Hi-Stat Discussion Paper

HITOTSUBASHI UNIVERSITY

Global COE Hi-Stat Discussion Paper Series 025

Research Unit for Statistical and Empirical Analysis in Social Sciences (Hi-Stat)

Career Progression and Comparative Advantage

Shintaro Yamaguchi

January 2009

Hi-Stat
Institute of Economic Research
Hitotsubashi University
2-1 Naka, Kunitatchi Tokyo, 186-8601 Japan
http://gcoe.ier.hit-u.ac.jp

Career Progression and Comparative Advantage

Shintaro Yamaguchi*

This paper constructs and structurally estimates a dynamic model of occupational choice where all occupations are characterized in a continuous multidimensional space of skill requirement using the data from the Dictionary of Occupational Titles and the NLSY79. This skill space approach allows the model to include hundreds of occupations at the three-digit census classification level without a large number of parameters. Thereby it provides more detailed analysis of occupations than previous papers. Parameter estimates indicate that skill demanding occupations offer higher returns to education and experience, which results in occupational sorting. They also suggest that the estimated skill prices by the OLS are severely biased due to this sorting.

Keywords: Occupational choice, occupational sorting, human capital, skills, structural estimation.

1 Introduction

This paper investigates the occupational mobility and the returns to skills using a sample of white male young workers from the National Longitudinal Survey of Youth 1979 (NLSY). The model departs from previous contributions in that it maps all occupations in a continuous multidimensional space of skill requirement using the objective measures of job characteristics from the Dictionary of Occupational Titles (DOT). This skill requirement space approach allows the model to deal with hundreds of occupations at three-digit census classification level and thus, this paper provides more extensive and more detailed analysis of occupations. After providing empirical evidence that characterizes the career dynamics of white male young workers, I structurally estimate the model. The results indicate that different occupations reward worker skills substantially differently, which results in worker sorting across occupations.

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

*Last Revision: July 2008, Address: Department of Economics, McMaster University, 1280 Main St. West, Hamilton, ON., Canada L8S 4M4, Phone: +1-905-525-9140 (x23672), URL: http://socserv.mcmaster.ca/yamtaro, Email: yamtaro@mcmaster.ca. The author acknowledges the use of SHARCNET computational facilities.

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 cycles and economic growth. Nevertheless, many recent papers including Kambourov and Manovskii (2008), Moscarini and Vella (2003b,a), and Moscarini and Thomsson (2008) examine only separation from the current occupation and pay little attention to the occupation to which individuals move. In contrast to these recent empirical studies, this paper focuses on the choice of occupations and its relation to wage structure.

In the model, an occupation is characterizing in a continuous multidimensional space of skill requirement. In other words, the model differentiates occupations both vertically and horizontally. Wages are determined not only according to individual attributes such as experience and education, but also according to skill requirement of the current occupation. Occupations with high skill requirement offer higher wages for experienced and/or educated workers. This wage structure sorts workers vertically into occupations with different skill requirement. Occupations are also horizontally differentiated: for example, some occupations are characterized by their high interpersonal-skill requirement, while others are characterized by their high motor-skill requirement. Heterogeneous individuals choose their occupations depending on their comparative advantages. Some individuals climb the career ladder among interpersonal-skill demanding jobs; others progress through careers that are motor-skill demanding. This multidimensionality of skill requirement 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 the complex occupational mobility in the data. This paper overcomes this problem by characterizing all occupations in terms of a four-dimensional skill requirement vector. In fact, the model deals with about 350 occupations at the three-digit census classification level. Handling occupations at three-digit classification level is important for a precise analysis of occupations, as pointed out by Moscarini and Vella (2003b,a).

The model is numerically solved and estimated by maximum likelihood. Parameter estimates indicate that wages increase according to skill requirement and that returns to education and experiences also increase according to skill requirement. 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, 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 skill requirement measures. Second, estimates of "skill price" (marginal effects of skill requirement 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 (2008) estimate some skill prices to be negative.

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 in a continuous multidimensional space of skill requirement, 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 (2008) 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 (2008), this paper categorizes occupational characteristics into four types of skill requirement. The first type is cognitive skill requirement. The DOT variables that measure cognitive skill requirement include Data, General Educational Development (reasoning, mathematical, and language), and Intelligence, Verbal, and Numerical aptitude factors. The second type is an interpersonal skill requirement. This is captured by the DOT variables including People, INFLU (adaptability to influencing people), and DEPL (adaptability to dealing with people). The third type is motor skill requirement, which is measured by Things and three aptitude variables: Motor Coordination, Finger Dexterity, and Manual Dexterity. The last type of skill requirement is physical demand.

The occupational characteristics in the DOT are aggregated to occupations defined by the 1970 Census three-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 requirement 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 as a skill index for each skill requirement. Percentile scores and the first principal component are calculated, after I augment the NLSY79 with the raw DOT variables. Thus, the weights are taken from the NLSY, not the April 1971 CPS. More specifically, I estimate a linear factor model of the following form for each skill requirement group:

$$x_{it} = \mu + \lambda s_{it}^{l} + \xi_{it} \tag{1}$$

$$\xi_{it} \sim N(0, \Sigma_{\xi}) \tag{2}$$

where i and t are indexes for an individual and age in the NLSY79, and l is an index for a skill requirement category: e.g. $l = 1$ for cognitive skill requirement; $l = 2$ for interpersonal skill requirement; $l = 3$ for motor skill requirement; and $l = 4$ for physical demand. A $p \times 1$ (e.g. 7×1 for cognitive skill requirement) vector of the DOT variables in a given skill requirement group is denoted by x_{it}. A $p \times 1$ vector of means is given by μ. The factor loadings are denoted by a $p \times 1$ vector λ. The unobserved skill requirement index is given by s_{it}^{l}, which is a scalar. A $p \times 1$ vector of random variables that are uncorrelated with the factors is given by ξ_{it}. The variance matrix Σ_{ξ} is diagonal, which implies that all of the correlation among the job characteristics is due to the common factor s_{it}^{l}. The factor loadings λ are chosen so that the underlying factor s_{it}^{l} explains the covariation in the observed variables x_{it} to the largest extent. Imposing that each underlying factor s_{it}^{l} have mean of one and the standard deviation of 0.1, I estimate the factor loadings by an eigenvector decomposition of the covariance matrix of x_{it}. The underlying factors s_{it}^{l} can also be recovered here. Table 1 presents the proportions of variances explained by the underlying factor. The constructed cognitive skill requirement index explains 61% of the variation in the seven DOT variables in the pooled white male sample from the NLSY. The interpersonal skill requirement index and the fine motor skill requirement index explain 53% and 59% of the variations, respectively. Tables 2, 3, and 4 show factor loadings for each skill requirement index. The results indicate that each DOT variable loads to each skill requirement index in a similar magnitude.

To see if the constructed standardized scores reasonably characterize occupations, means of skill requirement are reported for each one-digit occupation in Table 5. Tasks of professionals require the highest level of cognitive skills, which is followed by managers. Laborers and household service workers are required the lowest level of cognitive skills. This cognitive skill requirement measure largely matches the conventional notion of skill in the empirical literature where skill is single dimensional. However, this index alone is not rich enough to describe heterogeneous tasks across occupations. For example, cognitive skill requirement is similar between sales occupations and craft occupations. But, the nature of tasks are very different; sales workers communicate with their customers and craft workers use tools and labor to make things.

Interpersonal skill requirement and motor skill requirement more clearly characterize the nature of occupation than a single skill index. Interpersonal skills are useful in professional, managerial, and sales occupations. In these occupations, workers have to direct their subordinates and persuade their clients. Laborers and household service workers use little of their interpersonal skills, because their tasks do not involve interactions with people. Motor skills are most required by tasks of craftsmen such as automobile mechanics and carpenters. Tasks of household service workers, managers, and sales workers require little motor skills. These patterns are quite intuitive, and thus, the statistics provide evidence for usefulness of the DOT task measures.

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, which is similar to the one used in Lee and Wolpin (2006): (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

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

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, 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.[2] 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 skill requirement. 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 skill requirement if the reported occupation is similar to the true occupation in terms of skill requirement.

2.3 Descriptive Analysis

2.3.1 Summary Statistics

Table 6 reports summary statistics of the sample by pooling all observations of the white male sample from the NLSY. 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 skill requirement 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). Skill

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

requirement indexes are highly correlated with each other, as shown in Table 7. Cognitive skill requirement is strongly and positively correlated with interpersonal skill requirement, 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 (2008) find. Another explanation is that learning cognitive skills and interpersonal skills 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.

Table 8 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 in a given survey year. 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.

2.3.2 Evolution of Occupational Skill Requirement

Evolution of means of skill requirement indexes are reported in Table 9. 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.

Skill requirement difference between education groups is substantially large. College graduates are engaged in more cognitive- and interpersonal-skill demanding tasks than high school graduates, while high school graduates are engaged in tasks that are more motor-skill and physical-strength demanding than college graduates. This is consistent with the fact that 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 demanding tasks, while they move to less physically demanding occupations. I find that the upward trends of cognitive skill and interpersonal skill requirement indexes are statistically significant for both education groups, by regressing each skill requirement index on age. The downward trend of the physical demand index for high school graduates is also found statistically significant. 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.

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 skill demanding tasks, (2) educated individuals occupying jobs with more skill demanding tasks, and (3) individuals moving between similar occupations in terms of skill requirement.

Individuals maximize the present value of their lifetime utility by choosing one of the following J mutually exclusive alternatives: staying at home, attending school, and working in one of $J-2$ occupations. They repeatedly choose an occupation every year from high school graduation until the retirement age T. The choice of occupation of individual i in age t is denoted by a_{it}, which takes an integer between 1 and J. I define this variable so that $a_{it} = J$ implies attending school, $a_{it} = J-1$ implies staying home, and $1 \leq a_{it} \leq J-2$ implies working. Any work experience before high school graduation does not count for their careers after high school. Individuals differ permanently in terms of ability to learn and earn, and mobility costs as described below.

3.1 Wage Equation

Individuals receive wages when they choose one of working alternatives. Wage is determined by the attributes of an individual and the skill requirement of the current occupation. Let s_j be a four-dimensional vector of skill requirement of occupation j. The l-th ($1 \leq l \leq 4$) element of the vector is denoted by s_j^l using a superscript. For example, s_j^1 is the cognitive skill requirement in occupation j. It is assumed that occupational skill requirement is constant over time and thus, it does not have a subscript for time. Years of post-secondary education and work experience of individual i in age t are EDU_{it} and GX_{it}, respectively. The wage of individual i in occupation j in age t is given by the following function of skill requirement and individual attributes,

$$\begin{aligned}\ln w_{ijt} &= \ln w_{ijt}(s_j, EDU_{it}, GX_{it}) + \varepsilon_{it} &(3)\\ &= \omega_{0,i} + \omega_1 EDU_{it} + \omega_2 GX_{it} + \omega_3 GX_{it}^2 + \sum_{l=1}^{4} \omega_{4,i}^{l} s_j^l + \sum_{l=1}^{4}\sum_{m=1}^{4} \omega_5^{lm} s_j^l s_j^l \\ &\quad + \sum_{l=1}^{4} \omega_6^l s_j^l EDU_{it} + \sum_{l=1}^{4} \omega_7^l s_j^l GX_{it} + \varepsilon_{it} &(4)\end{aligned}$$

where ε_{it} is a normally distributed measurement error with a zero mean and a variance σ_ε^2. The intercept is allowed to differ across individuals to account for heterogeneous earning ability. The next three terms of education and experience are quite commonly included in a wage regression.

The last two terms in the first line of Equation 4 captures how workers are rewarded according to skill requirement of their jobs. Notice that the coefficients for the first order term $\omega_{4,i}^l$ are heterogeneous across individuals. A greater magnitude of this parameter indicates that a worker has a higher ability in this skill dimension. Hence, these coefficients capture workers' comparative advantages. To be better rewarded, workers sort themselves into occupations in which they have comparative advantage. For example, those who have a large value of $\omega_{4,i}^1$ relative to the other coefficients tend to occupy cognitive skill demanding occupations, because they are paid better in those occupations. Interaction terms between different dimensions of skill requirement are included in the wage equation to account for complementarity between tasks, which is consistent with the observed correlations between skill requirement indexes (see Table 7).

The interaction effects of skill requirement and education and experience (the first two terms in the second line of Equation 4) are included in an attempt to capture under- and over-qualification of a worker. Assume coefficients ω_6^l and ω_7^l are positive. Educated and/or experienced workers have to take a job with complex tasks to be rewarded fully for their qualifications. In contrast, uneducated and/or inexperience workers are not paid very well even if they are in skill demanding occupations. Both worker qualification and occupational skill requirement must be high to earn high wages. This reward structure can explain why educated workers tend to occupy professional jobs. Professional occupations are characterized by their high cognitive skill requirement. If the coefficient for the interaction term between cognitive skill requirement and education (ω_6^1) is large, educated workers are likely to enter those occupations. Similarly, experienced workers tend to enter managerial positions if the coefficient for the interaction term between interpersonal skill requirement and experience (ω_6^2) is large. As workers get experienced, they become managers because their experience is better rewarded by taking on tasks that require more and better interpersonal communications.

3.2 Occupation Entry Cost

A worker pays an entry cost in the form of disutility when he moves to a different occupation, because workers have to prepare for the new tasks. This disutility for a new job can be large, if the new task is substantially more complex than the previous task. To implement this observation, I first define skill deficiency as the difference between the skill requirement of the new occupation s_j and that of the previous occupation s_k

$$d_{jk}^l = \begin{cases} s_j^l - s_k^l & \text{if } s_j^l > s_k^l \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where superscript l is for a skill dimension. If the previous task is more skill demanding than the new task in a given skill dimension, there is no skill deficiency. This variable measures how much skill demanding the tasks of the new occupation are, relative to the previous ones.

The entry cost to a new occupation is given by

$$c(d_{jk}, t) = \alpha_{0,ij} + \alpha_1 t_i + \sum_{l=1}^{4} \alpha_{2,i}^l d_{jk}^l + \sum_{l=1}^{4} \sum_{m=l}^{4} \alpha_3^{lm} d_{jk}^l d_{jk}^m. \tag{6}$$

The first term is a fixed component of occupation entry cost, which varies across individual types. Moreover, this component is common to the same one-digit occupations, but varies across one-digit occupations, to represent the costs not captured by the skill 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 his household structure such as marital status and children. The remaining last two terms capture how the disutility cost changes according to skill deficiency measure. Notice that the coefficients for the first order term $\alpha_{2,i}^l$ differ across individuals, which also captures comparative advantage of workers. For example, if a worker has a smaller value for $\alpha_{2,i}^1$ than other skill dimensions, he has comparative advantage in learning cognitive skills, because he needs a small cost to be ready for the new job regarding that skill. The comparative advantage in learning ability complements the comparative advantage captured by the wage equation above, to provide a better fit to the data. Interaction terms between different dimensions of skill deficiency are included in the last term to account for complementarity between different task dimensions, which is necessitated by the observed strong correlation between skill requirement indexes.

The skill deficiency measure is well-defined between any two labor market occupations, but not between a non-working state and a labor market occupation. To make the model complete, the "skill requirement" of non-working state (either staying home or attending school) is estimated. The location of non-working state in a skill requirement space for individual i in age t is denoted by $s_{0,it}$;

$$s^l_{0,it} = (1-y^l_{0,it})s^l_{min} + y^l_{0,it}s^l_{max} \quad (7)$$

$$y^l_{0,it} = \frac{\exp(\delta^l_0 + \delta^l_1 EDU_{it})}{1+\exp(\delta^l_0 + \delta^l_1 EDU_{it})} \quad (8)$$

where s_{max} (s_{min}) is the highest (lowest) skill requirement in the data. Thus, the location of non-working state satisfies $s^l_{min} < s^l_{0,it} < s^l_{max}$. Education affects the location of non-working state, to account for the differences in initial occupations across different education groups. Education increases the likelihood of entering a skill demanding occupation, as shown by Sicherman and Galor (1990).

3.3 School Attendance Cost

Individuals pay a cost when they attend a post-secondary school. This cost of school attendance includes both monetary and non-monetary cost such as disutility from effort. Remember that $a_{it-1} = J$ implies that an individual has attended a school in the last period (i.e. in age $t-1$.) The cost of attending school is given by

$$c^s = c^s_{0,i} + c^s_1 I(EDU_{it} \geq 4) + c^s_2 I(a_{it-1} \neq J) + c^S_3 I(a_{it-1} = J \wedge EDU_{it} = 4) \quad (9)$$

where $I(\cdot)$ is an indicator variable that takes one if the argument is true and takes zero otherwise. The first term differs across individuals to capture heterogeneity. The second term c^s_1 is an additional cost for a graduate school. Because returning to school after a period of non-attendance is rare, a psychic cost of re-entry c^s_2 is included. The last term c^s_3 is the cost paid by an individual who attends a graduate school immediately after undergraduate study.

3.4 Value Function

The worker's problem can be recursively formulated by the Bellman equation. I first describe the instantaneous reward function corresponding to each alternative. Consider individual i at age t who have worked in occupation k in the last period (i.e., $a_{it-1} = k$). If this individual chooses occupation j ($1 \leq j \leq J-2$, i.e., working state) today, his utility in this period is given by

$$U_{ijt} = \gamma_{0,i} + \gamma_1 \ln w_{ijt}(s_j, EDU_{it}, GX_{it}) - c(d_{jk}, t) + \nu_{ijt} \qquad (1 \leq j \leq J-2) \quad (10)$$

where $\gamma_{0,i}$ captures the cost of labor force participation and varies across individuals, d_{jk} is skill deficiency between the new occupation (j) and the previous occupation (k) which is defined above, and ν_{ijt} is a choice-specific preference shock that follows type I extreme value distribution.[3] As discussed above, a working individual receives wage and pays the cost if he starts a new job.

The instantaneous utility for an individual staying home is simply

$$U_{iJ-1t} = \nu_{iJ-1t} \tag{11}$$

where ν_{iJ-1t} is a preference shock for staying home that follows type I extreme value distribution. No other utility terms are included here for normalization. As is well known in the discrete choice model literature, only the difference of utility between alternatives is identified. Thus, the deterministic utility component of home alternative is set to zero. Lastly, the instantaneous utility for an individual attending school is

$$U_{iJt} = c^s(EDU_{it},\, a_{it-1}) + \nu_{iJt} \tag{12}$$

where a_{it-1} is the occupation in the last period and ν_{iJt} is a preference shock for attending school that follows type I extreme value distribution.

Individuals start making decisions from the age of high school graduation, denoted by t_i^0 and retire from the labor market at age T. Let $\Omega_{it} = \{EDU_{it}, GX_{it}, a_{it-1}\}$ be a subset of state variables of individual i at age t that includes education, experience, and the previous occupation. The value function for individual i in age t is given by

$$V_{it}(\Omega_{it}) = \max_{1\le j\le J} U_{ijt} + \rho E(V_{it+1}(\Omega_{it+1})) \qquad (t_i^0 \le t \le T) \tag{13}$$

The law of motion of the state variables is

$$GX_{it+1} = \begin{cases} GX_{it}+1 & \text{if } 1 \le j \le J-2 \\ GX_{it} & \text{otherwise} \end{cases} \tag{14}$$

$$EDU_{it+1} = \begin{cases} EDU_{it}+1 & \text{if } j = J \\ EDU_{it} & \text{otherwise} \end{cases} \tag{15}$$

$$a_{it} = j. \tag{16}$$

[3] I also estimate the model where wage level, instead of logwage, is included in the utility function. Results are very similar.

Because experience before graduating high school does not count, the initial conditions are

$$GX_{it_i^0} = 0 \tag{17}$$

$$EDU_{it_i^0} = 0 \tag{18}$$

$$a_{it_i^0-1} = J. \tag{19}$$

3.5 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 likelihood function is constructed using this numerical solution to the dynamic programming. Observations of individual i consists of history of wages and occupational choice, $w_i = \{w_{it_i^0}, \ldots, w_{i\bar{t}_i}\}$ and $a_i = \{a_{it_i^0}, \ldots, a_{i\bar{t}_i}\}$ where $\bar{t}_i$ is the last period when individual i is seen in the data. Due to computational burden, individual heterogeneity is included in the form of finite mixture. More specifically, individuals are in one of H types. The likelihood contribution of observations for individual i is given by

$$P(a_i, w_i|\Theta) = \sum_{h=1}^{H} \pi_h(t_i^0) \prod_{t=t_i^0}^{\bar{t}_i} P_h(a_{it}, w_{it}|\{a_{i\tau}\}_{\tau=t_i^0}^{t-1}; \Theta) \tag{20}$$

where the vector of parameters is Θ, $\pi_h(t_i^0)$ 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. Notice that all the relevant state variables included in Ω_{it} is fully recovered from the history of occupational choice $\{a_{i\tau}\}_{\tau=t_i^0}^{t-1}$.

The type weight is given by the following logit formula

$$\pi_h(t_i^0) = \frac{\exp(p_h(t_i^0))}{\sum_{r=1}^{4} \exp(p_r(t_i^0))} \tag{21}$$

$$p_h(t_i^0) = \begin{cases} 0 & \text{if } h = 1 \\ \pi_{h,0} + \pi_{h,1} t_i^0 & \text{if } 2 \le h \le 4 \end{cases} \tag{22}$$

The likelihood of the whole sample is given by

$$P(\{a_i, w_i\}_{i=1}^{N}|\Theta) = \prod_{i=1}^{N} P(\{a_{it}, w_{it}\}_{t=t_i^0}^{\bar{t}_i}|\Theta) \tag{23}$$

where N is the number of individuals in the sample.

4 Estimation Results

4.1 Parameter Estimates

I discuss some selected structural parameter estimates and their economic implications. All parameter estimates including those not discussed here are reported in Tables 10 through 15.

Wage Equation To summarize the relationship between skill requirement and wages, the marginal effects of skill requirement measures on wage are reported in Table 16. The first two columns report the marginal effects at mean skill requirement, no experience, and no post-secondary education. For all skill dimensions, wages increase in skill requirement except for type 1. The effects of cognitive skill requirement and physical demand are stronger than interpersonal skill and motor skill requirement. 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 the physical demand factor and close to the difference between laborers and the average of all occupations, wages increase by about 2-7%.

The effects of skill requirement on wages vary with education and experience. The next two columns report the marginal effects of skill requirement on logwage at the mean skill requirement, 10-year experience, and four-year post-secondary education. The marginal effects of requirement for cognitive skill, interpersonal skill, and motor skill are significantly greater than those for inexperience high school graduates. If the cognitive skill requirement index increases by 0.10, which is close to the difference between managers and the average of all occupations, wages increase by about 1-6%. An increase of the interpersonal skill requirement 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 requirement 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 lower for experienced college graduates than for inexperience high school 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 17. They are not uniform across occupations, which is consistent with the previous finding by Keane and Wolpin (1997). Returns to education are increasing in skill requirement, 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. Thus, the full return to education is greater than this estimate.[4] Returns to experience are also different across occupations. They are increasing in skill requirement, particularly in the dimensions of cognitive skill and interpersonal skill. In an average occupation (i.e. skill requirement 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%. The results indicate that the returns to experience and education are greater in cognitive and interpersonal skill-demanding occupations, which implies that experienced and educated workers sort themselves into those occupations to be better rewarded.

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.[5] Because this cost must be paid even when an individual moves down to a less skill demanding 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 of moving to a more skill demanding occupation increases in the skill deficiency measure. When an individual in an average occupation (skill requirement 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 a more skill demanding occupation.

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

[4]The full retrun to education could be calculated by simulation.

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

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 The location of non-work activities in the skill requirement space is reported in Table 19. The estimated location 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' location of non-work activity is close to occupations such as stock handlers, vehicle washers, oilers and greasers, where similarity is measured by the Mahalanobis distance.[6] The estimated location of college graduates' non-work activity is close to that of clerical workers and mail handlers.

4.2 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. 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 20 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 8. 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 21 reports the simulated distribution of skill requirement. The corresponding statistics in the data can be found in Table 9. The simulated skill requirement is remarkably close to the data in all skill dimensions and in all age groups. skill requirement difference between high school graduates and college graduates is also well replicated.

[6] Using German data, Gathmann and Schönberg (2007) measure the similarity of occupations by the Euclidean distance. It is a special case of the Mahalanobis distance when each dimension of skill requirement is uncorrelated with the others. This is clearly not the case in my data.

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 22. 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 skill requirement of each type is presented in Table 23. 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 interpersonal skills 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 demanding 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.

5.1.1 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 24 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 skill requirement 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 requirement is explained by unobserved heterogeneity. Higher fractions of the variance of physical demand are explained by unobserved heterogeneity at 83%. The effect of unobserved heterogeneity is even higher for interpersonal skill and motor skill requirement. 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 skill requirement differences are accumulated and increase over time, because experiencing a skill demanding job today helps individuals move to a more skill demanding occupations 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 if unobserved heterogeneity is not accounted for.

5.2 Skill Price and Endogeneity Bias

The results in the previous subsection indicate that permanent individual heterogeneity strongly influences occupational choices. This implies that the skill prices (i.e. coefficients for skill requirement indexes) estimated by the OLS are likely to be biased. To examine the directions and the extent of the biases of the OLS estimates, a wage equation comparable to the structural model is estimated by the OLS and the estimates are compared with those of the structural estimation.

Parameter estimates by the OLS are presented in Table 27 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 skill requirement, education, and experience are also constructed for comparison with the corresponding estimates from the structural model. As clearly shown in Table 25, estimated marginal effects of skill requirement are very different from structural parameter estimates in Table 16. According to the OLS estimates, an increase of the cognitive skill requirement 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 effects 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 (indeed, 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 26. 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 the 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 27. 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 the 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.

This exercise might explain why Ingram and Neumann (2006) and Bacolod and Blum (2008) estimate some skill prices to be negative, which is counterintuitive. The estimated negative skill prices are likely to result from occupational sorting: individuals with low unobserved earning ability tend to enter physically demanding occupations such as laborers. If an econometrician does not correctly accounts for this issue, the estimates are downward biased. The structural estimation in this paper provides a possible solution to address this endogeneity bias.[7] Indeed, the parameter estimates are quite intuitive, in contrast to the OLS estimates.

6 Conclusion

This paper contributes to the career dynamics literature in two ways. First, I provide empirical evidence to characterize the occupational mobility of white male workers over their careers using objective skill requirement measures of an occupation from the DOT. Second, I construct and estimate a dynamic occupational choice model where all occupations are characterized in a continuous multidimensional space of skill requirement, 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 skill requirement and

[7] The conventional instrumental variable method is also valid for this issue. However, one has to find at least as many instruments as skill dimensions (e.g. four, in this paper), which is certainly difficult.

that cognitive-skill intensive occupations offer higher returns to education and experience. This wage structure gradually sorts workers into occupations with different skill requirement. The results also suggest that the endogeneity bias of the OLS wage regression estimates is substantial, which accounts for the negative skill prices estimated in 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 skill requirement 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.

References

AUTOR, D. H., F. LEVY, AND R. J. MURNANE (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics*, 118(4), 1279–1333.

BACOLOD, M., AND B. S. BLUM (2008): "Two Sides of the Same Coin: U.S. "Residual" Inequality and the Gender Gap," University of California-Irvine.

BELZIL, C. (2007): "The return to schooling in structural dynamic models: a survey," *European Economic Review*, 51(5), 1059–1105.

GATHMANN, C., AND U. SCHÖNBERG (2007): "How General is Specific Human Capital," Stanford University.

GIBBONS, R., L. F. KATZ, T. LEMIEUX, AND D. PARENT (2005): "Comparative Advantage, Learning and Sectoral Wage Determination," *Journal of Labor Economics*, 23(4), 681–724.

GIBBONS, R., AND M. WALDMAN (2006): "Enriching a Theory of Wage and Promotion Dynamics inside Firms," *Journal of Labor Economics*, 24(1), 59–107.

INGRAM, B. F., AND G. R. NEUMANN (2006): "The Returns to Skill," *Labour Economics*, 13, 35–59.

JOVANOVIC, B., AND Y. NYARKO (1997): "Stepping-stone Mobility," *Carnegie-Rochester Conference Series on Public Policy*, 46, 289–325.

KAMBOUROV, G., AND I. MANOVSKII (2007): "Occupational Specificity of Human Capital," University of Toronto.

——— (2008): "Rising Occupational and Industry Mobility in the United States: 1968-1997," *International Economic Review*, 49(1), 41–79.

KEANE, M. P., AND K. I. WOLPIN (1997): "The Career Decisions of Young Men," *Journal of Political Economy*, 105(3), 473–522.

LEE, D., AND K. I. WOLPIN (2006): "Intersectoral Labor Mobility and the Growth of the Service Sector," *Econometrica*, 74(1), 1–46.

MILLER, R. A. (1984): "Job Matching and Occupational Choice," *Journal of Political Economy*, 92(6), 1086–1120.

MOSCARINI, G., AND K. THOMSSON (2008): "Occupational and Job Mobility in the US," *Scandinavian Journal of Economics*, 109(4), 807–36.

MOSCARINI, G., AND F. VELLA (2003a): "Aggregate Worker Reallocation and Occupational Mobility in the United States: 1976-2000," Yale University.

——— (2003b): "Occupational Mobility and Employment Reallocation: Evidence From The NLSY79," Yale University.

NEAL, D. (1995): "Industry-Specific Human Capital: Evidence from Displaced Workers," *Journal of Labor Economics*, 13, 653–77.

——— (1999): "The Complexity of Job Mobility among Young Men," *Journal of Labor Economics*, 17, 237–61.

PAVAN, R. (2006): "Career Choice and Wage Growth," University of Rochester.

SICHERMAN, N., AND O. GALOR (1990): "A Theory of Career Mobility," *Journal of Political Economy*, 98(1), 169–192.

YAMAGUCHI, S. (2007): "The Effect of Match Quality and Specific Experience on Career Decisions and Wage Growth," McMaster University.

A Tables

Table 1: Proportions of Variances

Cognitive	Interpersonal	Motor
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 2: Factor Loadings For Cognitive Skill Requirement 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 3: Factor Loadings For Interpersonal Skill Requirement 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 4: Factor Loadings For Fine Motor Skill Requirement 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.

Table 5: Mean Skill Requirement Indexes by One-digit Occupation

	Cognitive	Interpersonal	Motor	Physical
Professional	1.147	1.059	0.998	0.893
Manager	1.103	1.091	0.888	0.913
Sales	1.009	1.188	0.901	0.916
Clerical	0.981	0.981	0.947	0.953
Craftsmen	0.993	0.935	1.132	1.067
Operatives	0.900	0.909	1.042	1.054
Transport	0.894	0.978	1.022	1.067
Laborer	0.876	0.912	0.964	1.126
Farmer	1.059	0.966	0.981	1.166
Farm Laborer	0.887	0.910	1.009	1.152
Service	0.928	0.989	0.982	1.030
ALL	1.000	1.000	1.000	1.000

Note: Skill indexes are constructed by the method explained in Section 2. The sample mean and the sample standard deviation are 1.00 and 0.10 by construction, respectively. Household service occupations are integrated into service occupation.

Table 6: 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: The number of observations is for person-year in the pooled sample from the NLSY79. Sample sizes are different across variables due to missing values and due to that skill requirement index and hourly wage are available only for working individuals. Education is years of post-secondary education. General and occupational experiences are measured by year. Skill requirement indexes and physical demand are constructed by the method explained in Section 2. Their means are one and the standard deviations are 0.1 by construction. Logwage is a log of an hourly wage deflated by the 2002 CPI. Yearly occupation change is an indicator variable that takes one if an individual changes an occupation and takes zero otherwise. Thus, the mean is the yearly occupational change rate.

Table 7: Skill Requirement Measures Are Correlated.

	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

Note: Skill indexes are constructed by the method explained in Section 2. Weights are taken from the pooled sample from the NLSY79.

Table 8: Labor Force Status, Logwage, Occupation Changes by Age and Education

	Choice Probability			Mean Hourly Logwage	Annual Occupation Change Rate
Age/Education	Work	Home	School		
All					
18-21	0.535	0.159	0.306	2.140	0.621
22-25	0.786	0.120	0.093	2.437	0.505
26-29	0.928	0.051	0.021	2.653	0.399
30-34	0.951	0.036	0.013	2.748	0.427
High School					
18-21	0.639	0.144	0.217	2.156	0.606
22-25	0.910	0.064	0.026	2.455	0.485
26-29	0.959	0.036	0.005	2.628	0.398
30-34	0.974	0.026	0.000	2.710	0.430
College					
22-25	0.661	0.161	0.178	2.612	0.480
26-29	0.900	0.052	0.048	2.824	0.371
30-34	0.950	0.022	0.028	2.927	0.352

Note: "All" includes all individuals regardless of the level of post-secondary education. 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.

Table 9: Evolution of Mean skill requirement

Age/Education	Cognitive	Interpersonal	Motor	Physical
All				
18-21	0.946	0.967	1.006	1.037
22-25	0.995	0.994	1.006	1.003
26-29	1.023	1.016	0.995	0.983
30-34	1.031	1.021	0.991	0.982
High School				
18-21	0.945	0.963	1.008	1.041
22-25	0.978	0.974	1.027	1.028
26-29	0.997	0.991	1.016	1.014
30-34	1.000	0.995	1.016	1.014
College				
22-25	1.079	1.055	0.956	0.922
26-29	1.093	1.073	0.954	0.915
30-34	1.094	1.078	0.952	0.923

Note: "All" includes all individuals regardless of the level of post-secondary education. 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.

Table 10: Wage Equation

	Estimates	Std. Dev.
Intercept	-5.819	0.947
Intercept (Type 2)	0.200	0.099
Intercept (Type 3)	0.499	0.095
Intercept (Type 4)	1.206	0.179
$S1$	6.151	0.717
$S1_{h=2}$	0.136	0.049
$S1_{h=3}$	0.231	0.048
$S1_{h=4}$	0.561	0.082
$S2$	3.425	0.774
$S2_{h=2}$	-0.030	0.054
$S2_{h=3}$	-0.060	0.053
$S2_{h=4}$	-0.159	0.068
$S3$	-0.820	0.488
$S3_{h=2}$	0.115	0.042
$S3_{h=3}$	0.135	0.041
$S3_{h=4}$	0.089	0.070
$S4$	6.236	0.757
$S4_{h=2}$	-0.064	0.047
$S4_{h=3}$	-0.079	0.045
$S4_{h=4}$	-0.669	0.159
$S1^2$	-1.925	0.246
$S2^2$	-0.712	0.222
$S3^2$	0.275	0.169
$S4^2$	-1.417	0.184
$S1S2$	-0.559	0.289
$S1S3$	0.191	0.250
$S1S4$	-1.951	0.296
$S2S3$	-0.228	0.278
$S2S4$	-1.315	0.350
$S3S4$	0.177	0.223
EDU	-0.128	0.021
$S1EDU$	0.044	0.010
$S2EDU$	0.061	0.009
$S3EDU$	0.033	0.007
$S4EDU$	-0.013	0.010
GX	0.077	0.010
$GX^2/100$	-0.244	0.014
$S1GX$	0.011	0.005
$S2GX$	0.006	0.004
$S3GX$	-0.003	0.003
$S4GX$	-0.005	0.005
S.D. of iid Shocks, σ_ε	0.331	0.001

Note: Parameters estimates for Equation 4 are reported. Subscripts h indicates a unobserved 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". Dummy variables for one-digit occupation are included, but not reported here (available upon request). S1 through S4 are cognitive skill, interpersonal skill, motor skill, and physical demand, respectively. EDU is years of post-secondary education. GX is years of general work experience.

Table 11: Mobility Cost Function

	Estimates	Std. Dev.
Intercept	4.830	0.162
Intercept (Type 2)	-0.133	0.134
Intercept (Type 3)	-0.732	0.145
Intercept (Type 4)	-1.407	0.227
$d1$	4.481	1.513
$d1_{h=2}$	0.389	1.465
$d1_{h=3}$	-2.124	1.489
$d1_{h=4}$	-8.093	1.814
$d2$	6.982	1.270
$d2_{h=2}$	0.380	1.116
$d2_{h=3}$	0.441	1.187
$d2_{h=4}$	3.788	1.540
$d3$	7.757	1.277
$d3_{h=2}$	0.435	1.182
$d3_{h=3}$	2.164	1.176
$d3_{h=4}$	-0.151	1.524
$d4$	3.661	1.373
$d4_{h=2}$	1.574	1.251
$d4_{h=3}$	1.748	1.226
$d4_{h=4}$	5.416	2.883
$d1^2$	17.737	3.946
$d2^2$	-1.272	3.416
$d3^2$	-5.232	3.540
$d4^2$	8.627	4.184
$d1S2$	-9.306	4.285
$d1S3$	-10.271	4.273
$d1S4$	16.301	8.476
$d2S3$	11.992	7.116
$d2S4$	20.793	9.867
$d3S4$	-9.976	4.162
Manager	-0.905	0.073
Sales	-1.786	0.099
Clerical	-0.544	0.082
Craftsmen	0.236	0.069
Operatives	0.113	0.080
Transportation	-0.687	0.104
Laborer	-1.285	0.086
Service	-0.303	0.080
Age	0.100	0.005
Lagged Labor Force Participation	-0.790	0.120

Note: Parameters estimates for Equation 6 are reported. Subscripts h indicates a unobserved 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”. Variables d1-d4 are skill deficiency measure (see Equation 5) for cognitive skill, interpersonal skill, motor skill, and physical demand, respectively.

Table 12: Location of Non-work State

	Estimates	Std. Dev.
Intercept: $S1$	-2.142	0.305
Intercept: $S2$	-2.581	0.304
Intercept: $S3$	-1.116	0.157
Intercept: $S4$	0.383	0.161
Education: $S1$	0.336	0.087
Education: $S2$	0.337	0.066
Education: $S3$	-0.025	0.065
Education: $S4$	-0.590	0.091

Note: Parameters estimates for Equation 8 are reported. S1 through S4 are cognitive skill, interpersonal skill, motor skill, and physical demand, respectively.

Table 13: Cost of Schooling

	Estimates	Std. Dev.
Intercept	1.921	0.201
Intercept (Type 2)	-2.130	0.155
Intercept (Type 3)	-3.712	0.280
Intercept (Type 4)	-6.141	0.488
Lagged School Attendance	-1.775	0.090
Graduate School	1.410	0.159
Just Graduated 4-year College	0.655	0.215

Note: Parameters estimates for Equation 9 are reported. 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 14: Utility Function

	Estimates	Std. Dev.
Intercept	-13.342	0.861
Intercept (Type 2)	-2.130	0.155
Intercept (Type 3)	-3.712	0.280
Intercept (Type 4)	-6.141	0.488
Log Hourly Wage	5.892	0.393

Note: Parameters estimates for Equation 10 are reported. 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 15: Individual Type Distribution

	Estimates	Std. Dev.
Intercept: Type 2	1.197	0.168
Age of High School Graduation: Type 2	-0.340	0.177
Intercept: Type 3	0.840	0.168
Age of High School Graduation: Type 3	-0.304	0.171
Intercept: Type 4	-0.112	0.206
Age of High School Graduation: Type 4	-0.691	0.255

Note: Parameters estimates for Equation 22 are reported.

Table 16: Marginal Effects of skill requirement 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 skill requirement variables on logwages are reported. In the first two columns, the marginal effects are evaluated at the mean skill requirement (1.00), no experience, and no post-secondary education. In the next two columns, the marginal effects are evaluated at the mean skill requirement (1.00), 10-year experience, and four-year post-secondary education.

Table 17: Returns to Education and Experience

	Estimates	Std. Dev.
Marginal 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

Note: Marginal and cumulative returns to education and work experience are reported. skill requirement is set at the mean of laborer and the mean of professional, which can be found in Table 5.

Table 18: 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 $\alpha_{ij,0}$). 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).

Table 19: 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

Note: skill requirement of non-working state is reported for high school graduates and college graduates. Estimates are obtained by Equations 7-8 using structural parameter estimates in Table 12.

Table 20: Simulation Results for Labor Force Status, Logwage, Occupation Changes by Age and Education

	Choice Probability			Mean Logwage	Hourly	Annual Occupation Change Rate
Age/Education	Work	Home	School			
All						
18-21	0.535	0.178	0.287		2.184	0.614
22-25	0.792	0.115	0.093		2.412	0.516
26-29	0.909	0.065	0.026		2.633	0.412
30-34	0.937	0.048	0.015		2.782	0.396
High School						
18-21	0.608	0.188	0.203		2.169	0.616
22-25	0.877	0.105	0.017		2.385	0.522
26-29	0.924	0.065	0.011		2.586	0.424
30-34	0.943	0.049	0.008		2.710	0.407
College						
22-25	0.639	0.151	0.210		2.582	0.483
26-29	0.893	0.062	0.045		2.788	0.378
30-34	0.949	0.036	0.015		2.973	0.362

Note: The estimated model is simulated for 50 times for each individual from his first year to the last year in the data. This table is comparable to Table 8. "All" includes all individuals regardless of the level of post-secondary education. 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.

Table 21: Simulation Results for skill requirement

Age/Education	Cognitive	Interpersonal	Motor	Physical
All				
18-21	0.948	0.961	1.008	1.039
22-25	0.983	0.985	1.008	1.014
26-29	1.013	1.005	1.002	0.994
30-34	1.035	1.021	0.995	0.979
High School				
18-21	0.942	0.956	1.010	1.046
22-25	0.961	0.966	1.018	1.037
26-29	0.980	0.977	1.018	1.026
30-34	0.999	0.991	1.013	1.013
College				
22-25	1.073	1.054	0.963	0.925
26-29	1.096	1.069	0.961	0.917
30-34	1.113	1.083	0.957	0.909

Note: The estimated model is simulated for 50 times for each individual from his first year to the last year in the data. This table is comparable to Table 9. "All" includes all individuals regardless of the level of post-secondary education. 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.

Table 22: Labor Force Status by Unobserved Type

	Choice Probability			Mean Logwage	Hourly	Annual Occupa-tion Change Rate
Age/Type	Work	Home	School			
Type 1						
18-21	0.644	0.234	0.122		1.780	0.600
22-25	0.820	0.151	0.029		1.971	0.517
26-29	0.888	0.097	0.015		2.168	0.414
30-34	0.919	0.070	0.011		2.333	0.302
Type 2						
18-21	0.624	0.202	0.174		2.127	0.644
22-25	0.825	0.128	0.047		2.324	0.549
26-29	0.899	0.080	0.021		2.521	0.445
30-34	0.934	0.052	0.015		2.688	0.331
Type 3						
18-21	0.490	0.149	0.360		2.488	0.555
22-25	0.804	0.084	0.112		2.656	0.454
26-29	0.940	0.036	0.024		2.857	0.343
30-34	0.969	0.019	0.012		3.053	0.235
Type 4						
18-21	0.167	0.069	0.763		2.811	0.682
22-25	0.592	0.087	0.321		2.951	0.519
26-29	0.900	0.035	0.064		3.160	0.386
30-34	0.962	0.015	0.023		3.402	0.254

Table 23: skill requirement Evolution by Unobserved Type

Age/Type	Cognitive	Interpersonal	Motor	Physical
Type 1				
18-21	0.928	0.952	1.002	1.056
22-25	0.942	0.962	1.008	1.049
26-29	0.956	0.975	1.008	1.040
30-34	0.977	0.999	0.995	1.022
Type 2				
18-21	0.941	0.957	1.011	1.044
22-25	0.966	0.973	1.017	1.029
26-29	0.989	0.990	1.015	1.014
30-34	1.019	1.012	1.006	0.993
Type 3				
18-21	0.961	0.968	1.010	1.030
22-25	1.003	0.997	1.009	0.999
26-29	1.038	1.022	1.002	0.976
30-34	1.071	1.045	0.988	0.952
Type 4				
18-21	1.055	1.022	0.974	0.931
22-25	1.107	1.057	0.949	0.897
26-29	1.132	1.070	0.940	0.886
30-34	1.152	1.078	0.928	0.876

Table 24: Fractions of Variances Due To Permanent Individual Heterogeneity

Age	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

Note: Variances of years of education, skill requirement indexes, and logwage are decomposed into between and within unobserved individual type. This table reports the fraction of these variances explained by unobserved type, i.e. between-type variance.

Table 25: Marginal Effects of skill requirement 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

Note: The marginal effects are calculated using the parameter estimates from OLS, which are presented in Table 27. For the corresponding results for structural estimation, see Table 16.

Table 26: 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

Note: The returns to education and experience are calculated using the parameter estimates from the OLS, which are presented in Table 27. For the corresponding results for the structural estimation, see Table 17.

Table 27: 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	

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