing of decisions in each age $t \geq 19$ is as follows. First, individuals receive instantaneous utilities including utility from wages and non-pecuniary benefit from the current occupation if they work. Then, individuals decide school attendance, labor force participation, and an occupation in the next year. Individuals pay the cost of entering school in the current period, before they attend school in the next year. Similarly, they pay an occupational entry cost in the current period before moving to the new occupation. When an individual changes occupations, he draws a match quality with the new occupation. An individual does not know a match quality until he begins a job. The match quality θ is randomly determined and its sampling distribution is common across occupations. It remains constant until he leaves from the occupation. However, when an individual returns to an occupation that he already had in the past, he must re-draw match quality (no recall.) Individuals repeat this decision making process until retirement age T.

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

$$\begin{aligned}
\ln w_{ijt} &= \ln w_{ijt}(x_j, EDU_{it}, GX_{it}, OX_{it}, \theta_{ij}, \epsilon_{it}) \\
&= \omega_{i,0} + \omega_1 EDU_{it} + \omega_2 EDU_{it}^2 + \omega_3 GX_{it} + \omega_4 GX_{it}^2 + \omega_5 OX_{it} + \omega_6 OX_{it}^2 + \\
&\quad \sum_{l=1}^{4} \omega_{i,6+l} x_j + \sum_{l=1}^{3} \sum_{m=l+1}^{4} \omega_{lm} x_j^l x_j^m + \sum_{l=1}^{4} \omega_{10+l} x_j EDU_{it} + \sum_{l=1}^{4} \omega_{14+l} \bar{x}_j GX_{it} + \qquad (2) \\
&\quad \theta_{ijt} + \epsilon_{it} \qquad (3)
\end{aligned}$$

where EDU_{it} is years of post-secondary education, GX_{it} is general work experience, OX_{it} is occupation specific experience, x_j is a vector of complexity of tasks of occupation j, x_j^l is the l-th element of the vector x_j, θ_{ijt} is a match quality with occupation j, and ϵ_{it} is a normally distributed transitory productivity shock with zero mean and a variance σ_ϵ^2. The sampling distribution of a match quality is normal with zero mean and the variance σ_θ^2. First-order interaction terms between task complexities are included in the wage equation to improve the model fit to the data. Bacolod and Blum (2005) also find that complementarity between tasks are important feature of the data. In addition, interaction terms between task complexity and education and experience are included. The intercept $\omega_{i,0}$ and the coefficients for task complexity vary across individuals to capture comparative advantages in earning ability.

Individuals pay an entry cost to an occupation. This cost increases when they move to an occupation with more complex tasks. The entry costs for individual i who enters to occupation j from occupation k in age t are given by a function of individual attributes and skill deficiency measures

$$\begin{aligned} c_{ijkt} &= c_{i,0} + c_1 t + \sum_{l=1}^{4} c_{i,l+1} d_{jk}^l + \sum_{l=1}^{3}\sum_{m=l+1}^{4} c_{lm} d_{jk}^l d_{jk}^m + \\ & \quad \sum_{l=1}^{4} c_{l+5} d_{jk}^l EDU_{it} + \sum_{l=1}^{4} c_{l+9} d_{jk}^l GX_{it} + \sum_{l=1}^{4} c_{l+13} d_{jk}^l \cdot I[k \notin work] \\ d_{jk}^l &= \max(x_j^l - x_k^l, 0) \end{aligned}$$

where d_{ijt}^l is a measure of skill deficiency. Notice that the constant term of the entry cost varies across individuals. When individuals are currently not working, their current task complexity is assumed x_0. Because this x_0 is specified to a certain value in the estimation, I allow for the cost function to be different when individuals are not working. Individuals pay a higher cost if they move to an occupation with more complex tasks. The definition of the skill deficiency measure d_{ijt}^l impose that individuals do not pay the cost or receive the benefit (or a negative cost) when they are qualified or over-qualified. The costs of skill learning may be reduced (or increased) by education and experience.

The cost of attending a post-secondary school for individual i in age t is given by c_{it}^{SCH},

$$c_{it}^{SCH} = c_{i,0}^{SCH} + c_1^{SCH} t + c_2^{SCH} \cdot I[edu \geq 4]$$

where the last term is an indicator variable that takes one if an individual enters a graduate school.

The non-monetary utility from job in occupation j is given by

$$v_j(x_j) = \sum_{l=1}^{4} v_l x_j^l + v_{0,j}$$

where the first term is the (dis)utility from complex and physically demanding tasks and the last term is an occupation specific utility value.

The decision problem of individuals is formulated in the followings from age T to age 18, as the model is solved by backward induction. The state variables of individual i at age t are education EDU_{it}, general work experience GX_{it}, occupational specific experience OX_{it}, a match quality with the current occupation θ, an idiosyncratic productivity shock ϵ_{it}, a choice specific transitory shock ν_{ijt}, and the decision variable that gives the current labor force status and occupation, a_{it-1}. Notice that the choice of the current labor force status and occupation is made in the last period.

In period T, the stochastic state variables θ, ϵ, and ν are realized at the beginning, and then, individuals receive wages and utilities and retire from labor force. No decision is made in period T. The value for individual i in period T is given by

$$V_{iT}(x_{iT}, GX_{iT}, \theta_{ij}, a_{iT-1} = j, \nu_{iT}; \Theta) \;=\; [\alpha(w_{ijt} - \tau(w_{ijt})) + v_j(x_j)] \cdot I[j \in work] + \nu_{ijT}$$

where τ is a tax function, v_j is an occupation specific non-pecuniary benefit, and Θ is a set of parameters. The choice specific preference shock ν_{ijT} is assumed to follow i.i.d. type I extreme value distribution.

The tax system is assumed to be fixed over time. More specifically, individuals pay taxes according to the 1987 federal income tax in the U.S. They are also assumed to be single with no kids. Following Taber (2002), the tax schedule is smoothed by a third order polynomial. The parameterized tax function is

$$\tau(w) \;=\; 0.428 + 0.859w - 0.393 \cdot 10^{-2}w^2 + 0.200 \cdot 10^{-4}w^3$$

where w is hourly wage measured in 2002 constant dollars.

In periods between age 18 and age $T-1$, the stochastic state variables θ, ϵ, and ν are realized and individuals receive wages and utilities at the beginning of each period. And then, they choose an occupation in the next period with paying the schooling cost or the entry cost to an occupation. The value for individual i in age $18 \leq t \leq T-1$ is given by

$$V_{it}(EDU_{it}, GX_{it}, OX_{it}, \theta_{ik}, a_{it-1} = k, \epsilon_{ikt}, \nu_{i \cdot t}; \Theta) = \max_j V_{ijt}$$

$$\begin{aligned} V_{ijt} \;=\; & [u(w_{ikt}) + v_k(x_k)] \cdot I[a_{it-1} \in work] \\ & - c_{ijkt} \cdot I[a_{it} \neq a_{it-1}] + c_{it}^{SCH} \cdot I[a_{it} = school] + \nu_{ijt} + \rho E_{\theta,\epsilon,\nu}[V_{it+1} | a_{it} = j] \end{aligned}$$

$$s.t.\; u(w_{ikt}) \;=\; \alpha[w_{ikt} - \tau(w_{ikt})]$$

$$\begin{aligned}
w_{ikt} &= w_i(EDU_{it}, GX_{it}, OX_{it}, \theta_{ik}, \epsilon_{ikt}) \\
c_{ijkt} &= c_{ijkt}(EDU_{it}, GX_{it}, t, x_j, x_k) \\
EDU_{it+1} &= EDU_{it} + I[a_{it} = school] \\
GX_{it+1} &= GX_{it} + I[a_{it} \in work] \\
CX_{it+1} &= CX_{it} + 1 \text{ if } a_{it} = a_{it+1},\ a_{it} \in work \\
&\quad 0 \text{ otherwise}
\end{aligned}$$

where ρ is the discount factor. Notice that the current wage or the non-pecuniary benefit from the current occupation do not affect the choice values, because individuals make decisions after they receive utilities from the current status. The initial decision period is age 18 and individuals are in high-school with no experience and no post-secondary education history, i.e. $EDU_{i,18} = GX_{i,18} = OX_{i,18} = 0$.

4.1 Solution and Estimation

The model is numerically solved by backward induction because this is a finite horizon problem. Each individual is assumed to start decisions in age 18 and to retire in age 65. Following Keane and Wolpin (1997), the value function is approximated by polynomial regressions, in order to decrease the computational burden. Specifically, the expected value function (sometimes called as Emax function) is first evaluated at some selected points in the dimensions of education, general experience, and specific experience given the current occupation and the match quality. Then the Emax function is approximated by a second-order polynomial. The distribution of a match quality θ and a productivity shock ϵ are approximated by a Gaussian quadrature with two support points. The discount rate is set to 0.9. The task complexity of non-work is assumed to be equal to the lowest occupation in each skill dimension, i.e., $x_0^l = \min_{j \in J} x_j^l \; l = 1, 2, 3, 4$ where J is the set of occupations and l is the index of task dimension.

The likelihood function is constructed using this numerical solution to the dynamic programming. I assume there are $R (= 2)$ unobserved types of individuals. Because education and experiences are functions of the history of the career choice variable a_{it}, the likelihood of an individual is given by

$$P(\{a_{it}, w_{it}\}_{t=18}^{T_i} | \Theta) = \sum_{r=1}^{R} \pi_r \prod_{t=1}^{T_i} P_r(a_{it}, w_{it} | \{a_{i\tau}\}_{\tau=18}^{t-1}; \Theta)$$

where T_i is the last period in which individual i is observed in the data, π_r is the probability that an individual is type r, and P_r is the conditional density of wage and occupational choice given individual type and the past decisions. The likelihood of the whole sample is given by

$$P(\{a_i, w_i\}_{i=1}^{N}|\Theta) = \prod_{i=1}^{N} P(\{a_{it}, w_{ijt}\}_{t=1}^{T_i}|\Theta)$$

where N is the number of individuals in the sample.

5 Estimation Results

5.1 Parameter Estimates

All parameter estimates are presented in table 5 through 8. The parameter estimates of the wage equation are presented in table 5. Wages increase with both general and occupational specific experience. The returns to education depend on the complexity of tasks. The coefficients for the interaction terms between education and task complexity for cognitive skills and interpersonal skills are significantly positive, but the interaction between education and motor skill is significantly negative. The results imply that educated workers need to take on complex tasks to be rewarded. The returns to experience are also enhanced by task complexity of cognitive skills, interpersonal skills, and motor skills, although they are not statistically significant. The returns to experience is reduced if individuals take on physically demanding tasks. These results for the returns to experience imply that wage-experience profile vary across occupations. More specifically, high skill occupations have a steeper wage profile. This is consistent with the fact that college graduates have higher wage growth rate than the college graduate as can be seen in figure 2. The utility function parameter is significantly positive, which means that individuals do care about wages.

The job preference parameters are in table 6. Individuals receive a negative utility from cognitive skill intensive jobs. This is consistent with the compensating wage differentials because the returns to cognitive skills are positive and large in scale.

The parameter estimates for occupational entry costs and skill learning costs are shown in table 7. The entry cost increases with age. Because the loss of the returns to occupational specific human capital is taken into account, it implies that not only the opportunity cost, but also the direct cost of occupation switch increases with age. The results indicate that the cost increases with the skill deficiency in each task dimension when an individual are qualified in the other dimensions of tasks. The coefficients of interaction terms of education and cognitive skill and interpersonal skill are negative, but those of education and motor skill and physical demand are positive. These results imply that education reduces the entry cost to occupations that require high cognitive skills and interpersonal skills, while it increases the entry cost to occupations that intensively use motor skills and physical strength.

Table 5: Parameter Estimates (Wage Equation and Utility Function)

	Estimates	Std. Dev.
Constant, Type 1	−10.9695	2.8995
Constant, Type 2	−11.5213	2.8998
EDU	−0.2808	0.0590
GX	0.0856	0.0352
OX	0.0113	0.0058
$EDU^2/100$	−0.7447	0.0753
$GX^2/100$	−0.3355	0.0244
$OX^2/100$	−0.1318	0.0895
S_1, Type 1	10.4011	1.7372
S_2, Type 1	8.2481	1.9408
S_3, Type 1	2.4243	1.7139
S_4, Type 1	5.6232	1.7190
S_1, Type 2	10.7070	1.7324
S_2, Type 2	8.5950	1.9348
S_3, Type 2	2.4554	1.7149
S_4, Type 2	5.9727	1.7140
S_1S_2	−5.5902	0.9751
S_1S_3	−1.7003	0.8329
S_1S_4	−3.2254	0.7893
S_2S_3	−0.7024	0.8836
S_2S_4	−2.8917	1.3880
S_3S_4	0.2101	0.9099
$EDU \cdot S_1$	0.2474	0.0321
$EDU \cdot S_2$	0.1705	0.0317
$EDU \cdot S_3$	−0.0817	0.0283
$EDU \cdot S_4$	0.0329	0.0342
$GX \cdot S_1$	0.0115	0.0176
$GX \cdot S_2$	0.0285	0.0205
$GX \cdot S_3$	0.0089	0.0154
$GX \cdot S_4$	−0.0468	0.0167
σ_θ	0.2291	0.0070
σ_ϵ	0.3052	0.0015
α (Utility from Wage)	0.0815	0.0081

Table 6: Parameter Estimates (Preferences)

	Estimates	Std. Dev.
S_1, Type 1	−1.4957	0.3488
S_2, Type 1	1.4890	0.2951
S_3, Type 1	1.8238	0.3003
S_4, Type 1	3.3053	0.2235
S_1, Type 2	−0.9413	0.3862
S_2, Type 2	0.6507	0.3042
S_3, Type 2	2.3039	0.3339
S_4, Type 2	3.3146	0.2376
Professoional	−6.8708	0.3877
Manager	−6.1551	0.3815
Sales	−5.8151	0.3838
Clerical	−6.8042	0.3731
Craftsmen	−6.6667	0.3839
Operatives	−6.6821	0.3746
Transport Opr.	−6.0331	0.3749
Laborer	−6.3027	0.3717
Service	−6.3497	0.3771

Table 7: Parameter Estimates (Switching Cost and Skill Learning Cost)

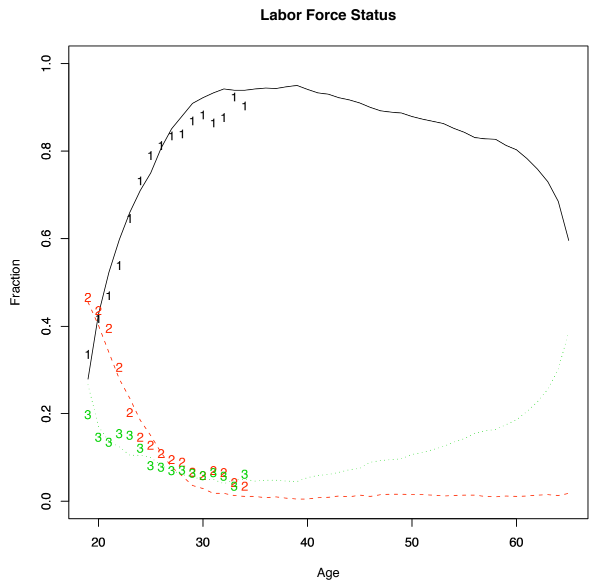
	Estimates	Std. Dev.
Constant, Type 1	3.0113	0.0599
Constant, Type 2	3.0466	0.0606
Age	0.0764	0.0060
d_1	4.9713	0.7791
d_2	10.7129	0.7670
d_3	7.2923	0.5797
d_4	10.8615	0.6421
$d_1 d_2$	−13.8787	3.1424
$d_1 d_3$	−13.1978	2.5427
$d_1 d_4$	−22.0325	1.8563
$d_2 d_3$	−5.2291	2.4120
$d_2 d_4$	24.8708	5.4744
$d_3 d_4$	7.6679	1.7913
d_1^2	1.0565	0.2044
d_2^2	−3.2572	0.1406
d_3^2	2.5360	0.1821
d_4^2	−0.4476	0.2167
$EDU \cdot d_1$	−0.4694	0.0859
$EDU \cdot d_2$	−0.2006	0.0574
$EDU \cdot d_3$	0.3437	0.1184
$EDU \cdot d_4$	0.2905	0.1336
$GX \cdot d_1$	0.3316	0.1054
$GX \cdot d_2$	0.1917	0.1096
$GX \cdot d_3$	0.2147	0.0850
$GX \cdot d_4$	−0.3277	0.0847
$I(j \neq work) \cdot d_1$	3.4509	0.7529
$I(j \neq work) \cdot d_2$	−2.3021	1.1572
$I(j \neq work) \cdot d_3$	−0.1415	0.7207
$I(j \neq work) \cdot d_4$	−6.0640	0.6431

Table 8: Parameter Estimates (Cost of Schooling)

	Estimates	Std. Dev.
Intercept (Type 1)	−0.9522	0.0993
Intercept (Type 2)	−1.6967	0.1058
Age	0.2328	0.0096
$I(EDU \geq 4)$	−0.3703	0.0807

5.2 Model Fit

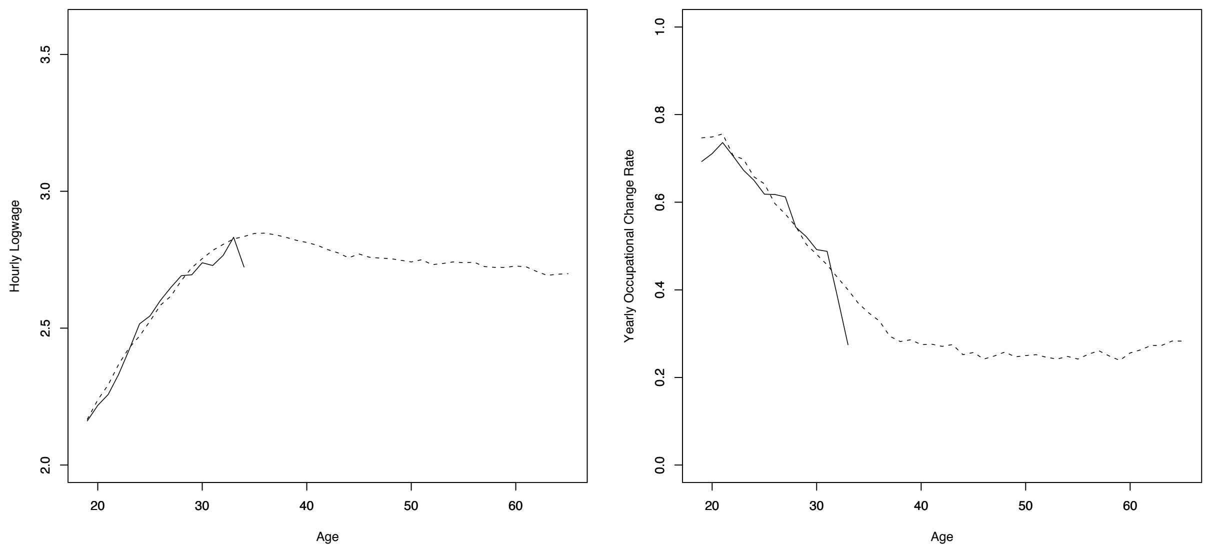
To assess an overall performance of the model, the model is simulated to evaluate the fit to the data. The simulation results are presented in figures 6, 7, and 8. The model fits the observed labor force status dynamics, as shown in figure 6. It also shows reasonable predictions for the out-of-sample periods. The predicted wage profile has a concave shape, and the predicted occupational change rate is decreasing in age (see figure 7.) One weakness is that the model predicts higher mobility rate than the data after age 35. This may result in understating wages after age 35, because high mobility implies that workers do not accumulate occupational specific human capital. The



Legend: (1) Work, (2) School, (3) Home. Lines show the simulation results. The figures show the numbers from the data.

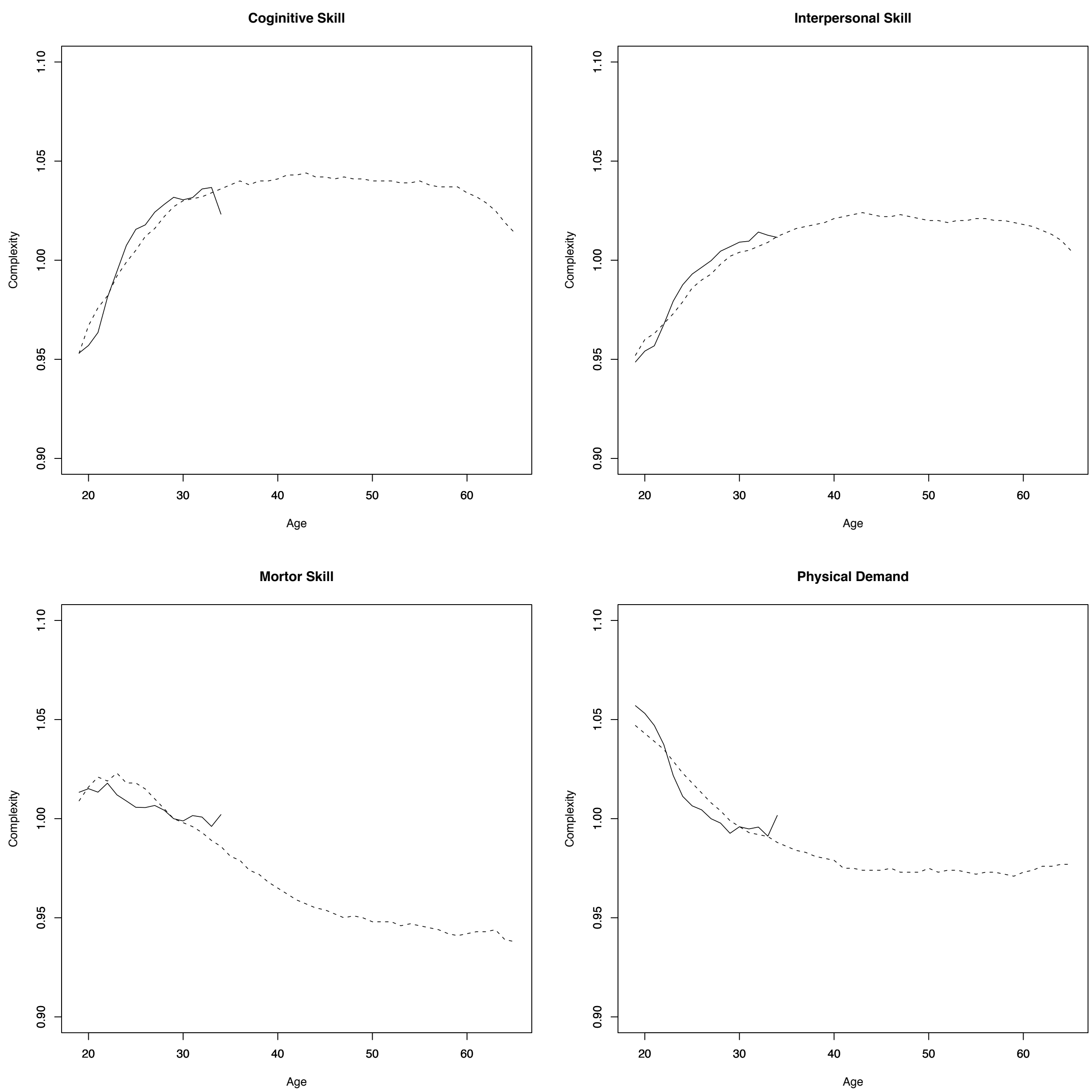
Figure 6: Model Fit (Labor Force Status)

predicted evolution of task complexity are found in figure 8. The model fits very well the observed patterns of all task dimensions.



Note: The solid lines for the data and the dashed lines are for the simulation results.

Figure 7: Model Fit (Logwage Profile and Occupational Change Rate)



Note: The solid lines for the data and the dashed lines are for the simulation results.

Figure 8: Model Fit (Task Complexity)

6 Application

6.1 Tuition Subsidy

(SIMULATION RESULTS TO BE ADDED.)

7 Summary

In this paper I have estimated a dynamic occupational choice model with multidimensional skills using the occupational definitions in the DOT and the work history from the NLSY 79. The model departs from the previous career choice models in two ways. First, skills used in one occupation help a worker enters a new occupation, depending on the similarity of tasks of the two. This is very different from occupational specific human capital, because it is completely useless in a new occupation by definition. Individuals build up their skills in low-paying occupations that provide relevant experience before they enter a high-paying occupation. Second, the model deals with occupations at the three-digit classification, which has been impractical for structural models that use years of occupational specific experience due to the curse of dimensionality. The proposed skill measure enables a researcher to overcome this limitation. I find that the model does a good job of fitting the data on occupational choices: individuals gradually move from low-skill occupations to high-skill occupations.

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A Details of the Data

A.1 Dictionary of Occupational Titles

The occupational definitions are taken from the Dictionary of Occupational Titles. Because 12,099 occupations are in the DOT, the occupational characteristics have to be aggregated into the 1970 Census three-digit occupational classification, which includes 574 occupations. This aggregation is conducted using the April 1971 Current Population Survey augmented with the fourth edition of the DOT which is constructed by the Committee on Occupational Classification and Analysis at National Academy of Sciences. Because the occupational characteristics in the augmented CPS file are based on the information collected during 70s, they are outdated for the analysis during 80s and 90s. The occupational information is updated using the revised fourth edition of the DOT published in 1991. Some occupations are deleted, or integrated into other occupations, while some are newly added in the revised fourth edition. The conversion table for the DOT occupation code is used to update the occupational characteristics.

A.2 Principal Component Analysis

Occupational characteristics are categorized into four types of skills. The first type is the cognitive skills. The DOT variables that measure cognitive skills include Data, General Educational Development (reasoning, mathematical, and language), and Intelligence, Verbal, Numerical in 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 a motor skill, which is measured by Things and seven aptitude variables: Spatial Perception, Form Perception, Motor Coordination, Finger Dexterity, Manual Dexterity, Eye-Hand-Foot Coordination, and Color Discrimination. The last type of skill is physical demand. The physical demand factor in the DOT is converted into five point scale for my measure of physical demand.

More than one variable are included in each skill category except for physical demand. To construct a single skill index from many variables, I use principal component analysis. Only the first principal components are used for the skill indices. Although only white male individuals are taken from the NLSY for the main analysis of the paper, all individuals included in the augmented CPS file are used in the principal component analysis. It is possible that tasks in a given occupation may vary across race and genders. However, the skill measures are sensitive to coding errors if I use a subsample of white males because the number of observations in some occupation is very small. For example, one observation in the augmented CPS has inconsistency between the three-digit occupation code and the DOT occupation code. His occupation is “store laborer” according to the DOT, but the 1970 Census three digit code says he is a flight attendant. Because this is the only observation in a white male sample, this error can be influential. One way is to omit such an observation as missing. But the sample includes too many occupations to do this manually. Moreover, such manipulation can be arbitrary. Another way is to take average over all individuals. Then, the error is averaged out as the number of observations included in a given occupation increases.