Tasks and Heterogeneous Human Capital∗

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Abstract

This paper proposes a new approach to modeling heterogeneous human capital using the task data from the Dictionary of Occupational Titles. The key feature of the model is that it conceives of an occupation as a bundle of tasks, departs from the Roy model in which occupations are treated as distinct categories. The proposed approach has advantages in that it can accommodate many occupations without computational burden and provides a clear interpretation as to how and why skills are differently rewarded across different occupations. The model is structurally estimated by the Kalman filter using the NLSY79.

Keywords: Roy model, task approach, human capital, occupational choice, Kalman filter, structural estimation.

JEL Codes: J24, J32

1 Introduction

Heterogeneity in worker skills is a central feature of labor economics. One approach to understanding the heterogeneity of human capital is to assume that workers classified by such criteria as race, sex, and education possess homogeneous skills. Another approach pays close attention to

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the sector affiliation of workers. In the Roy model, workers are sorted across occupations in which they have a comparative advantage. This approach is more economically meaningful because it clearly relates the unobserved skills to the observed sector affiliation and wages. Heckman and Sedlacek (1985), Keane and Wolpin (1997), and many subsequent papers including Lee (2005), Lee and Wolpin (2006), and Sullivan (2010) are based on the Roy model and study issues in which heterogeneous human capital plays a central role. While this paper is in the same spirit as the Roy model, it departs from the previous Roy-type models by taking a more direct look at what workers perform on the job using the occupational task information provided by the Dictionary of Occupational Titles (DOT).

This paper conceives of an occupation as a bundle of tasks. Different occupations involve different tasks at different levels of complexity. For example, high levels of complicated quantitative analysis would be required to perform the tasks of an actuary, while the task associated with being a cashier require relatively low levels. On the other hand, the tasks performed by a tailor require high levels of finger and manual dexterity, while much lower levels of them are necessary for the tasks performed by a sales worker. The data from the DOT allows me to construct a low dimensional vector of continuous measures of task complexity. Occupations are therefore characterized in a continuous and multidimensional space of task complexity in the model. This approach is very different from the Roy-type models mentioned above, because these models deal with each occupation as a distinct category. When occupations are treated as categories, one cannot quantify how they are similar to each other. However, in the proposed approach, similarity of occupations is readily measured by the distance between occupations in the task complexity space.

The proposed approach has two advantages over other Roy-type models. First, the model accommodates many occupations without a large number of parameters and state variables, because the preference and wage function are defined not over occupations, but over a low-dimensional vector of occupational tasks. My approach can be interpreted as an application of the characteristic approach proposed by Lancaster (1966) to the Roy model, and thus, has a strength similar to that of the characteristic approach. In Roy-type models, returns to skills differ across occupations in an arbitrary way. This implies that the number of parameters increases with the number of occupations in the model, because the returns to skills are estimated for each occupation in the model. When skills are measured by occupation specific experiences like Keane and Wolpin (1997), the number of state variables also increase with the number of occupations. Because computational burden for solving a dynamic programming problem exponentially increases with the number of state variables, this model structure has prevented previous papers from including several occupations. This is not satisfactory because the apparent heterogeneity within broadly defined occupations is ignored. Indeed, the empirical evidence from the DOT indicates that tasks are significantly different across the 3-digit census occupation that are grouped in the same 1-digit census occupation. This
paper overcomes this limitation by assuming that the returns to skills change with task complexity. In an occupation that involves complex tasks, worker skills are more intensely used, and thus better rewarded. This assumption makes the number of parameters and state variables independent of the number of occupations in the model, and thus, the model deals with about 500 occupations at the census 3-digit level. This modeling strategy is useful not only for complicated structural estimations, but also for reduced-form wage regressions. Economists may want to estimate wage equations across occupations to understand the extent of skill transferability and/or differences in the wage structure across occupations. However, there is not enough occupational mobility in the data to do so at any reasonable precision. A common solution to this problem is either to aggregate occupations or to make a strong restriction about the transferability of skills across occupations. The task-based approach is a way of dealing with this data limitation.

The second and more important advantage is that the proposed approach provides a clear explanation as to why and how skills are differently rewarded and transferable across occupations. In Keane and Wolpin (1997) and subsequent papers that adopt their framework, it is not quite clear how and why experience accumulated in one occupation is rewarded in others. While this is less problematic if the model includes only a couple of occupations, interpretation of the differences between occupations is not necessarily straightforward when the model includes more than a few occupations; as in Sullivan (2010) and Johnson and Keane (2007). In this paper I interpret differences in returns to skills across occupations from the viewpoint of tasks. Skills are similarly rewarded between occupations that involve similar tasks, while they are less so between occupations that involve very different tasks. Skill transferability changes with the task complexity-measured similarity of occupations.

In the model, workers are endowed with heterogeneous (or multidimensional) skills. They synthesize all types of skills to perform the tasks involved in any occupation, but their skills are differently rewarded across occupations. Occupations also offer different learning opportunities depending on the complexity of tasks. For example, if skills are acquired through learning-by-doing, performing complicated tasks help workers develop their skills faster. Workers also possess preferences over task complexity itself. For example, some workers like complicated manual tasks while other workers may find them unpleasant. Due to the presence of differing job preferences, workers with identical skills may choose different occupations. In each period, a worker chooses an occupation that maximizes the expected present value of lifetime utility. Unlike the previous career decision models, occupational choice is modeled as a continuous choice problem rather than a discrete choice problem, because choosing an occupation is equivalent to choosing a set of tasks in a continuous space. Individual heterogeneity in initial skill endowment, learning ability, and job preferences is included in the model.

I show that, under my functional form assumptions, the optimal policy function for occupa-
tional choice can be represented by a linear function of observed worker characteristics, unobserved skills, and unobserved preference shocks. This result implies that the observed task complexity can be interpreted as a noisy signal of unobserved skills. Hence, I can estimate the dynamics of unobserved skills from the observed task complexity. This closed-form solution also allows me to estimate the model with little computational burden. The previous models based on discrete choice dynamic programming such as Keane and Wolpin (1997) require a numerical solution for each grid point in the discretized state space, which could take several hours or even days. It is also worth noting that the present model can include many observed worker characteristics including continuous variables. This is often intractable for dynamic structural models because the value function and the policy function are solved for all types of individuals as defined by observed characteristics.

I draw data for the measurement of task complexity from the DOT, which defines occupations in terms of several tasks. For example, the complexity of tasks in terms of mathematical development is evaluated in a six-point scale. Tasks at the lowest level of complexity involve adding and subtracting two digit numbers, while tasks at the highest level of complexity involve the use of advanced calculus and statistical inference. The DOT measures the complexity of tasks with respect to 62 characteristics, but many of them are highly correlated and redundant. I therefore summarize the information of the DOT by constructing a complexity measurement for two broadly defined tasks: cognitive tasks and motor tasks. In order to construct wage and task complexity histories for young male workers, the task complexity measures are combined with the National Longitudinal Survey of Youth (NLSY) 79 by using the 3-digit census occupation code.

I estimate the model by the Kalman filter. The results indicate that returns to skills and rate of learning differ across occupations according to task complexity. The parameter estimates are used to evaluate the roles of cognitive and motor skills in determining cross-sectional wage variance and wage growth. I find that both cognitive and motor skills account for a considerable fraction of the wage variance. The differences existing between workers prior to labor market entry account for about 35% of the logwage variance 10 and 20 years after entry. For wage growth, cognitive skills are the main driver; accounting for all of the wage growth for those who completed high school or higher. The growth of motor skills is important for high school dropouts; it accounts for half of their wage growth.

This paper is also related to the growing literature that attempts to look into the skills associated with job tasks. My contribution to this literature is a novel use of task information which makes a clear distinction between worker skills and job tasks. A common approach in the literature (see Autor, Levy, and Murnane (2003), Ingram and Neumann (2006), and Bacolod and Blum (2010), for example) is that tasks are used as proxies for unobserved worker skills and thus, they do not play any substantial role in the model. In those models, skill prices are assumed to be constant.
1 INTRODUCTION

across occupations. For example, Ingram and Neumann (2006) and Bacolod and Blum (2010) include task complexity measures in their wage regressions and interpret the coefficients as returns to skills.

However, this approach has a limitation from the theoretical and empirical viewpoints. On the theoretical side, Rosen (1983) criticizes the model presented by Welch (1969) in which skill prices are uniform across occupations. He shows that when workers are sorted across occupations, the uniform skill prices arise in a very special circumstance and skill prices are likely to differ across occupations. On the empirical side, Heckman and Scheinkman (1987) and other papers based on the Roy models show evidence that returns to skills are systematically different across sectors.1 Building on the Roy model, my model distinguishes tasks and skills and characterizes the relationship between the two. The derived policy function for occupational choice suggests that the observed tasks can be interpreted as a noisy signal of the unobserved skills. It is also shown that the structural model can be estimated by the Kalman filter under the parametric assumptions.

Poletaev and Robinson (2008) and Gathmann and Schönberg (2010) examine wage losses following occupation changes using U.S. and German data, respectively. They find that the losses increase with the task distance measure between occupations. This paper provides an economic model that helps interpret their empirical findings. Autor and Handel (2009) consider the relationship among skills, tasks, and occupation. They have task information at the individual level, unlike task-based approach papers that use the occupation level data contained in the DOT. Autor and Handel (2009) assume that skills are measured by the observed tasks and are rewarded differently across occupations. However, in contrast to this paper, they do not conceive of occupations as bundles of tasks; therefore, the differences between occupations remain ambiguous. Consequently, like the Roy model, it is not quite clear in their model how and why skills are differently rewarded across occupations. My paper also differs in that I empirically analyze the dynamics of skills and wages, while Autor and Handel (2009) test a few predictions in a static setup.

Lazear (2009) presents an idea similar to this paper. In his skill-weights approach, returns to skills change with the weights that a job places on skills. Workers are attracted by jobs that place more weight on skills in which the workers have a comparative advantage. Lazear (2009) assumes that a high weight on one skill necessarily means a low weight on the other skills. This trade-off is necessary to avoid a situation in which all workers enter the same occupation. In contrast, in this paper some occupations may reward all types of skills better than other occupations. This is consistent with empirical evidence from the DOT which demonstrates that some occupations involve more complex tasks than other occupations in all dimensions. Lazear (2009) develops a theoretical analysis of the model and provides a useful insight into the relationship between skills

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1In their recent paper, Firpo, Fortin, and Lemieux (2011) also argue in favor of the Roy model approach against the uniform skill price models to study the changes in the U.S. wage structure using the occupational task data.
and job tasks, but it is not quite clear how the model could be estimated or tested due to the lack of skill weights data. The main contribution of this paper is to propose a new model that is empirically implementable with task data, such as the DOT, and provide an extensive empirical analysis of the dynamics of skills and wages.

The rest of the paper is organized as follows: Section 2 lays out the structural dynamic model of occupational choice and shows that a closed-form solution to the policy function exists. Section 3 explains the estimation strategy. Section 4 describes how task complexity measures are constructed using the DOT and sampling criteria for the NLSY. The estimation results including the model fit are presented in Section 5. Section 6 discusses the effects of each type of skills on the distribution and growth of wages. Section 7 concludes. Tables and figures are collected in the Appendix. Supplementary appendix extensively discusses robustness of the results.

2 Model

In this section I describe a dynamic model of occupational choice and skill formation. In the model, each individual who has made a long term transition to the full-time labor market has a finite decision horizon ending in an exogenously fixed retirement age. Jobs in the same occupation are homogeneous in terms of task complexity, i.e., jobs and occupations are not distinguished. In each year \( t \), an individual chooses an occupation that lies in a \( K \)-dimensional continuous space of task complexity \( x_t \) that is observable and takes non-negative values. The task complexity indexes take non-negative values and sufficiently many occupations exist so that an individual can choose any occupation in the task complexity space. Skills in year \( t \) are denoted by a \( K \)-dimensional vector \( s_t \) that is unobserved by the econometrician. The skills index \( s_t \) can take any real numbers including negative values.

Labor is the only factor of production in the economy. Each firm offers jobs of a single type, which implies that the products of each firm can be characterized by a task complexity vector. The products are heterogeneous and consumed by households. The price of the product characterized by task \( x_t \) is denoted by \( \pi(x_t) \). The productivity of a worker with skill \( s_t \) in a job with task complexity \( x_t \) is \( q(x_t, s_t) \).

\(^2\)See Section 4.1 for detailed discussion for task complexity measurement.

\(^3\)This assumption is not restrictive for two reasons. First, the model contains about 500 occupations at the census 3-digit level. Second and more importantly, the observed distribution of occupations in task complexity space does not necessarily reflect the constraints faced by workers. It may reflect the equilibrium outcomes of workers and firms without constraints in their supply of and demand for occupations. In other words, certain types of occupation may not be seen in the data, simply because no workers find them attractive.

\(^4\)This assumption is for expositional convenience. Alternatively, the products of each job can be viewed as intermediate outputs for homogeneous final products. Both interpretations are observationally equivalent.
2.1 Wage Function

Workers are paid in accordance with their marginal value product. The marginal value product of a worker with skill \( s_t \) in an occupation with task complexity \( x_t \) is

\[
W_t = \pi(x_t)q(x_t, s_t)\exp(\eta_t),
\]

where \( \eta_t \sim N(0, \sigma^2_\eta) \) can be interpreted as an iid productivity shock or as measurement error. As in the Roy model, skills are rewarded differently across occupations. I assume that labor productivity may be represented as the inner product of skills and their implicit prices;

\[
\ln q(x_t, s_t) = \theta'(x_t)s_t,
\]

where \( \theta(x_t) \) is a \( K \)-dimensional vector of implicit skill prices and represents the contribution of skills \( s_t \) to an occupation with task \( x_t \). Skills are more intensely used, and contribute to productivity more, when the corresponding tasks are complex \( \partial \theta_k(x)/\partial x_k > 0 \), where subscript \( k \) is an index for the task dimension.\(^5\) For example, quantitative skills are essential for actuaries, but do not contribute to a truck driver’s productivity. Similarly, finger and manual dexterity are required for a tailor’s tasks, but they are not useful for an accountant’s tasks. I parametrize the output price and productivity as

\[
\ln \pi(x_t) = p_0 + p_1'x_t \quad \text{(3)}
\]

\[
\ln q(x_t, s_t) = \theta'(x_t)s_t = [p_2 + P_3'x_t]'s_t, \quad \text{(4)}
\]

where \( p_0 \) is a scalar, \( p_1 \) and \( p_2 \) are \( K \)-dimensional vectors, and \( P_3 \) is a \( K \)-dimensional diagonal matrix. Therefore, the logwage is given by

\[
\ln w_t = p_0 + p_1'x_t + [p_2 + P_3'x_t]'s_t + \eta_t. \quad \text{(5)}
\]

In a Roy-type model, such as in Keane and Wolpin (1997), the output price \( \pi \) and the implicit skill prices \( \theta \) are allowed to differ across occupations in an arbitrary way. Since this approach does not impose a restriction on how they vary, the parameters \( \pi \) and \( \theta \) must be estimated for each occupation. Many Roy-type models do not include more than a few occupations, because the number of parameters increases with the number of occupations. My paper overcomes this limitation by imposing structure on how the parameters \( \pi \) and \( \theta \) vary across occupations from the viewpoint of occupational tasks. If two occupations are similar in terms of tasks \( x \), say a cognitive-

\[^5\]Teulings (1995) and Gibbons, Katz, Lemieux, and Parent (2005) also assume that returns to skills increase with task complexity. This paper extends their wage equations for the case in which skills and tasks are multidimensional.
skilled worker switches their occupation from bank officer to office manager, the wage change following the occupation change would be small, which can be interpreted as the existence of high skill transferability between the two occupations. In contrast, if two jobs involve very different tasks, say a motor-skilled worker changes occupations from mechanic to clerk, he would suffer a large wage loss, which implies a low skill transferability between the two. In a Roy-type model, it is not necessarily clear why experience in one occupation is rewarded in other occupations. The present model can answer this question, because similarity between occupations is clearly characterized in terms of tasks. The proposed approach facilitates an interpretation of the wage structure and decreases computational burden by reducing the number of parameters.

This wage function also provides an interpretation about job match quality introduced by Jovanovic (1979). While many empirical papers find that the wage gain from job search is substantial for young workers, their models do not explicitly explain why match quality varies across jobs. In my model, a worker receives a wage gain when he moves to an occupation in which the returns to skills are high. The size of this wage gain depends on the skill endowment of the worker. Consider a worker with high motor skills and little cognitive skills. This worker can expect a large wage gain by taking a job that involves complex motor tasks, but cannot expect a significant wage gain by taking a job that involves complex cognitive tasks. Desirable occupations from the viewpoint of wage gains vary across individuals, according to their skill endowments. The job search process could be interpreted as a worker attempting to reach an occupation that offers a higher return to skills that the worker has abundantly, in an environment in which the worker does not know the location of the job he prefers, while the present model assumes he does.

### 2.2 Skill Formation

The technology of skill formation is represented by a linear function of task complexity, worker characteristics, the current skill level, and skill shocks. Let $d$ be a $L$-dimensional vector of individual characteristics which are fixed at labor market entry, such as race and education. A vector of skill shocks $\varepsilon_t$ is normal, independent and identically distributed with mean zero and variance $\Sigma_\varepsilon$: $\varepsilon_t \sim N(0, \Sigma_\varepsilon)$. Skills grow from year $t$ to year $t + 1$ according to the following skill transition equation

$$s_{t+1} = Ds_t + a_0 + A_1 x_t + A_2 d + \varepsilon_{t+1},$$

where $D$ is a $K$-dimensional diagonal matrix for skill depreciation, $a_0$ is a $K$-dimensional vector of parameters, $A_1$ is a $K \times K$ diagonal matrix of the marginal effects of task complexity on learning.

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6The contributions in this area include Topel and Ward (1992), Pavan (forthcoming), Schönberg (2007), Yamaguchi (2010b), and Sullivan (2010).
and $A_2$ is a $K \times L$ dimensional matrix that represents heterogeneous learning ability.

Two interpretations of the model are possible depending on the sign of $A_1$. When $A_1$ is positive definite, this specification can be interpreted as an extension of a learning-by-doing model to the case in which jobs are heterogeneous. For example, if a worker spends many years in occupations that involve complex motor tasks, this person should have developed significant motor skills. When $A_1$ is negative definite, this skill formation technology explains a worker’s occupational mobility over their career, which is shown by Rubinstein and Weiss (2006). Notice that a trade-off between returns to skills and skill learning opportunities exists in this case: occupations with complex tasks provide higher returns to skills, but skill growth is slow in those occupations. In this environment, a typical young worker starts his career in an occupation with simple tasks in order to develop more skills. Later in his career, he moves to an occupation characterized by complex tasks in order to receive higher returns to the skills he has developed in the early stages of his career. Both interpretations are plausible and are empirically examined below.

Individuals start their careers with initial skills $s_1$ that differ across individuals in both observable and unobservable ways. The initial skill endowment is given by

$$s_1 = h + Hd + \varepsilon_1,$$  \hspace{1cm} (7)

where $h$ is a $K$-dimensional vector, $H$ is a $K \times L$ matrix of parameters, $d$ is observed individual characteristics at labor market entry, and $\varepsilon_1$ is an unobserved component of initial skills which is distributed as $\varepsilon_1 \sim N(0, \Sigma_{\varepsilon_1})$.

### 2.3 Job Preference

I examine the role that job preferences play in occupational choices for two reasons. First, it is plausible that workers with identical skills may choose different occupations according to their differing tastes for tasks. Accounting for job preferences is particularly important to understanding differences in skills between demographic groups. For example, significant occupational gaps exist between men and women, and Blacks and Whites. The gaps may reflect gaps in their skills to some extent, but they may be due to differences in job preferences. Ignoring differences in job preferences will result in biased estimates of skill endowments across demographic groups. The second reason to consider job preferences is to rationalize the observed occupational choices. The proposed wage function and skill formation technology have the potential to sort workers into different occupations on the basis of their skills. However, the sign conditions discussed above may not be satisfied empirically. Even if they are, the model without job preferences may not fit the data very well. The empirical results below strongly support the necessity of job preferences in the model.
The following quadratic function of task complexity determines the utility derived from work,

\[ v_t = v(x_t, \bar{x}_t, s_t, \tilde{\nu}_t; d) \]

\[ = (g_0 + G_1d + G_2s_t + \tilde{\nu}_t)'x_t + x_t'G_3x_t + (x_t - \bar{x}_t)'G_4(x_t - \bar{x}_t), \]

where \( g_0 \) is a \( K \)-dimensional vector of preference parameters, \( G_1 \) is a \( K \times L \) matrix of preference parameters, \( \tilde{\nu}_t \) is a \( K \)-dimensional vector of preference shocks with zero mean, \( G_2, G_3, G_4 \) are \( K \times K \) diagonal matrices, and \( \bar{x}_t \) is a \( K \)-dimensional vector of work habits.

The utility from job tasks varies across individuals according to their individual characteristics \( d \), skill levels \( s_t \), a preference shock \( \tilde{\nu}_t \), and work habits \( \bar{x}_t \). Skilled workers prefer complex tasks if the parameter matrix \( G_2 \) is positive definite. I assume that the matrix \( G_3 \) is negative definite. This restriction implies that, for a very high value of \( x_t \), the marginal utility from task complexity is negative; this is the cost of entering an occupation with complex tasks. The parameters \( g_0, G_1 \), and \( G_2 \) are unrestricted. The last term in the above equation captures the effect of work habits on utility.

The work habits of individuals are measured by the weighted average of the task complexities of previous occupations that the individual has held. Individuals may have difficulty in adjusting themselves to a new work environment. The mental and physical costs of this adjustment are high when an individual enters into an occupation that is very different from the past occupations held. This effect can also be interpreted as a sort of search friction because individuals are unlikely to receive a job offer for a position that involves very different tasks from the recent jobs held. This work habit effect is introduced to approximate the fact that workers do not change occupations every year.\(^7\) It is true that the model can predict more realistic worker mobility patterns by introducing a fixed entry cost to a new occupation or by assuming that workers do not receive job offers every period, but the proposed specification is necessary to derive the linear policy function shown below. I argue that the benefit from this approximation exceeds its loss of realism.

This utility function allows for a rich form of heterogeneity in job preferences: it varies across individuals according to skills, work habits, other observed worker characteristics, and unobserved preference shocks. Consider the utility change of a worker being promoted to a job with complex tasks. If he is unskilled, this promotion may decrease the utility from job tasks because he may not like the complex tasks and will suffer from adjusting himself to the new tasks. In contrast, if

\(^7\)It is well known in the literature that individuals’ choices are serially correlated. One common approach to accounting for persistence in workers’ choice is to include a lagged choice variable. For example, in Keane and Wolpin (1997), a worker pays a job finding cost if he did not work in the occupation in the previous period. Altug and Miller (1998) allows for work disutility to depend on hours worked in previous years. The work habits in this paper are in the same line as these papers.
he is skilled this promotion may increase his utility from job tasks despite the work habit effect, because a skilled worker likes complex tasks.

Individuals form their work habits through the following transition equation

\[
\bar{x}_{t+1} = A_3 \bar{x}_t + (I - A_3)x_t,
\]

(10)

where \(A_3\) is a \(K\)-dimensional diagonal matrix of which elements take values between zero and one, and \(I\) is a \(K\)-dimensional identity matrix. Hence, work habits \(\bar{x}\) are a weighted average of the task complexities of the past jobs. When \(A_3 = 0\), only the tasks in the last occupation affect work disutility. In contrast, when \(A_3 = I\), work habits remain constant at the initial value \(\bar{x}_1\). For all other cases where the elements of \(A_3\) are between 0 and 1, the tasks of all past jobs affect work disutility.

Individuals may have experienced part-time jobs and/or been engaged with other activities in and out of school before they transit to the full-time labor market. These experiences outside the full-time labor market form individuals’ initial work habits as well as the initial skill endowment. The initial condition for \(\bar{x}_t\) varies across individuals according to initial observed characteristics \(d\) such that

\[
\bar{x}_1 = \bar{x}_{1,0} +Xd,
\]

(11)

where \(\bar{x}_{1,0}\) is a \(K\)-dimensional vector of parameters and \(X\) is a \(K \times L\) matrix of parameters.

### 2.4 Bellman Equation

The Bellman equation for an individual is given by

\[
V_t(s_t, \bar{x}_t, \tilde{\nu}_t, \eta_t; d) = \max_{x_t} \ln w_t(x_t, s_t, \eta_t) + v(x_t, \bar{x}_t, s_t, \tilde{\nu}_t; d) + \beta EV_{t+1}(s_{t+1}, \bar{x}_{t+1}, \tilde{\nu}_{t+1}, \eta_{t+1}; d)
\]

(12)

s.t.

\[
\ln w_t = p_0 + p'_1 x_t + [p_2 + P'_3 x_t] s_t + \eta_t
\]

(13)

\[
v_t = (g_0 + G_1 d + G_2 s_t + \tilde{\nu}_t)' x_t + x_t' G_3 x_t + (x_t - \bar{x}_t)' G_4 (x_t - \bar{x}_t)
\]

(14)

\[
s_{t+1} = Ds_t + a_0 + A_1 \bar{x}_t + A_2 d + \epsilon_{t+1}
\]

(15)

\[
\bar{x}_{t+1} = A_3 \bar{x}_t + (I - A_3)x_t
\]

(16)

\[
s_t = h + Hd + \epsilon_t
\]

(17)

\[
\bar{x}_1 = \bar{x}_{1,0} +Xd.
\]

(18)
The objective of workers is to maximize the present value of lifetime utility by choosing occupation \( x_t \). Workers take into consideration that different occupations offer different wage returns, skill learning opportunities, and disutilities from the tasks. Note that the differing wage returns represented by Equation (5) alone can account for worker sorting across occupations based on skills, although all of the three factors affect workers’ decisions. To see this point, differentiate the wage equation by \( x_t, \frac{\partial \ln w_t}{\partial x_t} = p_1 + P_3 s_t \), which indicates that the more skills workers have, the more benefit they receive. Notice that \( s_t \) can take a negative value. Thus, unskilled workers (i.e. workers with large negative values of \( s_t \)) do not want to enter an occupation with high \( x_t \), because doing so would reduce their wages.

The optimal policy function is a linear function of skills, work habits, individual characteristics, and preference shocks, because the flow utility \( \ln w + v \) is a quadratic function of the state variables and the transition equations of the state variables are linear in state variables. Notice that normality of the random variables are not necessary to derive the linear policy function. It can be expressed as

\[
x_t^* = c_{0,t} + C_{1,t} d + C_{2,t} s_t + C_{3,t} \bar{x}_t + \nu_t,
\]

where \( c_{0,t} \) is a \( K \)-dimensional vector, \( C_{1,t} \) is a \( K \times L \) matrix, \( C_{2,t} \) and \( C_{3,t} \) are \( K \)-dimensional diagonal matrices, and \( \nu_t \) is a \( K \)-dimensional vector of rescaled preference shocks (i.e., I can write \( \nu_t = M_t \tilde{\nu}_t \), where \( M_t \) is a \( K \)-dimensional diagonal matrix). The proof is shown in Appendix E.

The rescaled preference shocks \( \nu_t \) are normal, independent, and identically distributed random variables with zero mean and non-diagonal variance matrix \( \Sigma \nu \). The parameters \( c_{0,t}, C_{1,t}, C_{2,t}, \) and \( C_{3,t} \) are functions of structural parameters and are not estimated as free parameters. Because the problem has a finite horizon, I solve the value function and the policy function by backward recursion.

The derived policy function provides a useful interpretation of the observed occupational choice: it is a noisy signal of underlying skills. Hence, I can estimate the dynamics of unobserved skills from the observed task complexity measures. This is an important departure from the previous papers that implicitly assume that workers in the same occupation have identical occupational skills and use the observed occupation as a proxy of skills. My model distinguishes occupation and worker skills and characterizes the relationship between the two through the policy function.

This analytical solution also dramatically reduces the computational time for estimation. In many papers that estimate a structural dynamic model of occupational choice, such as Keane and Wolpin (1997), no analytical solution is available and the model is solved for at each grid

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8This class of problems is known as a stochastic optimal linear regulator problem.

9Many other methods are available for infinite horizon problems. See Anderson, Hansen, McGrattan, and Sargent (1996) for a survey.
point in the discretized state space for each parameter value throughout the estimation.\textsuperscript{10} With the analytical solution, I can avoid calculating the numerical solutions that account for most of the computational burden in those papers. Another advantage of having an analytical solution is that it allows me to accommodate many state variables, including continuous variables for observed worker characteristics, which is intractable in previous structural models. This paper accounts for the heterogeneity of occupation and workers in a rich way with little computation cost.

Although modeling occupational choice as a continuous choice problem instead of a discrete choice problem has advantages in interpretation and computation, there is a limitation in the predicted pattern of worker mobility. The model predicts that $x_t^*$ changes every period due to skill and preference shocks $\varepsilon_t$ and $\nu_t$, which means workers change occupations every year. This is different from what is observed in the data; most workers do not change occupations every year and thus, the time profile of task complexity $x_t$ at the individual level is a step function. While the model cannot match this feature of the data, it can approximate the profile of task complexity over time. A fixed cost of an occupation change would allow the model to overcome this limitation. But the linear policy function would also be lost. Because the purpose of the paper is not to match the frequency of occupational change, I do not include a fixed cost of an occupation change in the model.

### 3 Estimation Strategy

#### 3.1 Identification

Notice that this model is an application of a state-space model. Like other state-space models, there is an identification issue related to unobserved skills. The scale parameters of skill are not identified because observed variables (i.e. wage and task complexity) are the product of unobserved skills and unknown parameters such as the returns to skills. Either a large amount of skills or high returns can rationalize an observed high wage. The location parameters of skills are also not identified, because no natural measures of skills exists. Hence, I normalize skills by assuming that the unconditional mean and variance of initial skills are 0 and 1, respectively.\textsuperscript{11} This normalization of

\textsuperscript{10}Hotz and Miller (1993) and many subsequent papers develop a method to avoid calculating numerical solutions in estimating a structural dynamic discrete choice model. Imai, Jain, and Ching (2009) also develop a Bayesian approach to reduce computational burden in estimating a model of the same class.

\textsuperscript{11}Specifically, it is imposed that

\begin{align}
E(s_1) &= h + HE(d) = 0 \\
\text{diag}[\text{Var}(s_1)] &= \text{diag}[HE(ddd')H' + \Sigma_{\varepsilon_1}] = \text{diag}[I],
\end{align}

where $0$ is a vector of zeros, $I$ is an identity matrix, and $\text{diag}$ is an operator that converts a matrix into a vector that consists of diagonal elements of the matrix. In the estimation, $h$ and $\text{diag}[\Sigma_{\varepsilon_1}]$ are not estimated as free parameters, but...
the location parameter affects the intercept $p_0$ and the coefficient vector $p_1$ in the wage equation. However, the marginal effect of $x$ on $\ln w$ (i.e., $\partial \ln w / \partial x = p_1 + P_3 s$) can be consistently estimated regardless of how I normalize the location parameter. The covariance of the initial unobserved skills and skill shocks (i.e., off-diagonal elements of $\Sigma_\varepsilon$ and $\Sigma_{e1}$) is identified by the conditional wage variance given tasks. For example, the estimated covariance of unobserved component of the skills is negative, if the conditional logwage variance decreases with the product of cognitive and motor task complexity indexes. More detailed argument can be found in Appendix C. The parameters for job preferences are identified by the occupational choices characterized by the policy function. However, they are not separately identified, because the number of these parameters in the job preference equation (9) is greater than the number of the parameters in the policy function (19). To avoid this unidentifiability, it is imposed that $G_3$ be the negative of an identity matrix. This normalization is innocuous as long as $G_3$ is negative definite, because the policy function parameters are consistently estimated regardless of how I normalize $G_3$. The structural parameters $G_1, G_2,$ and $G_4$ are identified by the variations of worker characteristics $d$, skills $s_t$, and work habits $\tilde{x}_t$, respectively. The parameter $g_0$ is identified by the constant term of the policy function.

### 3.2 Kalman Filter

I use the Kalman filter to calculate the likelihood. The Kalman filter is an algorithm used to estimate recursively the distribution of unobserved state variables (i.e. skills) from observed noisy signals (i.e. the task complexity of occupation and wages).

Suppose that skills are normally distributed given task complexity $x_t$ and wages $w_t$ up to year $t - 1$, the initial work habit $\tilde{x}_1$, and the fixed worker characteristics $d$. The conditional mean and variance of skills are

$$E(s_t|x_1, w_1, \ldots, x_{t-1}, w_{t-1}; \tilde{x}_1, d) \equiv E(s_t|Y_{t-1})$$

recovered from these restrictions. The off-diagonal elements of $\Sigma_{e1}$ are unrestricted and estimated as free parameters.

To understand this point, let $s_1$ be $s_1 = \mu_e + \tilde{s}_1$ where $\mu_e$ is a vector of constants and $\tilde{s}_1$ is a vector of normal random variables with zero mean. In this paper, I assume $\mu_e = 0$ for normalization, but let us suppose not. The wage equation can be rewritten as $\ln w = (p_0 + P_2 \mu_e) + (p_1 + P_3 \mu_e + P_3 \tilde{s}_1) x_1 + (p_1 \tilde{s}_1 + \eta_1).$ With parametric assumptions, $(p_0 + P_2 \mu_e)$ and $(p_1 + P_3 \mu_e)$ are identified. This implies that the parameter values of $p_0$ and $p_1$ depend on $\mu_e$. To see this unidentifiability, consider the optimal choice of occupation at the terminal period $T$. The optimal task complexity $x_T$ is given by

$$x_T^* = -\frac{1}{2}(G_3 + G_4)^{-1}[g_0 + G_1 d + (P_3 + G_2) s_T - 2G_4 \tilde{x}_T + \nu_T]$$

$$\equiv c_0 + C_1 x_T + C_2 s_T + C_3 \tilde{x}_T + \nu_T.$$  

Here, the number of structural parameters to be estimated is $(4 + L)K$, while the number of parameters in the policy function is $(3 + L)K$. To proceed, $K$ parameters have to be fixed. The exact relationships between the structural parameters and the policy function parameters are outlined in Appendix E.
where $Y_{t-1}$ summarizes all the information up to year $t - 1$. The optimal choice of task complexity is also normally distributed, because the policy function (see Equation 19) is linear in skills, work habits (i.e. the weighted average of the task complexities of the past occupations), and preference shocks $\nu_t$. The conditional mean and variance of $x_t$ given $Y_t$ are

$$E(x_t | Y_{t-1}) = c_{0,t} + C_{1,t}d + C_{2,t}\hat{s}_{t|t-1} + C_{3,t}\bar{x}_t \quad (28)$$

$$Var(x_t | Y_{t-1}) = C_{2,t}\Sigma_{t|t-1}C_{2,t} + \Sigma_\nu. \quad (29)$$

I then update the conditional distribution of skills using task complexity in the current period $x_t$ so that

$$E(s_t | Y_{t-1}, x_t) = \hat{s}_{t|t-1} + \Sigma_{t|t-1}^s C_{2,t}(C_{2,t}\Sigma_{t|t-1}^s C_{2,t}^\prime + \Sigma_\nu)^{-1}\hat{\nu}_t \quad (30)$$

$$Var(s_t | Y_{t-1}, x_t) = \Sigma_{t|t-1}^s - \Sigma_{t|t-1}^s C_{2,t}^\prime (C_{2,t}\Sigma_{t|t-1}^s C_{2,t}^\prime + \Sigma_\nu)^{-1}C_{2,t}\Sigma_{t|t-1}^s \quad (31)$$

where $\hat{\nu}_t$ is a vector of residuals and $\hat{\nu}_t = x_t - E(x_t | Y_{t-1})$. Notice that the logwage is a linear function of normal random variables given information up to $t - 1$ and the current occupational tasks $x_t$. Thus, the logwage is also normally distributed given $Y_{t-1}$ and $x_t$. The conditional mean and variance of the logwage are

$$E(\ln w_t | Y_{t-1}, x_t) = p_0 + p_1^\prime x_t + [p_2 + P_3^\prime x_t]E(s_t | Y_{t-1}, x_t) \quad (32)$$

$$Var(\ln w_t | Y_{t-1}, x_t) = [p_2 + P_3^\prime x_t]Var(s_t | Y_{t-1}, x_t)[p_2 + P_3^\prime x_t] + \sigma_{\eta_t}^2. \quad (33)$$

Again, I then update the conditional distribution of skills using the information obtained in the current period,

$$E(s_t | Y_{t-1}, x_t, w_t) = E(s_t | Y_{t-1}, x_t) + Var(s_t | Y_{t-1}, x_t)[p_2 + P_3^\prime x_t][Var(\ln w_t | Y_{t-1}, x_t)]^{-1}\hat{\eta}_t \quad (34)$$

$$Var(s_t | Y_{t-1}, x_t, w_t) = Var(s_t | Y_{t-1}, x_t) - Var(s_t | Y_{t-1}, x_t)[p_2 + P_3^\prime x_t][Var(\ln w_t | Y_{t-1}, x_t)]^{-1}[p_2 + P_3^\prime x_t]Var(s_t | Y_{t-1}, x_t), \quad (35)$$

where $\hat{\eta}_t$ is a logwage residual and $\hat{\eta}_t = \ln w_t - E(\ln w_t | Y_{t-1}, x_t)$. Finally, I calculate the conditional
distribution of skills in year $t + 1$ given information up to year $t$ using the skill transition equation (see Equation 6). Because skills in year $t + 1$ are linear in current skills and task complexity, they are also normally distributed with mean and variance,

$$\hat{s}_{t+1|t} = DE(s_t|Y_{t-1}, x_t, w_t) + a_0 + A_1x_t + A_2d$$

(36)

$$\Sigma_{s_{t+1|t}} = DVar(s_t|Y_{t-1}, x_t, w_t)D + \Sigma_e.$$  

(37)

When the wage is missing in the data, it is integrated out to construct the likelihood. Given the linear skill transition equation (6), the conditional distribution of $s_{t+1}$ given $Y_{t-1}$ and $x_t$ is normal with mean and variance

$$E(s_{t+1}|Y_{t-1}, x_t) = Ds_t + a_0 + A_1x_t + A_2d$$

$$= D\hat{s}_{t|t-1} + a_0 + A_1x_t + A_2d$$

(38)

$$Var(s_{t+1}|Y_{t-1}, x_t) = D\Sigma_{s_{t+1|t}}D + \Sigma_e.$$  

(39)

which replace Equations (36) and (37) in this case.\textsuperscript{14} This algorithm allows me to calculate the conditional distribution of skills, wages, and occupational tasks sequentially from the first period $t = 1$ to the last period $t = T$, because the initial skills are normally distributed by assumption. More specifically, using the Kalman filter I calculate the likelihood contribution of each individual as a product of the conditional likelihoods. I have observations of wage and task complexity measures of occupations for each individual $(w_{i1}, x_{i1}, \cdots, w_{iT_i}, x_{iT_i})$, where $i$ is an index for individual and $T_i$ is the last period in the sample for individual $i$. The likelihood contribution of individual $i$ is

$$l(w_{i1}, x_{i1}, \cdots, w_{iT_i}, x_{iT_i} | \bar{x}_{i1}, d_i)$$

$$= l(x_{i1} | \bar{x}_{i1}, d_i)l(w_{i1} | x_{i1}; \bar{x}_{i1}, d_i) \times \cdots \times l(x_{iT_i} | Y_{iT_i-1})l(w_{iT_i} | Y_{iT_i-1}, x_{iT_i}).$$

(40)

The likelihood for the whole sample consisting of $N$ individuals is given by

$$l = \prod_{i=1}^{N} l(w_{i1}, x_{i1}, \cdots, w_{iT_i}, x_{iT_i} | \bar{x}_{i1}, d_i).$$

(41)

\textsuperscript{14}When $x_t$ is missing, all the observations from that period on are dropped. This is because the Kalman filter algorithm here relies on that $\bar{x}$ is observed. If $x$ is missing, $\bar{x}$ is an additional unobserved state variables that are serially correlated. If $\bar{x}$ is dropped from the model, i.e. $G_4 = 0$, the method here can be easily extended to the case in which $x_t$ is missing.
4 Data

4.1 Dictionary of Occupational Titles

The DOT contains information on 12,099 occupations that are defined on the basis of the tasks performed. It is constructed by the U.S. Department of Labor to provide standardized occupational information for an employment service matching job applicants with job openings. The information included in the DOT is based on the on-site observation of jobs as they are performed in diverse business establishments and, for jobs that are difficult to be observed, on information obtained from professional and trade associations.\textsuperscript{15} On this basis, in the revised fourth edition of the DOT, analysts rate each occupation with respect to 62 characteristics that include the aptitudes, temperaments, and interests necessary for adequate performance; the training time necessary to prepare for an occupation; the physical demands of the occupation; and the working conditions under which work in the occupation typically occurs.

Many characteristics are measured by a multi-point scale and have detailed definitions. For example, the variable \textsc{data} measures the complexity of tasks in relation to information, knowledge, and conceptions by integers from 0 to 6. Tasks at the lowest level of complexity involve judging the readily observable characteristics of data. Examples include sorting hats according to color and size as specified, comparing invoices of incoming articles with actual number and weights of articles, and so on. Tasks at the intermediate level of task complexity involve compiling information. Examples include summarizing details of transactions, collecting, classifying, and recording data, and receiving customer complaints to record and file them for future processing. Tasks at the highest level of complexity involve integrating analysis of data to discover facts or developing knowledge concepts of interpretations. Examples include formulating hypotheses and experimental designs, writing critical reviews of art for publication, and conducting research. Other tasks such as interpersonal communication and operating machines or equipment are also evaluated in a similar manner. Some tasks, particularly those measuring physical demand, are measured by a binary variable that takes one if the occupation involves the task and zero otherwise.

To facilitate interpretation of the data, I summarize the detailed information in the DOT by constructing a low dimensional vector of occupational tasks through Principal Component Analysis (PCA). Previous studies take two major different approaches. The first approach, which is employed by Bacolod and Blum (2010) and Yamaguchi (2010a), assumes that a subset of DOT

\textsuperscript{15}One might be concerned that task complexity cannot be correctly measured by observing jobs performed, because what analysts observe is a realized combination of job tasks and worker skills in equilibrium: even when the task is simple, an analyst might consider it complex if the worker is skilled. This confusion should be at least partially avoided because the job information is obtained from other sources as well (e.g. interviewing incumbents and supervisors.) It is also worth noting that the DOT explicitly states that each occupation is defined on the basis of the tasks performed. See Miller, Treiman, Cain, and Roos (1980) for a critical review of the DOT.
variables measures the complexity of a single task. For example, it is assumed that three General Educational Development (reasoning, mathematics, and language) variables measure cognitive task complexity, but do not measure other types of tasks such as motor tasks. This approach requires a priori knowledge about which variables measures which types of tasks. The second approach assumes that a DOT variable contains information about several underlying task complexities that are orthogonally distributed. For example, unlike the first approach, it is assumed that the General Educational Development variables above contain information about both cognitive and motor task complexity. The second approach does not require the a priori knowledge mentioned above, but does impose that task complexity be orthogonally distributed. Ingram and Neumann (2006) employ a method similar to this.

It seems impossible to determine which approach is better than the other in general, because these two approaches impose different restrictions. Nevertheless, I find the first approach to be more suitable for this paper given the data, because the constructed task complexity vector has a clear interpretation. This is not necessarily the case under the orthogonality assumption in the second approach, particularly when two seemingly unrelated DOT variables have high loadings on the same factor. For example, it is hard to interpret a factor when a variable that is related to worker intelligence and a variable related to physical strength have high loadings for that factor. In the first approach, this possibility is excluded by construction: a variable related to worker intelligence is not used to construct a physical strength measure.

In light of the job analysis literature as well as previous economics papers that use the DOT, this paper assumes that tasks are broadly categorized into either cognitive tasks or motor tasks. While I assume these two task categories a priori, PCA conducted with the orthogonality assumption also yields a similar set of factors.\textsuperscript{16}

Autor, Levy, and Murnane (2003) consider different task groups, including routine and non-routine manual tasks, in order to understand the role of technological change in the labor market, but these tasks capture different aspects of the motor tasks needed to perform a job. More narrowly defined task categories could also be considered instead of cognitive and motor tasks. For example, cognitive tasks could be separated into intelligent and communication tasks. However, these two are highly correlated with each other (the correlation coefficient is .73) and do not seem to provide any additional insights.\textsuperscript{17} Breaking down tasks increases the number of free parameters and thus, complicates the analysis.\textsuperscript{18}

\textsuperscript{16}See supplementary appendix for the robustness check on this issue.

\textsuperscript{17}I construct communication task complexity indexes and estimate the structural model with them. With three tasks including the communication tasks as well as the cognitive and motor tasks, the estimation results are not robust to the choice of the sampling criteria. As can be seen in the supplementary appendix, the results for the presented model with two tasks are robust.

\textsuperscript{18}Although cognitive and motor tasks seem most suitable for my sample of men, different task categorization may be more useful for a different demographic group. For example, if one is interested in the highly educated, considering
By examining the textual definitions of the DOT variables, I assume what variables measure which type of task complexity. The following choices seem to be reasonable and I confirm that the constructed task complexity index is robust to the choice of the DOT variables. The DOT variables that measure cognitive task complexity consists of 2 worker function variables (Data and People), 3 General Educational Development variables (reasoning, mathematical, and language), 3 aptitude variables (Intelligence, Verbal, and Numerical), and 3 adaptability variables (influencing people, accepting responsibility for direction and dealing with people). Motor task complexity is measured by 1 worker function variable (Things), Motor Coordination, Finger Dexterity, Manual Dexterity, Eye-hand-foot Coordination, Spatial Perception, Form Perception, Color Discrimination, Setting Limits, Tolerance or Standards, and 20 physical demand variables.

In the PCA, factor loadings are calculated so that variation of the data explained by the constructed variables is maximized (or minimize the information loss, equivalently.) For this purpose, I take a sample of occupational characteristics from the April 1971 CPS augmented by the fourth edition of the DOT. This augmented CPS file contains the 1970 census occupation code, the DOT occupation code, and the DOT variables. I update occupational characteristics using the revised fourth edition by matching the DOT occupation code. The result of the PCA is available in the supplementary appendix and shows that the factor loadings are intuitive. Following Autor, Levy, and Murnane (2003), I further convert these first principal components into percentile scores using the weights from the augmented CPS file. The resulting indexes at the individual level are aggregated into the level of the 1970 census occupation by taking the sample mean for each of the 3-digit occupations so that they can be merged with the NLSY.

To see if the constructed variables characterize occupations reasonably, I report the mean and standard deviation of the task complexity measures for each census 1-digit occupation in Table 1. The cognitive tasks of professionals are most complex, followed by those of managers. Cognitive tasks of laborers and household service workers are at the lowest level of complexity. This cognitive task complexity measure largely matches the conventional one-dimensional notion of skill numerical tasks and verbal tasks may make more sense than cognitive and motor tasks, because the highly educated are unlikely to be in occupations in which they are rewarded for their physical abilities. Task categories should be chosen depending on the purpose of analysis.

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19 See supplementary appendix for the robustness check on this issue.
20 See supplementary appendix for a technical discussion on PCA.
21 Most previous studies, including Ingram and Neumann (2006), Bacolod and Blum (2010), and Poletaev and Robinson (2008), use the 1995 DOT which does not contain the number of workers holding each occupation. Those authors are forced to assume the weights of each DOT occupation are equal, despite the fact that, in the real economy, some occupations may have few workers and some occupations may have thousands. This limitation may bias the task complexity index in an unpredictable direction. I avoid this problem because the augmented CPS contains the number of workers in each DOT occupation.
22 The DOT occupational code crosswalk between the fourth and the revised editions is used for matching.
23 I also estimate the model using the first principal components without converting them into percentile scores. The results are almost unchanged. See supplementary appendix for detail.
levels seen in the empirical literature (Gibbons, Katz, Lemieux, and Parent (2005), for example). However, this index alone is not rich enough to describe heterogeneous tasks across occupations. For example, cognitive task complexity is similar between sales and craft occupations, although the complete nature of tasks differs very much between the two. Motor task complexity more clearly characterizes the difference between sales workers and craft workers. Motor tasks of craftsmen such as automobile mechanics and carpenters are most complex, while those of sales workers, household service workers, and managers are least complex. These features are quite intuitive and the proposed measurement is a useful description of the heterogeneity of occupations. Another important finding here is that task complexity varies within 1-digit occupation. The reported standard deviation is large in all 1-digit occupations. To assess the extent of heterogeneity within occupations more formally, I decompose the total task complexity variance into the within-occupation variance and the between-occupation variance. For cognitive task complexity, about 59% of the total variance is explained by the within-occupation variance. For motor task complexity, the within-occupation variance explains a larger fraction of the total variance at 75%. This variance decomposition indicates that tasks are greatly heterogeneous within 1-digit occupations and that quite a large part of task complexity variation would be lost if one relies on the 1-digit occupation code. Dealing with occupations at the 3-digit level is essentially important in accounting for heterogeneity of jobs thoroughly.

Dispersion of the task complexity index within 1-digit occupation is so large that two different 1-digit occupations overlap in terms of task complexity. Figure 1 is a scatter plot of the task complexity indexes for 3-digit occupations. In the top panel, I show a plot of task complexity indexes of 3-digit occupations that are broadly categorized into professional and clerical occupations at 1-digit level. By and large, professionals’ cognitive tasks are more complex than those of clerical workers. However, for some professional occupations, cognitive tasks are less complex than those of some clerical workers. The bottom panel also shows a similar pattern for craftsmen and operatives. Broadly speaking, craftsmen work on more complex cognitive and motor tasks than operatives. But, there are some operatives whose cognitive and motor tasks are more complex than those of some craftsmen. The results indicate that the idea that a certain 1-digit occupation is uniformly more skilled than the other is questionable.

The National Longitudinal Survey of Youth (NLSY) 1979 is particularly suitable for this study because it contains detailed individual career histories and focuses on young individuals who change occupations more frequently than older individuals. I concentrate on male workers who make a long-term transition to the full-time labor market during the period between 1979 and

\[^{24}\]The law of total variance states that \( \text{Var}(X) = E(\text{Var}(X|O)) + \text{Var}(E(X|O)) \), where \( X \) is the task complexity index and \( O \) is the occupational affiliation at 1-digit level. The first term is the within-occupation variance and the second term is the between-occupation variance.
I define a long-term transition to occur when an individual spends three consecutive years working 30 hours per week or more. After removing those who do not make a long-term transition and those with missing values, I have the career histories of 2,417 men, with 32,849 person-year observations of occupational choices and 27,063 person-year observations of wages. The full details of data set construction and the robustness of estimates to sampling criteria are discussed in Appendix F and supplementary appendix, respectively. The sample mean AFQT score divided by 100 is 0.50 and the sample standard deviation is 0.29. The sample mean years of education is 13.22 and the sample standard deviation is 2.45. In the sample, 10% of individuals are Black and 7% are Hispanic.

Previous empirical papers, including Neal (1999) and Sullivan (2009), report that the occupation codes in the NLSY are often misclassified. One possible way to correct these errors is to assume that all occupation changes within the same employer are false. Neal (1999), Pavan (forthcoming), and Yamaguchi (2010b) take this approach to identify their broadly defined occupation changes. However, this edit is likely to result in a downward bias in the mean task complexity, because many occupation code changes within the same employer are promotions to managers. Another editing method assumes that cycles of occupation code are false. If an individual’s occupation code changes from A to B, and then comes back to A in the next year, I edit the code so that he remains in occupation A in all of these three years regardless of whether he changes an employer or not. I also edit missing occupation code similarly. If I find the same occupation codes in the years bracketing a year in which the occupation code is missing, the missing code is replaced with that found in the bracketing years. I estimate the model using both the unedited data and the data edited by the method outlined here. The results available in supplementary appendix indicate that this editing method affects the parameter estimates little. A possible explanation for this is that an occupation is often mis-coded to other occupations that are similar in terms of job characteristics. If this is the case, when the NLSY falsely classifies the same occupation as different, it may result in only a small measurement error in task complexity. Because there is no evidence that this editing method makes the data close to the truth and editing makes little difference in the parameter estimates, I take the data as it is.

Observations after year 2000 are not included in the sample, because in surveys later than 2002 the occupation code is not compatible with that used until 2000. Since 2002 survey, the NLSY adopts the 2000 census three-digit occupation code and it is quite different from the 1970 census code. Although IPUMS-CPS provides an occupational crosswalk, some occupations in the 2000 census code do not exist in the 1970 census code and thus, the DOT occupational characteristics are missing. O*NET, which is the successor of the DOT, contains occupational characteristics for these recent occupations, but the O*NET variables are not compatible with those of the DOT. Due to these limitations, I drop the post-2000 observations in the NLSY.
4.2 Career Progression Patterns

The time profiles of the average wage and occupational task complexity are presented in Figures 2, 3, 4, and 5. At the point of long-term transition to the labor market, the average cognitive task complexity index of men is 0.41. Individuals take on more and more complex cognitive tasks over time; the cognitive task complexity index reaches 0.52 in 10 years and 0.55 in 20 years. The mean motor task complexity slightly decreases over time: at the entry to the labor market, it is 0.53 and decreases to 0.52 in 10 years and 0.51 in 20 years. Mean wages grow by 48% in 10 years and by 64% in 20 years as measured by logwage differences.

These profiles are also presented for three different schooling levels: high school dropouts (education less than 12 years), high school graduates (12 years of education), and college workers (education more than 12 years). The cognitive task complexity indexes at labor market entry are substantially different across education groups, with more educated workers taking jobs that involve more complex cognitive tasks. The average indexes at entry are 0.28 for dropouts, 0.33 for high school graduates, and 0.53 for college workers. But, for all education groups, cognitive task complexity increases over time. It grows to 0.36 in 10 years and 0.44 in 20 years for dropouts and 0.41 in 10 years and 0.50 in 20 years for high school graduates. The profile for college workers is concave. The cognitive task complexity for college workers grows to 0.67 in 10 years, but the speed of the growth slows down and it reaches 0.69 in 20 years.

The profiles of motor task complexity are also very different across education groups. Less educated workers tend to take jobs that involve more complex motor tasks. The motor task complexity at labor market entry is 0.57 for dropouts, 0.55 for high school graduates, and 0.50 for college workers. Unlike cognitive task complexity, motor task complexity does not increase over time for all education levels. For high school dropouts, it monotonically grows to 0.63 in 10 years and 0.64 in 20 years. The profile for high school graduates is hump-shaped. It peaks at 0.60 in 6 years and decreases to 0.53 in 20 years. The motor task complexity for college workers monotonically decreases to 0.45 in 10 years and 0.44 in 20 years.

5 Estimation Results

5.1 Model Fit

Using the estimated parameters, I calculate the predicted paths of the mean wage and task complexity of occupations through simulation. I simulate each individual in the sample 1,000 times, from his entrance to the full-time labor market until the last year when he is seen in the data. To avoid potential attrition problems, if information about wage and/or occupational choice is missing in a certain year, I treat the corresponding simulation outcomes as missing.
Figures 2, 3, 4, and 5 compare the actual and predicted profiles of mean task complexity and hourly logwage over time. The predicted profiles for all men are very close to the actual profiles from the data. For high school dropouts, the model fit to the profiles of motor task complexity and logwage is good, but the predicted cognitive task complexity is lower than the actual profile. For high school graduates, cognitive task complexity is slightly over-predicted, but the level of the predicted motor task complexity and logwage is close to that of the data. Finally, for college workers, the model fit is very well for all of three dimensions. All in all, the model shows an ability to fit these interesting features of the data.

To see how well the model is able to match the variation in wages over time across people within the broadly defined educational categories, Figures 6 and 7 show wage profiles at the 10th, 30th, 50th, 70th, and 90th percentiles of the wage distribution in the actual and simulated data. At the 10th percentile, the model under-predict the wages, but the differences are small. The model shows a good fit to the data in this dimension as well.

### 5.2 Parameter Estimates

#### 5.2.1 Wage Equation

Table 2 presents the parameter estimates of the wage equation (see Equation 5) and their standard errors. The implicit skill prices are given by \( p_2 + P_3 x_t \), and significantly increase with task complexity \( x_t \). The estimated implicit skill prices imply that an increase of cognitive skills by one unit (i.e. one standard deviation of the initial skills) raises logwage by 0.74 for the job at the 90th percentile in cognitive task complexity and by 0.65 for the job at the 10th percentile. An increase of motor skills by one unit raises logwage by 0.62 for the job at the 90th percentile in motor task complexity and by 0.58 for the job at the 10th percentile. These estimates indicate that differences in returns to skills across occupations are sizable.

Using the estimated wage equation, I calculate the potential wage losses following job displacement. This exercise can also be interpreted as measuring the extent of skill transferability across jobs. To see the cognitive skill transferability, consider an average college worker with 10 years of experience. He has 1.405 units of cognitive skills. Suppose that this worker occupies a job at the 90th percentile in cognitive task complexity. If he moves to a job with the same motor tasks, but it is at the 10th percentile in cognitive task complexity, then he suffers a 13% of wage loss. Next consider an average high school dropout worker with 10 years of experience to see the motor skill transferability. He has 0.871 units of motor skills. If this worker moves from a job at the 90th percentile in motor task complexity to a job at the 10th percentile, while cognitive task complexity remains the same, his wage loss would be 12%. These estimates show that displacement of a worker to a very different occupation results in a significant wage loss.
How could these estimates be interpreted in the context of the related literature? Kambourov and Manovskii (2009) estimate the returns to occupation-specific experience by the IV approach proposed by Altonji and Shakotko (1987) and find that 5 years of occupation-specific experience increase wages by 12-20\%. Note that they do not estimate the contribution of occupation match quality to the wage growth during the first 10 years. Pavan (forthcoming) estimates a structural model of two-stage job search in the style of Neal (1999). His wage growth decomposition results show that a worker with 10 years of experience would suffer a 5-12\% of wage loss by an exogenous job displacement. Yamaguchi (2010b) also estimates a similar model to Pavan (forthcoming) and finds that the wage loss would be 20-23\%. These results must be carefully interpreted because all of these papers and this paper use more or less different samples and models.

Nevertheless, smaller wage losses following job displacement (or more skill transferability, equivalently) in this paper than Kambourov and Manovskii (2009) and Yamaguchi (2010b) may suggest a limitation of the current model: a lack of truly occupation-specific skills. Two occupations could have very similar cognitive and motor tasks, but could also require very different occupation-specific knowledge. For example, using the definition of occupations presented in the model, the three digit occupations of economist and actuary are very similar since both require high cognitive skills, but very low motor skills. However, certainly there are large amounts of economist and actuary specific knowledge that distinguish these occupations. In addition, firm-specific component of wage is missing. Job search literature shows that a substantial amount of wage growth is from job search. This effect may be absorbed in the skill shocks in the present model. These issues should be addressed in the future research to improve understanding of skill transferability.

5.2.2 Skill Transition

Parameter estimates for the skill transition equation (see Equation 6) and the initial skill endowment (see Equation 7) are reported in Table 3. The parameters for all diagonal elements of $A_1$ are positive and significant, indicating that skills grow faster when tasks are more complex. This result is consistent with skill acquisition through learning-by-doing and does not support the occupational choice mechanism due to the trade-off between returns to skills and learning opportunities, which is postulated by Rubinstein and Weiss (2006).

Education and AFQT scores are also positively associated with faster cognitive skill growth, while they are negatively associated with motor skill growth. No significant differences in learning ability are found across race. Skill shocks are about 15\% of one standard deviation for the initial skill distribution. Cognitive and motor skill shocks are highly and negatively correlated with the

\footnote{Although occupation is differently defined, Yamaguchi (2010b) reports that the average occupation-specific experience is about 5 years for workers with 10 years of experience.}
correlation coefficient -.83, which is calculated from the estimates for the variance-covariance matrix $\Sigma_e$. The annual skill depreciation rates for cognitive and motor skills are slightly less than 10%, which implies that skills are highly persistent over time.\footnote{These estimates seem reasonable, although no other papers estimate parameters that can be directly compared with mine. Mincer and Ofek (1982) and many other papers estimate the depreciation of human capital by extracting the variation of time out of work. This paper cannot apply this identification strategy, because all individuals in the model work full time. Nevertheless, skill depreciation parameters are still identified by the extent to which the task complexity of previous jobs affects the current wage and the current occupational choice.}

The initial skill endowment differs across individuals in an unobserved way. For both cognitive and motor skills, about two thirds of the skill variance present at labor market entry is due to unobserved skills. The unobserved component of the initial skill endowment is negatively correlated with the correlation coefficient of -.77, which is calculated from the estimates for the variance-covariance matrix $\Sigma_{e1}$. The AFQT score is positively associated with initial cognitive skills, while it is negatively associated with initial motor skills, although neither association is statistically significant. A year of education is significantly associated with .18 more units of initial cognitive skills and .20 less units of initial motor skills. I do not find that initial skill endowments are significantly different across race after controlling for AFQT scores and education.

### 5.2.3 Job Preference

The parameter estimates for job preferences (see Equation 9) are reported in Table 4. The AFQT score and education are positively and significantly correlated with preferences for complex cognitive tasks. They are also positively correlated with preferences for complex motor tasks, although not significantly. Blacks significantly dislike complex cognitive tasks. Otherwise, no significant differences in job preferences are found across race. The results indicate that substantial heterogeneity in job preferences exists across individuals. The parameter $G_2$ is positive for both tasks, although it is only significant for motor tasks. This implies that workers endowed with plenty of motor skills enjoy complex motor tasks.

The estimate of the parameter $G_4$ suggests that workers suffer a large adjustment cost when entering into an occupation which involves very different tasks from what they have experienced. The transition parameter for work habits is significantly positive for cognitive tasks at $.475$, but almost zero for motor tasks, which implies that the tasks of jobs held more than a year ago do not influence occupational choice through job preferences. Initial work habits also vary across individuals. The AFQT score and education are positively and significantly correlated with the initial conditions for work habit for cognitive tasks, while they are positively, but insignificantly correlated with the initial conditions for work habit for motor tasks. Hispanics have slightly, but significantly higher initial conditions for work habit for cognitive tasks. Otherwise, no significant differences in the initial work habits are found across race.
6 Discussion

6.1 Do Cognitive and Motor Skills Account for Wage Variance?

To assess the importance of each type of skill in explaining the variation of wages, I decompose the logwage variance. Because the wage consists of two skill components and a white noise term, the logwage variance is the sum of the variance of the cognitive skill component, the variance of the motor skill component, the covariance of the two, and the variance of the white noise.

Table 5 presents the results for different education levels for the years 1, 10, and 20 following labor market entry. In Year 1, i.e. at labor market entry, for all education groups, both cognitive and motor skill wage components have large variances. As the level of education increases, the ratio of the variance of the cognitive skill component to that of the motor skill component increases. The covariance term is large and negative, which reflects the estimation results that the initial unobserved cognitive and motor skills as well as cognitive and motor skills shocks are highly and negatively correlated.29 As years progress, the logwage variance grows to .293 in Year 10 and to .360 in Year 20 for all males. This growth is achieved through the growth of both cognitive and motor skill wage components. However, the ratio of the variance of the cognitive skill component to that of the motor skill component grows over time for all levels of education.

What are the sources of the skill and wage differences across individuals? Are they due to the differences established by the labor market entry or do they result from the shocks that individuals receive over their careers? Individuals enter the labor market with different initial skill endowments, learning abilities, job preferences, and initial work habits. While the effect of the differences in the initial skill endowments and work habits on inequality later in the life decreases over time due to depreciation, differences in learning abilities and job preferences may have persistent effects on inequality throughout the life cycle. Job preferences affect wages through the choice of occupation, because implicit skill prices and learning opportunities are different across occupations. To evaluate the effects of the initial conditions on life cycle skill and wage inequality, the model is simulated under the restriction that individuals are homogeneous at labor market entry. When eliminating heterogeneity, I assume that the distributions are degenerated at the mean.30

The wage can be written as

\[ \ln w_t = p_0 + [p^C_{x_t} + p(x_t)^C S_t^C] + [p^M_{x_t} + p(x_t)^M S_t^M] + \eta_t, \]

where superscripts C is for cognitive skills and M is for motor skills. I call the term \( p^C_{x_t} + p(x_t)^C S_t^C \) the cognitive skill component and the term \( p^M_{x_t} + p(x_t)^M S_t^M \) the motor skill component.

This result is partly driven by the use of percentile scores as task complexity indexes. When task indexes are normally distributed, the estimated correlation coefficient is greater (or smaller in absolute value.) See Appendix D for a detailed discussion on this issue.

To simulate homogeneous agents, replace the vector of individual characteristics \( d_i \) by the sample mean \( \bar{d} \) and set \( \Sigma_{e1} = 0 \). All other parameters remain the same.
This assumption does not change the profiles of mean skills. The simulations are conducted under five different assumptions: (1) a benchmark simulation in which initial conditions are heterogeneous, (2) task preferences are homogeneous, (3) the initial skill endowments are homogeneous, (4) learning abilities are homogeneous, and (5) all initial conditions are homogeneous.

Table 6 presents the results for the logwage variance decomposition over years. In Year 1, about \(70\%\) \((= 1 - 0.061/0.206)\) of the logwage variance in Year 1 is explained by differences in the initial skill endowments and the most of the remaining is due to the white noise. The differences in preference and learning abilities do not affect the logwage variance in Year 1. In Year 10, the logwage variance in the benchmark simulation is 0.292. It decreases to 0.260 when preferences are homogeneous, to 0.234 when initial skill endowments are homogeneous, to 0.241 when learning abilities are homogeneous, and to 0.190 when all the initial conditions are homogeneous. These results imply that about 35\% of the logwage variance in Year 10 is explained by the initial conditions and that these three different factors have similar effects. In Year 20, the logwage variance in the benchmark simulation is 0.359. It decreases to 0.297 when preferences are homogeneous, to 0.335 when initial skill endowments are homogeneous, to 0.257 when learning abilities are homogeneous, and to 0.232 when all the initial conditions are homogeneous. When put together, the initial conditions account for about 35\% of the logwage variance in Year 20. This is a similar result to that for Year 10, but the three factors affect the logwage variance differently. Notice that the effect of the initial skill endowments on the logwage variance almost disappears in 20 years since labor market entry. While the differences in preference substantially affect the logwage variance and the differences in learning ability has the largest effect on the logwage variance in the same year.

The college / high-school logwage gaps are also examined by using the same set of simulations. Table 7 presents the results except for the simulation (5) in which all initial conditions are homogeneous, because no difference between the two groups exist by construction. Remember that college workers in this paper is those who went to a college for at least one year and may not have earned a degree. In Year 1, the logwage gap in the benchmark simulation is 0.126 and explained almost entirely by the difference in initial skill endowments. The effect of the differences in the initial skill endowments on the logwage gap diminishes over time: they account for the logwage gap by 0.028 \((= 0.460 - 0.432)\) out of 0.460 in Year 20. The differences in preference significantly accounts for the logwage gap by 0.109 \((= 0.340 - 0.231)\) in Year 10 and 0.152 \((= 0.460 - 0.308)\) in Year 20, which implies that heterogeneity in preference accounts for about a third of the college / high-school wage gap in Year 20. The differences in learning ability have the largest and increasing influence on the logwage gap. When high school and college workers have the same learning ability, the logwage gap decreases by 0.185 \((= 0.340 - 0.155)\) in Year 10 and by 0.293 \((= 0.460 - 0.167)\) in Year 20, which implies that heterogeneity in learning ability accounts for about
two thirds of the wage gap in Year 20.

The variance decomposition exercise reveals that both cognitive and motor skills substantially account for wage variances, but cognitive skills are more important than motor skills for educated and experienced individuals. Differences established at labor market entry account for about 35% of the logwage variance 10 and 20 years after labor market entry. The remaining fraction of inequality is explained by shocks received over the careers of individuals. The college/high-school wage gap is largely explained by the differences in learning ability. The difference in task preference also accounts for the gap substantially at about 30%. The effect of the initial skill endowments gradually decreases and almost disappears in 20 years since labor market entry.

6.2 The Growth of Skills and Wages

How do unobserved skills grow over the careers of workers? Are the skill growth patterns different across groups? Remember that the observed task complexity does not necessarily mirror the underlying skills, because not only skills, but also job preferences affect the choice of occupations. It is possible that one worker has more skills than the other even though the former’s tasks are less complex than the latter’s. Time profiles of the underlying skills cannot be uncovered without the model.

Using the parameter estimates, I calculate the time profiles of mean unobserved skills by education in Table 8. In Year 1, initial skill endowments are different according to education. Remember that mean of the initial skill distribution is set zero and that the skill scale is normalized by making the standard deviation of the initial skill distribution one. The initial cognitive skills are -0.813 for high school dropouts, -0.269 for high school graduates, and 0.498 for college workers. In contrast, initial motor skills decrease with education: they are 0.731 for high school dropouts, 0.240 for high school graduates, and -0.448 for college workers. Cognitive skills grow over time for all levels of education, but they grow faster for the educated for two reasons. First, educated workers have a better learning ability. Second, educated workers tend to enter occupations with high cognitive task complexity and thus, enjoy more opportunities of skill learning on the job. Consequently, the cognitive skill gap across education levels grows over time because of self-selection into occupations and learning-by-doing. Motor skills grow for high school dropouts, but they are constant for high school graduates and decrease for college workers, which results in a growing gap in motor skills across education levels and over time. This result on motor skills is also driven by different learning abilities, self-selection, and learning-by-doing.

How does the growth of these skills translate into wages? To answer this question, I decompose

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31 Differences in task complexity contribute to skill differences. However, for individuals with homogeneous initial conditions, the task complexity differences are due to i.i.d. shocks $\nu_t$ and $\varepsilon_t$. This is why all differences are either due to initial conditions or due to shocks.
wage growth into contributions from cognitive skills and contributions from motor skills. Notice that the profile of skills itself, even if observed, does not answer this question, because a rapid growth of skills does not translate into a sizable wage growth if the skill prices are low. Table 9 presents the wage growth accumulated during the first five, ten, and twenty years following labor market entry. Cognitive skills are the main source of wage growth for all education groups, with the importance of cognitive skills to wage growth increasing in education level. Cognitive skills increase wages by about 12% for high school dropouts, 36% for high school graduates, and 72% for college workers during the first ten years. The wage growth due to cognitive skill growth slows down in the next ten years for all levels of education. Motor skills contribute to wage growth differently across education. For college workers, wages decrease due to the deterioration of motor skills by 7% in 5 years, 12% in 10 years, and 19% by 20 years. Motor skill growth contributes little to the wage growth of high school graduates. However, for high school dropouts, the growth of motor skills is an important source of wage growth. Their wages grow by 13% in 5 years, 22% in 10 years, and 34% in 20 years, which implies that motor skills account for about a half of high school dropouts’ wage growth. The results indicate that cognitive skills are generally the main source of wage growth and they are more important for more highly educated workers. Motor skills contribute only to the wage growth of high school dropouts and account for about a half of their wage growth in the first twenty years following their full time transition to the labor market.

The wage growth is driven by changes in tasks as well as changes in skills. To see the contribution of changes in tasks to the wage growth, I calculate counterfactual wages under two assumptions. In the first simulation, I calculate the wages over time when workers are stuck in their first jobs to evaluate the overall contribution of changes in task complexity over time. The results in column (7) of Table 9 show that the wages in this simulation are about 4 and 7 percentage points lower than those in the benchmark simulation in Years 10 and 20, respectively. The wage differences are accounted for by that lower task complexity leads lower skill prices and less opportunity of skill learning. To isolate the effects of the lower skill prices resulting from lower task complexity, I calculate the counterfactual wages when task complexity is held fixed at the first period level, but skills are identical with the benchmark simulations. The results in column (6) of Table 9 show that the wage growth rate of men 20 years since labor market entry drops by 3 percentage points. The modest effects of the changes in task complexity might indicate again that the model does not fully account for truly occupation-specific skills.

7 Conclusion

In this paper I propose a new approach to modeling heterogeneous human capital through a novel application of the DOT. While task information is usually used as a skill proxy, this paper clearly
distinguishes between tasks and skills. A key feature of the model is that an occupation is a bundle of tasks, and thus, it is characterized in a continuous space of task complexity. This approach has two advantages over the previously employed Roy-type models. First, it accounts for many heterogeneous occupations without computational burden and loss of precision of the parameter estimates, because the number of parameters and state variables do not increase with the number occupations in the model. This feature is appealing both to structural estimation and to reduced form estimation. Second, the model facilitates an interpretation as to how and why skills are differently rewarded across occupations. In addition, I show that a closed form solution for optimal occupational choice exists under some functional form assumptions. This analytical simplicity dramatically reduces computational burden and allows me to include many observed worker characteristics, which is often intractable for structural dynamic models. The solution also allows for an interpretation of the observed task complexity as a noisy signal of underlying skills, which helps me identify the dynamics of unobserved skills from the observed task information.

The model is estimated by the Kalman filter, using the task complexity measures from the DOT and career and wage histories from the NLSY. The parameter estimates indicate that returns to skills increase with task complexity and that skills grow faster when the worker is employed in an occupation characterized by more complex tasks. The logwage variance decomposition analysis shows that both cognitive and motor skills account for significant fraction of cross-sectional logwage variances. In terms of wage growth, cognitive skills play a central role. They account for all of wage growth for high school and college workers. However, for high school dropouts, the growth of motor skills accounts for about half of their wage growth.

While this paper demonstrates that the proposed model is useful in empirical human capital research, it still leaves some important areas for extensions and future research. First, truly occupation-specific and firm-specific components of wages are missing in the present model. Second, it would be useful to make schooling decisions endogenous. The empirical results indicate that large differences in skills and wages exist across education, but the sources of the differences remain unknown. Third, it would be useful to allow for endogenous labor force participation and hours of work. Although assuming that all individuals work full-time does not seem a serious concern for male workers, this extension is essential for the analysis of female workers. The extended model would be useful for understanding gender gaps in labor market outcomes from the viewpoint of tasks and skills, for example.

References


### Table 1: Task Complexity by Occupation at 1-Digit Classification

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Cognitive Task</th>
<th>Motor Task</th>
<th>Nobs.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std.Dev.</td>
<td>Mean</td>
</tr>
<tr>
<td>Professional</td>
<td>0.85</td>
<td>0.14</td>
<td>0.45</td>
</tr>
<tr>
<td>Manager</td>
<td>0.79</td>
<td>0.15</td>
<td>0.21</td>
</tr>
<tr>
<td>Sales</td>
<td>0.57</td>
<td>0.17</td>
<td>0.23</td>
</tr>
<tr>
<td>Clerical</td>
<td>0.49</td>
<td>0.16</td>
<td>0.56</td>
</tr>
<tr>
<td>Craftsmen</td>
<td>0.52</td>
<td>0.20</td>
<td>0.82</td>
</tr>
<tr>
<td>Operatives</td>
<td>0.20</td>
<td>0.18</td>
<td>0.58</td>
</tr>
<tr>
<td>Transport</td>
<td>0.28</td>
<td>0.15</td>
<td>0.63</td>
</tr>
<tr>
<td>Laborer</td>
<td>0.15</td>
<td>0.16</td>
<td>0.46</td>
</tr>
<tr>
<td>Farmer</td>
<td>0.68</td>
<td>0.19</td>
<td>0.78</td>
</tr>
<tr>
<td>Farm Laborer</td>
<td>0.18</td>
<td>0.19</td>
<td>0.53</td>
</tr>
<tr>
<td>Service</td>
<td>0.32</td>
<td>0.22</td>
<td>0.44</td>
</tr>
<tr>
<td>Household Service</td>
<td>0.20</td>
<td>0.11</td>
<td>0.24</td>
</tr>
<tr>
<td>All Occupations</td>
<td>0.49</td>
<td>0.29</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Source: The sample consists of all working individuals in the 1971 April CPS augmented with occupational characteristics variables from the Revised Fourth Edition of the DOT (1991). The sample size is 53,353. Task complexity measures are percentile scores divided by 100.

### Table 2: Wage Equation

<table>
<thead>
<tr>
<th>Notation</th>
<th>Estimates</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_0$</td>
<td>2.294</td>
<td>0.014</td>
</tr>
<tr>
<td>$p_1(1)$</td>
<td>0.015</td>
<td>0.012</td>
</tr>
<tr>
<td>$p_1(2)$</td>
<td>0.106</td>
<td>0.019</td>
</tr>
<tr>
<td>$p_2(1)$</td>
<td>0.646</td>
<td>0.065</td>
</tr>
<tr>
<td>$p_2(2)$</td>
<td>0.575</td>
<td>0.078</td>
</tr>
<tr>
<td>$P_3(1,1)$</td>
<td>0.108</td>
<td>0.010</td>
</tr>
<tr>
<td>$P_3(2,2)$</td>
<td>0.047</td>
<td>0.012</td>
</tr>
<tr>
<td>$\sigma^2_{\eta}$</td>
<td>0.061</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Source: NLSY79 through 1979-2000. The sample consists of 2,417 men.

Note: The parameter estimates for the wage equation $\ln w_t = p_0 + p_1 x_t + (p_2 + P_3 x_t) s_t + \eta_t$, where $\eta_t \sim N(0, \sigma^2_{\eta})$. The first element of vectors and (1,1) element of matrices are for cognitive skills and the second element of vectors and (2,2) element of matrices are motor skills.
Table 3: Transition Equation and Initial Conditions for Skills

<table>
<thead>
<tr>
<th>Notation</th>
<th>Estimates</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D(1,1)$</td>
<td>0.925</td>
<td>0.002</td>
</tr>
<tr>
<td>$D(2,2)$</td>
<td>0.911</td>
<td>0.008</td>
</tr>
<tr>
<td>$a_0(1)$</td>
<td>-0.309</td>
<td>0.034</td>
</tr>
<tr>
<td>$a_0(2)$</td>
<td>0.227</td>
<td>0.048</td>
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<tr>
<td>$A_1(1,1)$</td>
<td>0.057</td>
<td>0.009</td>
</tr>
<tr>
<td>$A_1(2,2)$</td>
<td>0.101</td>
<td>0.036</td>
</tr>
<tr>
<td>$A_2(1,1)$, AFQT</td>
<td>0.071</td>
<td>0.032</td>
</tr>
<tr>
<td>$A_2(1,2)$, Edu</td>
<td>0.026</td>
<td>0.003</td>
</tr>
<tr>
<td>$A_2(1,3)$, Black</td>
<td>0.015</td>
<td>0.025</td>
</tr>
<tr>
<td>$A_2(1,4)$, Hispanic</td>
<td>-0.040</td>
<td>0.026</td>
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<tr>
<td>$A_2(2,1)$, AFQT</td>
<td>-0.044</td>
<td>0.044</td>
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<tr>
<td>$A_2(2,2)$, Edu</td>
<td>-0.020</td>
<td>0.005</td>
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<tr>
<td>$A_2(2,3)$, Black</td>
<td>-0.036</td>
<td>0.033</td>
</tr>
<tr>
<td>$A_2(2,4)$, Hispanic</td>
<td>0.050</td>
<td>0.035</td>
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<tr>
<td>$\Sigma \epsilon(1,1)$</td>
<td>0.156</td>
<td>0.019</td>
</tr>
<tr>
<td>$\Sigma \epsilon(2,1)$</td>
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<td>0.019</td>
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<td>$\Sigma \epsilon(2,2)$</td>
<td>0.145</td>
<td>0.021</td>
</tr>
<tr>
<td>$H(1,1)$, AFQT</td>
<td>0.514</td>
<td>0.410</td>
</tr>
<tr>
<td>$H(1,2)$, Edu</td>
<td>0.184</td>
<td>0.040</td>
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<tr>
<td>$H(1,3)$, Black</td>
<td>0.500</td>
<td>0.327</td>
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<td>$H(1,4)$, Hispanic</td>
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<td>0.344</td>
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<td>$H(2,1)$, AFQT</td>
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<td>0.469</td>
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<tr>
<td>$H(2,2)$, Edu</td>
<td>-0.202</td>
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<tr>
<td>$H(2,3)$, Black</td>
<td>-0.638</td>
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<tr>
<td>$H(2,4)$, Hispanic</td>
<td>0.371</td>
<td>0.388</td>
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<tr>
<td>$\Sigma \epsilon_1(1,1)$</td>
<td>0.654</td>
<td>0.075</td>
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<tr>
<td>$\Sigma \epsilon_1(2,1)$</td>
<td>-0.519</td>
<td>0.080</td>
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<tr>
<td>$\Sigma \epsilon_1(2,2)$</td>
<td>0.685</td>
<td>0.089</td>
</tr>
</tbody>
</table>

Source: NLSY79 through 1979-2000. The sample consists of 2,417 men.

Note: The parameter estimates for the skill transition equation $s_{t+1} = Ds_t + a_0 + A_1x_t + A_2d + \epsilon_{t+1}$, where $\epsilon \sim N(0, \Sigma \epsilon)$. The initial skills are given by $s_1 = h + Hd + \epsilon_1$, where $\epsilon_1 \sim N(0, \Sigma \epsilon_1)$, $d$ is a vector of AFQT percentile score divided by 100, years of education, and dummy variables for race with Whites being the reference group. The unconditional mean and variance of initial skills are normalized to 0 and 1, respectively. The first element of vectors and (1,1) element of matrices are for cognitive skills and the second element of vectors and (2,2) element of matrices are motor skills.
Table 4: Job Preference and Work Habits

<table>
<thead>
<tr>
<th>Notation</th>
<th>Estimates</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$g_0(1)$</td>
<td>0.075</td>
<td>0.119</td>
</tr>
<tr>
<td>$g_0(2)$</td>
<td>-0.171</td>
<td>0.278</td>
</tr>
<tr>
<td>$G_1(1,1)$, AFQT</td>
<td>0.295</td>
<td>0.074</td>
</tr>
<tr>
<td>$G_1(1,2)$, Edu</td>
<td>0.038</td>
<td>0.009</td>
</tr>
<tr>
<td>$G_1(1,3)$, Black</td>
<td>-0.190</td>
<td>0.056</td>
</tr>
<tr>
<td>$G_1(1,4)$, Hispanic</td>
<td>0.055</td>
<td>0.063</td>
</tr>
<tr>
<td>$G_1(2,1)$, AFQT</td>
<td>0.047</td>
<td>0.172</td>
</tr>
<tr>
<td>$G_1(2,2)$, Edu</td>
<td>0.043</td>
<td>0.020</td>
</tr>
<tr>
<td>$G_1(2,3)$, Black</td>
<td>0.142</td>
<td>0.134</td>
</tr>
<tr>
<td>$G_1(2,4)$, Hispanic</td>
<td>-0.208</td>
<td>0.141</td>
</tr>
<tr>
<td>$G_2(1,1)$</td>
<td>0.037</td>
<td>0.020</td>
</tr>
<tr>
<td>$G_2(2,2)$</td>
<td>0.326</td>
<td>0.030</td>
</tr>
<tr>
<td>$G_4(1,1)$</td>
<td>-13.048</td>
<td>0.780</td>
</tr>
<tr>
<td>$G_4(2,2)$</td>
<td>-0.146</td>
<td>0.045</td>
</tr>
<tr>
<td>$A_3(1,1)$</td>
<td>0.475</td>
<td>0.007</td>
</tr>
<tr>
<td>$A_3(2,2)$</td>
<td>0.000</td>
<td>0.074</td>
</tr>
<tr>
<td>$\bar{x}_{1,0}(1)$</td>
<td>-0.218</td>
<td>0.024</td>
</tr>
<tr>
<td>$X(1,1)$, AFQT</td>
<td>0.152</td>
<td>0.019</td>
</tr>
<tr>
<td>$X(1,2)$, Edu</td>
<td>0.040</td>
<td>0.002</td>
</tr>
<tr>
<td>$X(1,3)$, Black</td>
<td>-0.017</td>
<td>0.015</td>
</tr>
<tr>
<td>$X(1,4)$, Hispanic</td>
<td>0.050</td>
<td>0.017</td>
</tr>
<tr>
<td>$\bar{x}_{1,0}(2)$</td>
<td>0.255</td>
<td>0.198</td>
</tr>
<tr>
<td>$X(2,1)$, AFQT</td>
<td>0.158</td>
<td>0.155</td>
</tr>
<tr>
<td>$X(2,2)$, Edu</td>
<td>0.007</td>
<td>0.017</td>
</tr>
<tr>
<td>$X(2,3)$, Black</td>
<td>0.219</td>
<td>0.125</td>
</tr>
<tr>
<td>$X(2,4)$, Hispanic</td>
<td>0.259</td>
<td>0.131</td>
</tr>
</tbody>
</table>

Source: NLSY79 through 1979-2000. The sample consists of 2,417 men.

Note: The utility from occupational characteristics is given by $v(x_t, \bar{x}_t, s_t, \nu_t) = (g_0 + G_1 d + G_2 s_t + \nu_t)' x_t + x_t' G_3 x_t + (x_t - \bar{x}_t)' G_4 (x_t - \bar{x}_t)$, where parameter $G_3$ is normalized as the negative of an identity matrix. The transition equation of work habit is $\bar{x}_{t+1} = A_3 \bar{x}_t + (I - A_3) x_t$, where $I$ is a $(2 \times 2)$ identity matrix. The initial work habit is given by $\bar{x}_1 = \bar{x}_{1,0} + X d$, where $d$ is a vector of AFQT percentile score divided by 100, years of education, and dummy variables for race with Whites being the reference group. The first element of vectors and (1,1) element of matrices are for cognitive skills and the second element of vectors and (2,2) element of matrices are motor skills.
### Table 5: Logwage Variance Decomposition

<table>
<thead>
<tr>
<th>Year</th>
<th>Cognitive</th>
<th>Motor</th>
<th>Covariance</th>
<th>Error</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.482</td>
<td>0.378</td>
<td>-0.715</td>
<td>0.061</td>
<td>0.205</td>
</tr>
<tr>
<td>All Men</td>
<td>0.353</td>
<td>0.339</td>
<td>-0.565</td>
<td>0.061</td>
<td>0.188</td>
</tr>
<tr>
<td>HS Dropouts</td>
<td>0.321</td>
<td>0.287</td>
<td>-0.471</td>
<td>0.061</td>
<td>0.198</td>
</tr>
<tr>
<td>High School</td>
<td>0.421</td>
<td>0.323</td>
<td>-0.600</td>
<td>0.061</td>
<td>0.204</td>
</tr>
<tr>
<td>College</td>
<td>0.913</td>
<td>0.546</td>
<td>-1.226</td>
<td>0.061</td>
<td>0.293</td>
</tr>
<tr>
<td>10</td>
<td>0.565</td>
<td>0.470</td>
<td>-0.871</td>
<td>0.061</td>
<td>0.224</td>
</tr>
<tr>
<td>20</td>
<td>0.502</td>
<td>0.399</td>
<td>-0.729</td>
<td>0.061</td>
<td>0.233</td>
</tr>
<tr>
<td>1</td>
<td>0.755</td>
<td>0.458</td>
<td>-0.997</td>
<td>0.061</td>
<td>0.277</td>
</tr>
<tr>
<td>HS Dropouts</td>
<td>0.571</td>
<td>0.431</td>
<td>-0.813</td>
<td>0.061</td>
<td>0.249</td>
</tr>
<tr>
<td>High School</td>
<td>0.934</td>
<td>0.506</td>
<td>-1.173</td>
<td>0.061</td>
<td>0.328</td>
</tr>
<tr>
<td>College</td>
<td>0.206</td>
<td>0.204</td>
<td>0.061</td>
<td>0.206</td>
<td>0.061</td>
</tr>
<tr>
<td>10</td>
<td>0.292</td>
<td>0.260</td>
<td>0.234</td>
<td>0.241</td>
<td>0.190</td>
</tr>
<tr>
<td>20</td>
<td>0.359</td>
<td>0.297</td>
<td>0.335</td>
<td>0.257</td>
<td>0.232</td>
</tr>
</tbody>
</table>

Source: The author’s estimates from the NLSY79 through 1979-2000. The sample consists of 325 high school dropouts, 1,009 high school graduates, and 1083 college workers.

### Table 6: Logwage Variance When Initial Conditions Are Homogeneous

<table>
<thead>
<tr>
<th>Year</th>
<th>Benchmark</th>
<th>Homogeneous Preference</th>
<th>Homogeneous Initial Skills</th>
<th>Homogeneous Learning Ability</th>
<th>Homogeneous in All</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.206</td>
<td>0.204</td>
<td>0.061</td>
<td>0.206</td>
<td>0.061</td>
</tr>
<tr>
<td>10</td>
<td>0.292</td>
<td>0.260</td>
<td>0.234</td>
<td>0.241</td>
<td>0.190</td>
</tr>
<tr>
<td>20</td>
<td>0.359</td>
<td>0.297</td>
<td>0.335</td>
<td>0.257</td>
<td>0.232</td>
</tr>
</tbody>
</table>

Source: The author’s estimates from the NLSY79 through 1979-2000. The sample consists of 2,417 men.
Table 7: College / High-School Logwage Gaps When Initial Conditions Are Homogeneous

<table>
<thead>
<tr>
<th>Year</th>
<th>Benchmark</th>
<th>Homogeneous Preference</th>
<th>Homogeneous Initial Skills</th>
<th>Homogeneous Learning Ability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.126</td>
<td>0.107</td>
<td>0.011</td>
<td>0.126</td>
</tr>
<tr>
<td>10</td>
<td>0.340</td>
<td>0.231</td>
<td>0.283</td>
<td>0.155</td>
</tr>
<tr>
<td>20</td>
<td>0.460</td>
<td>0.308</td>
<td>0.432</td>
<td>0.167</td>
</tr>
</tbody>
</table>

Source: The author’s estimates from the NLSY79 through 1979-2000. The sample consists of 2,417 men.

Table 8: Mean Skill Profiles by Education

<table>
<thead>
<tr>
<th>Year</th>
<th>All Men</th>
<th>HS Dropouts</th>
<th>High School</th>
<th>College</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cognitive Skills</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.000</td>
<td>−0.813</td>
<td>−0.269</td>
<td>0.498</td>
</tr>
<tr>
<td>10</td>
<td>0.631</td>
<td>−0.650</td>
<td>0.206</td>
<td>1.405</td>
</tr>
<tr>
<td>20</td>
<td>0.996</td>
<td>−0.539</td>
<td>0.489</td>
<td>1.923</td>
</tr>
<tr>
<td></td>
<td>Motor Skills</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.000</td>
<td>0.731</td>
<td>0.240</td>
<td>−0.448</td>
</tr>
<tr>
<td>10</td>
<td>−0.066</td>
<td>0.871</td>
<td>0.240</td>
<td>−0.637</td>
</tr>
<tr>
<td>20</td>
<td>−0.108</td>
<td>0.950</td>
<td>0.238</td>
<td>−0.750</td>
</tr>
</tbody>
</table>

Source: The author’s estimates from the NLSY79 through 1979-2000. The sample consists of 325 high school dropouts, 1,009 high school graduates, and 1083 college workers.
Table 9: Accumulated Wage Growth by Skill Type and Education

<table>
<thead>
<tr>
<th>Years Since Entry</th>
<th>Cognitive Skills</th>
<th>Benchmark (1)</th>
<th>Benchmark (2)</th>
<th>Benchmark (3)</th>
<th>C.F. 1 (4)</th>
<th>C.F. 2 (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dropouts</td>
<td>High School</td>
<td>College</td>
<td>All Men</td>
<td>All Men</td>
<td>All Men</td>
</tr>
<tr>
<td>5</td>
<td>0.068</td>
<td>0.209</td>
<td>0.416</td>
<td>0.282</td>
<td>0.276</td>
<td>0.271</td>
</tr>
<tr>
<td>10</td>
<td>0.124</td>
<td>0.362</td>
<td>0.716</td>
<td>0.487</td>
<td>0.472</td>
<td>0.454</td>
</tr>
<tr>
<td>15</td>
<td>0.166</td>
<td>0.472</td>
<td>0.927</td>
<td>0.634</td>
<td>0.612</td>
<td>0.580</td>
</tr>
<tr>
<td>20</td>
<td>0.197</td>
<td>0.549</td>
<td>1.074</td>
<td>0.737</td>
<td>0.710</td>
<td>0.665</td>
</tr>
</tbody>
</table>

| Motor Skills      |                  |               |               |               |            |            |
| 5                 | 0.061            | 0.003         | -0.069        | -0.021        | -0.026     | -0.027     |
| 10                | 0.098            | 0.003         | -0.120        | -0.038        | -0.045     | -0.044     |
| 15                | 0.124            | 0.002         | -0.156        | -0.052        | -0.059     | -0.055     |
| 20                | 0.141            | 0.000         | -0.183        | -0.063        | -0.071     | -0.062     |

| Total             |                  |               |               |               |            |            |
| 5                 | 0.129            | 0.212         | 0.347         | 0.261         | 0.249      | 0.244      |
| 10                | 0.222            | 0.365         | 0.596         | 0.448         | 0.427      | 0.410      |
| 15                | 0.291            | 0.474         | 0.771         | 0.582         | 0.552      | 0.525      |
| 20                | 0.337            | 0.549         | 0.892         | 0.674         | 0.639      | 0.603      |

Source: The author’s estimates from the NLSY79 through 1979-2000. The sample consists of 325 high school dropouts, 1,009 high school graduates, and 1,083 college workers.
B Figures

![Professional vs Clerical](image1)


Figure 1: Task Complexity Comparison
Source: The author’s estimates from the NLSY79 through 1979-2000. The sample consists of 325 high school dropouts, 1,009 high school graduates, and 1083 college workers.
Note: COG is for profiles of cognitive task complexity and MTR is for profiles of motor task complexity.

Figure 2: Model Fit (All Men)
Source: The author’s estimates from the NLSY79 through 1979-2000. The sample includes 325 high school dropouts. Note: COG is for profiles of cognitive task complexity and MTR is for profiles of motor task complexity.

Figure 3: Model Fit (High School Dropouts)
Source: The author’s estimates from the NLSY79 through 1979-2000. The sample includes 1,009 high school graduates.
Note: COG is for profiles of cognitive task complexity and MTR is for profiles of motor task complexity.

Figure 4: Model Fit (High School Workers)
Source: The author’s estimates from the NLSY79 through 1979-2000. The sample includes 1083 college workers.
Note: COG is for profiles of cognitive task complexity and MTR is for profiles of motor task complexity.

Figure 5: Model Fit (College Workers)
Source: The author’s estimates from the NLSY79 through 1979-2000. The sample consists of 325 high school dropouts, 1,009 high school graduates, and 1083 college workers.
Note: 10th, 30th, 50th, 70th, and 90th percentiles of hourly logwages are plotted over time.

Figure 6: Model Fit: Wage Growth by Percentile (All men and High School Dropouts)
High School

College

Source: The author’s estimates from the NLSY79 through 1979-2000. The sample includes 1,009 high school graduates and 1083 college workers.
Note: 10th, 30th, 50th, 70th, and 90th percentiles of hourly logwages are plotted over time.

Figure 7: Model Fit: Wage Growth by Percentile (High School and College Workers)
C Identification

This section discusses identification of the wage equation, skill equation, and the covariance skill distribution in a simplified setting. Denote the k-th element of a vector \( z \) by \( z(k) \). Similarly, denote the \((k,l)\) element of a matrix \( Z \) by \( Z(k,l) \). The wage equation can be rewritten as

\[
\ln w = p_0 + \sum_{k=1}^{K} p_1(k)x(k) + \sum_{k=1}^{K} [p_2(k) + P_3(k,k)x(k)]s(k) + \eta.
\]

To simplify the discussion, assume that skills are given by

\[
s(k) = \alpha_1(k)z_1(k) + \alpha_2(k)z_2 + \bar{s}(k),
\]

where \( z_1 \) is a vector of variables of which \( k \)-th element affects the \( k \)-th skills only (i.e. task complexity of the past job), \( z_2 \) is a scalar variable that can affect all types of skills (i.e. education, AFQT score, race) and \( \bar{s} \) is a vector of unobserved components of skills. Because skills have no natural unit, they must be normalized. Here, I normalize skills by setting \( \alpha_1(k) = 1 \) and \( E(\bar{s}(k)) = 0 \), because it simplifies the analysis below. In the main text, I normalized skills by setting the initial skill variance to be one and the mean of the initial skills to be zero, because it facilitates interpretation of the empirical results. Both ways of normalization are valid. Substituting the skill equation, I rewrite the wage equation as

\[
\ln w = p_0 + \sum_{k=1}^{K} p_1(k)x(k) + \sum_{k=1}^{K} [p_2(k) + P_3(k,k)x(k)]z_1(k) + \alpha_2(k)z_2 + \bar{s}(k) + \eta.
\]

Rearranging terms, I have

\[
\ln w = p_0 + \sum_{k=1}^{K} [p_1(k) + P_3(k,k)\bar{s}(k)]x(k) + \sum_{k=1}^{K} p_2(k)z_1(k) + \sum_{k=1}^{K} P_3(k,k)\alpha_2(k)z_2 + \left( \sum_{k=1}^{K} p_2(k)\bar{s}(k) + \eta \right).
\]

Consider the conditional mean of the log-wage,

\[
E(\ln w|x,z_1,z_2) = p_0 + \sum_{k=1}^{K} p_1(k)x(k) + \sum_{k=1}^{K} p_2(k)z_1(k) + \sum_{k=1}^{K} p_2(k)\alpha_2(k)z_2 + \sum_{k=1}^{K} P_3(k,k)x(k)z_1(k) + \sum_{k=1}^{K} P_3(k,k)\alpha_2(k)x(k)z_2.
\]
The variation of $x, z_1, z_2, xz_1, xz_2$ and the conditional mean of the logwage identifies the parameters $p_0, p_1, p_2, P_3$, and $\alpha_2$. The variance and covariance of unobserved skills are identified by the conditional variance of logwage, which is given by

$$V(\ln w|x,z_1,z_2) = \sum_{k=1}^{K} \sum_{l=1}^{K} [p_2(k) + P_3(k,k)x(k)][p_2(l) + P_3(l,l)x(l)]\text{Cov}[\tilde{s}(k),\tilde{s}(l)] + \sigma_\eta^2.$$ 

Given that $p_2$ and $P_3$ are identified by the conditional mean logwage, variance and covariance of unobserved skills are identified by the variation of $x(k)x(l)$ and the conditional variance.

## D Robustness: Normally Distributed Task Indexes

This section examines whether the main results are robust to the choice of the method to construct task complexity indexes. In the main text of the paper, I use the percentile scores, because they are easily interpreted. However, any monotonic transformation of the percentile scores is also valid as a task complexity measurement, because the original DOT variables are ordinal. To examine robustness of the main results, I estimate and simulate the model using task complexity indexes that are normally distributed. While this is not the only possible alternative to the percentile score, this is one of the sensible choices for at least two reasons. First, task indexes are normally distributed given the observed characteristics when the model is true. Because the skills and other stochastic variables are assumed to be normally distributed and tasks are linear in these variables, the tasks indexes are normally distributed as well. Of course, these stochastic variables may not be normally distributed, but assuming that tasks are normally distributed is consistent with the model assumptions. Second, the shape of a normal distribution is very different from the shape of the task distribution implied by percentile scores, which is a uniform distribution. Hence, this exercise is suitable for an examination of the possible effects of a distributional assumption on the main results.

The percentile scores are converted into normally distributed indexes in the following way. The percentile scores are truncated at 0.001 and 0.999 to avoid outliers. Then, the percentile scores are mapped onto the normal distribution with mean 0.5 and standard deviation 0.16. The mean and the standard deviation are chosen so that the new task indexes lie between 0 and 1 like the percentile scores.

For most parameters, the estimates are similar to those in the main text. However, an important difference is found for the estimates of the correlation coefficients of unobserved skills. Table 10 presents the estimates for the correlation coefficients for the unobserved variables for two different task measures. The correlation coefficients for the unobserved initial skills is negative for both indexes. However, the magnitude is significantly different: it is -0.776 when the percentile
scores are used while it is lower at -0.575 when the normally distributed task indexes are used. A similar pattern can be found for the correlation coefficient for the skill shocks: it is -0.833 for the percentile scores and -0.687 for the normal task indexes. The correlation coefficient for the preference shock is little affected by the choice of task indexes. These changes in the estimates for the correlation coefficients are reflected in the simulation results. Table 11 presents the log-wage variance decomposition results for the normally distributed task indexes. As expected, the covariance term is significantly smaller than that in the main results in Table 5. However, the qualitative result that both cognitive and motor skills are important for accounting the log-wage variance remains the same. Table 12 shows the results for decomposition of the wage growth for the normally distributed task indexes. Because the correlation coefficient for skills is smaller, the contributions of both cognitive and motor skills to the wage growth shift toward zero. However, again, the qualitative results remain the same.

The exercise in this section shows that most parameter estimates and simulation results are robust to choice of the task complexity indexes with one exception: the correlation coefficient of skills. Unfortunately, it is not possible to unanimously decide which index is better than the other, because both are valid. This problem comes from the restriction that the task is a linear function of unobserved skills. When the distribution of skills itself is of interest, one should allow for a more flexible functional form for the policy function for the task choice, although it means that the analytical solution and Kalman filter algorithm are no longer available.

Table 10: Estimates of Correlation Coefficients for Unobserved Variables

<table>
<thead>
<tr>
<th>Notation</th>
<th>Percentile Score Estimates</th>
<th>Std. Error</th>
<th>Normally Distributed Index Estimates</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Corr}(\epsilon_1(1), \epsilon_1(2))$</td>
<td>-0.7757</td>
<td>0.0498</td>
<td>-0.5751</td>
<td>0.0779</td>
</tr>
<tr>
<td>$\text{Corr}(\epsilon(1), \epsilon(2))$</td>
<td>-0.8332</td>
<td>0.0351</td>
<td>-0.6865</td>
<td>0.0587</td>
</tr>
<tr>
<td>$\text{Corr}(\nu(1), \nu(2))$</td>
<td>-0.0295</td>
<td>0.0038</td>
<td>0.0102</td>
<td>0.0038</td>
</tr>
</tbody>
</table>

Source: NLSY79 through 1979-2000. The sample consists of 2,417 men. The variables $\epsilon_1$, $\epsilon$, and $\nu$ are initial unobserved skills, skill shocks, and preference shocks, respectively. For each variable, the first element is for cognitive skills/tasks and the second element is for motor skills/tasks.
Table 11: Logwage Variance Decomposition for Normally Distributed Task Indexes

<table>
<thead>
<tr>
<th>Year</th>
<th>Cognitive</th>
<th>Motor</th>
<th>Covariance</th>
<th>Error</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Men</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>0.466</td>
<td>0.301</td>
<td>-0.622</td>
<td>0.061</td>
<td>0.206</td>
</tr>
<tr>
<td>Dropouts</td>
<td>0.287</td>
<td>0.219</td>
<td>-0.374</td>
<td>0.061</td>
<td>0.193</td>
</tr>
<tr>
<td>High School</td>
<td>0.221</td>
<td>0.136</td>
<td>-0.219</td>
<td>0.061</td>
<td>0.198</td>
</tr>
<tr>
<td>College</td>
<td>0.347</td>
<td>0.209</td>
<td>-0.412</td>
<td>0.061</td>
<td>0.205</td>
</tr>
<tr>
<td>Year 10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>0.818</td>
<td>0.393</td>
<td>-0.978</td>
<td>0.061</td>
<td>0.293</td>
</tr>
<tr>
<td>Dropouts</td>
<td>0.434</td>
<td>0.281</td>
<td>-0.547</td>
<td>0.061</td>
<td>0.228</td>
</tr>
<tr>
<td>High School</td>
<td>0.329</td>
<td>0.186</td>
<td>-0.341</td>
<td>0.061</td>
<td>0.235</td>
</tr>
<tr>
<td>College</td>
<td>0.589</td>
<td>0.276</td>
<td>-0.654</td>
<td>0.061</td>
<td>0.272</td>
</tr>
<tr>
<td>Year 20</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>1.025</td>
<td>0.435</td>
<td>-1.165</td>
<td>0.061</td>
<td>0.355</td>
</tr>
<tr>
<td>Dropouts</td>
<td>0.499</td>
<td>0.304</td>
<td>-0.617</td>
<td>0.061</td>
<td>0.247</td>
</tr>
<tr>
<td>High School</td>
<td>0.370</td>
<td>0.202</td>
<td>-0.382</td>
<td>0.061</td>
<td>0.251</td>
</tr>
<tr>
<td>College</td>
<td>0.720</td>
<td>0.304</td>
<td>-0.771</td>
<td>0.061</td>
<td>0.313</td>
</tr>
</tbody>
</table>

Source: The author’s estimates from the NLSY79 through 1979-2000. The sample consists of 325 high school dropouts, 1,009 high school graduates, and 1083 college workers.
Table 12: Accumulated Wage Growth by Skill Type and Education for Normally Distributed Task Indexes

<table>
<thead>
<tr>
<th>Years Since Entry</th>
<th>All Men</th>
<th>HS Dropouts</th>
<th>High School</th>
<th>College</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cognitive Skills</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.272</td>
<td>0.086</td>
<td>0.210</td>
<td>0.387</td>
</tr>
<tr>
<td>10</td>
<td>0.466</td>
<td>0.153</td>
<td>0.361</td>
<td>0.662</td>
</tr>
<tr>
<td>20</td>
<td>0.699</td>
<td>0.237</td>
<td>0.542</td>
<td>0.983</td>
</tr>
<tr>
<td><strong>Motor Skills</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>−0.008</td>
<td>0.041</td>
<td>0.006</td>
<td>−0.036</td>
</tr>
<tr>
<td>10</td>
<td>−0.015</td>
<td>0.066</td>
<td>0.009</td>
<td>−0.062</td>
</tr>
<tr>
<td>20</td>
<td>−0.030</td>
<td>0.093</td>
<td>0.008</td>
<td>−0.100</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.264</td>
<td>0.128</td>
<td>0.216</td>
<td>0.352</td>
</tr>
<tr>
<td>10</td>
<td>0.451</td>
<td>0.219</td>
<td>0.370</td>
<td>0.599</td>
</tr>
<tr>
<td>20</td>
<td>0.669</td>
<td>0.328</td>
<td>0.550</td>
<td>0.884</td>
</tr>
</tbody>
</table>

Source: The author’s estimates from the NLSY79 through 1979-2000. The sample consists of 325 high school dropouts, 1,009 high school graduates, and 1083 college workers.

E Model Solution

The goal of this section is to prove that (1) the value function is a quadratic function of the state variables \( z_t' = \{d_t, s_t, \bar{x}_t, \bar{v}_t\} \) and (2) the optimal policy function is a linear function of the state variables \( z_t \).

To simplify the problem, rewrite the original Bellman equation (12) in the following form

\[
V_t(z_t) = \max_{x_t} r_0 + r_1' x_t + r_2' z_t + x_t R_3 x_t + x_t R_4 z_t + z_t R_5 z_t + \beta E V_{t+1}(z_{t+1})
\]  

s.t.

\[
z_{t+1} = l_0 + L_1 z_t + L_2 x_t + \xi_{t+1}
\]

\[
V_{T+1} = 0,
\]

where

\[
\begin{align*}
    z_t' &= (d_t', s_t', \bar{x}_t', \bar{v}_t') \\
    \xi_{t'} &= (0', \epsilon_{t}', 0', 0')
\end{align*}
\]
\( r_0 = p_0 + \eta_t \) \hspace{1cm} (47)

\( r_1 = p_1 + g_0 \) \hspace{1cm} (48)

\( r_2' = (0', p_2', 0', 0') \) \hspace{1cm} (49)

\( R_3 = G_3 + G_4 \) \hspace{1cm} (50)

\( R_4 = (G_1, P_3 + G_2, -2G_4, I) \) \hspace{1cm} (51)

\( R_5 = \begin{pmatrix}
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & G_4 & 0 \\
0 & 0 & 0 & 0
\end{pmatrix} \) \hspace{1cm} (52)

\( l_0' = (0', a_0', 0', 0') \) \hspace{1cm} (53)

\( L_1 = \begin{pmatrix}
I & 0 & 0 & 0 \\
A_2 & D & 0 & 0 \\
0 & 0 & A_3 & 0 \\
0 & 0 & 0 & 0
\end{pmatrix} \) \hspace{1cm} (54)

\( L_2 = \begin{pmatrix}
0 \\
A_1 \\
I - A_3 \\
0
\end{pmatrix} \) \hspace{1cm} (55)

The claim (1) is trivially true in \( t = T + 1 \), because \( V_{T+1}(z_{T+1}) = 0 \). I show in the following that the value function in period \( t \) can be represented by a quadratic function of the state variables \( z_t \), if the value function in period \( t + 1 \) is given by a quadratic function of the state variables,

\[ V_{t+1}(z_{t+1}) = q_{0,t+1} + q_{1,t+1}'z_{t+1} + z_{t+1}'Q_{2,t+1}z_{t+1}, \] \hspace{1cm} (56)

where \( Q_{2,t+1} \) is a symmetric matrix. Consider the value function in period \( t \),

\[ V_t(z_t) = \max_{x_t} r_0 + r_1'x_t + r_2'z_t + x_t'R_3x_t + x_t'R_4z_t + z_t'R_5z_t + \beta E \left[ q_{0,t+1} + q_{1,t+1}'(l_0 + L_1z_t + L_2x_t + \xi_{t+1}) + (l_0 + L_1z_t + L_2x_t + \xi_{t+1})'Q_{2,t+1}(l_0 + L_1z_t + L_2x_t + \xi_{t+1}) \right]. \] \hspace{1cm} (57)

The first order condition for optimality is

\[ 0 = r_1 + 2R_3x_t + R_4z_t + \beta E \left[ L_2^t q_{1,t+1} + 2Q_{2,t+1}(l_0 + L_1z_t + \xi_{t+1}) \right] + 2L_2Q_{2,t+1}L_2x_t. \] \hspace{1cm} (58)
Solving this equation for \( x_t^* \), I find the optimal policy function

\[
x_t^* = -\frac{1}{2} (R_3 + L_2'Q_{2,t+1}L_2)^{-1} \left[ r_1 + \beta L_2'(q_{1,t+1} + 2Q_{2,t+1}l_0) + (R_4 + 2\beta L_2'Q_{2,t+1}L_1)z_t \right]
\]

(59)

\[
\equiv b_{0,t} + B_{1,t}z_t,
\]

(60)

where

\[
b_{0,t} = -\frac{1}{2} (R_3 + \beta L_2'Q_{2,t+1}L_2)^{-1} \left[ r_1 + \beta L_2'(q_{1,t+1} + 2Q_{2,t+1}l_0) \right]
\]

(61)

\[
B_{1,t} = -\frac{1}{2} (R_3 + \beta L_2'Q_{2,t+1}L_2)^{-1} \left[ R_4 + 2\beta L_2'Q_{2,t+1}L_1 \right].
\]

(62)

Substituting the optimal policy function (60) into the instantaneous utility function, I find

\[
\begin{align*}
r_0 + r_1'x_t^* + r_2'z_t + x_t^*R_3x_t^* + x_t^*R_4z_t + z_t^*R_5z_t \\
= r_0 + r_1'(b_{0,t} + B_{1,t}z_t) + r_2'z_t + (b_{0,t} + B_{1,t}z_t)'R_3(b_{0,t} + B_{1,t}z_t) + (b_{0,t} + B_{1,t}z_t)'R_4z_t + z_t^*R_5z_t \\
= \left[ r_0 + r_1'b_{0,t} + b_{0,t}'R_3b_{0,t} \right] + \left[ B_{1,t}r_1 + r_2 + 2B_{1,t}'R_3b_{0,t} + R_4b_{0,t} \right]'z_t + \\
z_t^* \left[ B_{1,t}'R_3B_{1,t} + B_{1,t}'R_4 + R_5 \right]z_t.
\end{align*}
\]

(63)

Notice that, using this expression for the optimal task complexity \( x_t^* \), I can rewrite the transition equation for the state variables as

\[
z_{t+1} = l_0 + L_1z_t + L_2(b_{0,t} + B_{1,t}z_t) + \xi_{t+1}
\]

(64)

\[
= (l_0 + L_2b_{0,t}) + (L_1 + L_2B_{1,t})z_t + \xi_{t+1}
\]

(65)

\[
\equiv f_{0,t} + F_{1,t}z_t + \xi_{t+1},
\]

(66)

where \( f_{0,t} = l_0 + L_2b_{0,t} \) and \( F_{1,t} = L_1 + L_2B_{1,t} \). Substituting this expression into the expected value function, I find

\[
EV_{t+1}(z_{t+1}) = E \left[ q_{0,t+1} + q_{1,t+1}z_{t+1} + z_{t+1}Q_{2,t+1}z_{t+1} \right]
\]

(67)

\[
= q_{0,t+1} + q_{1,t+1}'(f_{0,t} + F_{1,t}z_t) + \\
(f_{0,t} + F_{1,t}z_t)'Q_{2,t+1}(f_{0,t} + F_{1,t}z_t) + E \left[ \xi_{t+1}'Q_{2,t+1}z_{t+1} \right]
\]

(68)

\[
= q_{0,t+1} + q_{1,t+1}'f_{0,t} + f_{0,t}'Q_{2,t+1}f_{0,t} + E[\xi_{t+1}'Q_{2,t+1}z_{t+1}] + \\
\left[ F_{1,t}(q_{1,t+1} + 2Q_{2,t+1}f_{0,t}) \right]'z_t + z_t^* \left[ F_{1,t}'Q_{2,t+1}F_{1,t} \right]z_t.
\]

(69)
The value function for period $t$ is therefore given by

$$V_t(z_t) = q_{0,t} + q_{1,t}z_t + z_t^2Q_{2,t}z_t,$$

(70)

where

$$q_{0,t} = \left[r_0 + r_1' b_{0,t} + b_{0,t}' R_3 b_{0,t}\right] + \beta \left[q_{0,t+1} + q_{1,t+1} f_{0,t} + f_{0,t}' Q_{2,t+1} f_{0,t} + E[z_{t+1}' Q_{2,t+1} z_{t+1}]\right]$$

(71)

$$q_{1,t} = \left[B_{1,t} r_1 + r_2 + 2B_{1,t}' R_3 b_{0,t} + R_4 b_{0,t}\right] + \beta \left[F_{1,t}' (q_{1,t+1} + 2Q_{2,t+1} f_{0,t})\right]$$

(72)

$$Q_{2,t} = \left[B_{1,t}' R_3 B_{1,t} + B_{1,t}' R_4 + R_5\right] + \beta \left[B_{1,t}' L_1 Q_{2,t+1} L_1 + 2B_{1,t}' L_2 Q_{2,t+1} L_1 + B_{1,t}' L_2 Q_{2,t+1} L_2 B_{1,t}\right]$$

(73)

It remains to be shown that $Q_{2,t}$ is symmetric. Rewrite the matrix $Q_{2,t}$ such that

$$Q_{2,t} = R_5 + \beta L_{1,t} Q_{2,t+1} L_1 + B_{1,t}' \left[(R_3 + \beta L_{2,t} Q_{2,t+1} L_2) B_{1,t} + (R_4 + 2\beta L_{2,t} Q_{2,t+1} L_1)\right]$$

(74)

Notice that

$$B_{1,t}' \left[(R_3 + \beta L_{2,t} Q_{2,t+1} L_2) B_{1,t} + (R_4 + 2\beta L_{2,t} Q_{2,t+1} L_1)\right]$$

$$= B_{1,t}' \left[-\frac{1}{2} (R_4 + 2\beta L_{2,t} Q_{2,t+1} L_1) + (R_4 + 2\beta L_{2,t} Q_{2,t+1} L_1)\right]$$

(76)

$$= -\frac{1}{4} \left[R_4 + 2\beta L_{2,t} Q_{2,t+1} L_1\right]' (R_3 + \beta L_{2,t} Q_{2,t+1} L_2)^{-1} \left[R_4 + 2\beta L_{2,t} Q_{2,t+1} L_1\right].$$

(77)

Substituting this expression into Equation (75), I find

$$Q_{2,t} = R_5 + \beta L_{1,t} Q_{2,t+1} L_1 - \frac{1}{4} \left[R_4 + 2\beta L_{2,t} Q_{2,t+1} L_1\right]' (R_3 + \beta L_{2,t} Q_{2,t+1} L_2)^{-1} \left[R_4 + 2\beta L_{2,t} Q_{2,t+1} L_1\right].$$

(78)

Because $Q_{2,t+1}$ and $R_5$ are symmetric by assumption, this equation implies that $Q_{2,t}$ is symmetric. The claim (1) has been proved through mathematical induction.

The claim (2) is also proved in Equation (60). Notice that the parameter $B_{1,t}$ can be written as
\( B_{1,t} = [C_{1,t}, C_{2,t}, C_{3,t}, C_{4,t}] \). Hence the policy function can be written as Equation (19), because

\[
\begin{align*}
    x_t^* &= b_{0,t} + B_{1,t} z_t \\
    &= c_{0,t} + C_{1,t} d + C_{2,t} s_t + C_{3,t} x_t + C_{4,t} \tilde{\nu}_t \\
    &= c_{0,t} + C_{1,t} d + C_{2,t} s_t + C_{3,t} x_t + \nu_t,
\end{align*}
\]

where \( c_{0,t} = b_{0,t} \) and \( \nu_t = C_{4,t} \tilde{\nu}_t \).

\[ F \quad \text{DETAILS OF SAMPLING CRITERIA FOR NLSY79} \]

In the NLSY cross-section sample, 3,003 men are included. I dropped 294 individuals who served actively in the armed forces during the sample period. Out of 2,709 individuals, 149 individuals did not make a long-term transition to the full-time labor market until 2000. I also excluded 11 individuals who made the long-term transition at age 16 or younger, because they are likely to be mis-measured. I also dropped 131 out of 2,549 remaining individuals whose AFQT scores are missing. Finally, 132 individuals are excluded because there are less than 3 years of observations for these individuals. Hourly wages are deflated by the 2005 constant dollar using the CPI. If the recorded hourly wage is greater than $100 or less than one dollar, they are regarded as missing because they are likely to be mis-measured. After imposing all sample restrictions, the sample contains the career histories of 2,417 men, and contains 32,849 person-year observations of occupational choices and 27,063 person-year observations of wages. As a robustness check, I relax the restriction of the full-time work and include part-time jobs in the sample. This change does not affect the main results greatly, because male workers take part-time jobs only in the beginning of their careers. The detailed results for this robustness check are available in the supplementary appendix.