Life Cycle Human Capital Formation, Search Intensity, and Earnings Dynamics

(Job Market Paper)

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Abstract

In this paper I develop an estimatable partial equilibrium model where both human capital investment and search intensity are endogenized. The motivations of this unification are twofold. First, this unification enables me to quantify the relative contributions of each mechanism to life cycle earnings dynamics. Second, there are interesting interactions between human capital investment and search behavior. I show that search and human capital production function parameters can be separately identified using both earnings information and information on job-to-job transitions and unemployment-to-job transitions over the full life cycle. The structural parameters are estimated via indirect inference using synthetic cohorts constructed from the National Longitudinal Survey of Youth and the Survey of Income and Program Participation. Preliminary results show that human capital investment and search intensity reinforce each other and the two forces working together are able to produce a concave life cycle earnings profile. Human capital accumulation is the most important source for the earnings growth over the life cycle, accounting for 67-80% of the total earnings growth. Job search accounts for 20-33% of the total earnings growth.

Keywords: Human Capital, Job Search, Life Cycle, Earnings Dynamics, Structural Estimation.

JEL codes: J24, J64, D91.

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1 Introduction

One of most well known stylized facts in the empirical labor literature is that the life cycle earnings profile is concave. Figure 1 plots the life cycle earnings profile for high school graduates using a synthetic cohort constructed from the Survey of Income and Program Participation (SIPP).[1] We can see from Figure 1 that earnings rise rapidly over the first half of the life cycle, from age 20 to 40, and stabilize from age 40 to 60.

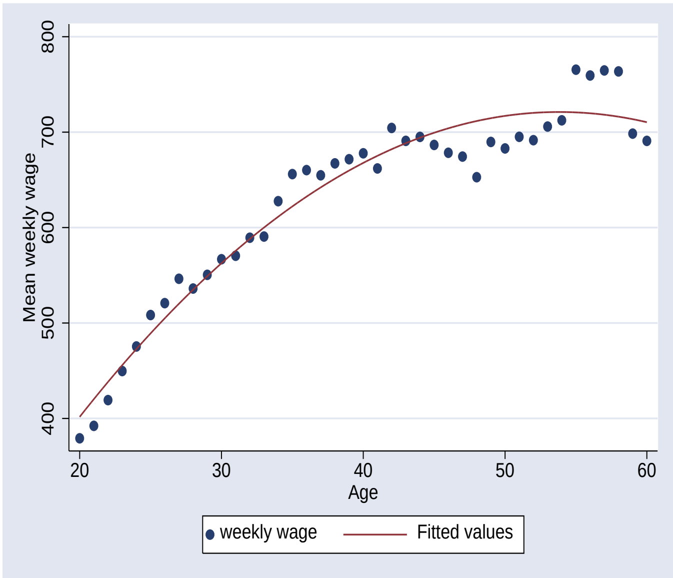


Figure 1: Life Cycle Earnings Profile

In their recent review, both theoretical and empirical, on post-schooling wage growth in the U.S., Rubinstein and Weiss (2005) acknowledge that human capital accumulation and job search are two main driving forces for this earnings dynamics over the life cycle.[2] Human capital theory argues that workers invest in human capital when they are young thus forgoing earnings and reaping the returns to investment when they become old. Search theory argues that workers climb up a job ladder, moving from low-paying to high-paying jobs. When they are young, workers are more likely to be in the lower tail of the wage distribution. This triggers a lot of job-to-job mobility associated with higher wage growth. As they age, the chance of accepting better outside options declines and fewer job-to-job transitions and lower wage growth result.

[1] See data section for details on sample construction.

[2] Rubinstein and Weiss (2005) also think that learning about job, worker or match quality is another potential explanation for the life cycle wage dynamics. However, learning is not considered in this paper.

This paper presents a life cycle model where both human capital investment and search intensity are endogenized to quantitatively examine the relative contributions of both mechanisms to the earnings dynamics over the life cycle. The motivation of this unification is twofold. First, as pointed out by Rubinstein and Weiss (2005), it is important and interesting to study the relative contributions of human capital accumulation and job search to life cycle earnings growth since they have different policy implications concerning training on the one hand and labor market mobility on the other hand. Understanding which mechanism is more important can provide theoretical grounds and support for policy makers to design policies and programs to improve workers' welfare. To do this, a framework which incorporates both human capital accumulation and job search is needed.

Second, there are interesting interactions between human capital investment and job search behavior over the life cycle as briefly discussed in Rubinstein and Weiss (2005). In their paper, they provide a fairly simple exercise where workers decide how much time to invest in human capital and receive exogenous job offers in the form of human capital rental rates. An interesting implication from their exercise is that workers invest more in human capital than they would without job search and with only a fixed rental rate of human capital. This is due to the upward drift in the distribution of the human capital rental rate, which is inherent in the search model. However, their model may miss the interactions in the other direction. That is, search behavior may change if human capital accumulation is allowed. The intuition is simple. Without human capital accumulation, the return to search is only realized for a fixed level of human capital. With human capital accumulation, the return to search is greater since it is now realized for growing human capital. Hence workers may tend to spend more effort on searching with human capital accumulation than without. Therefore, it is interesting to endogenize both human capital investment and job search within a single framework to examine the joint interactions.

The literature on quantifying the relative contributions of human capital accumulation and job search to life cycle earnings growth is relatively new. It can be divided into papers that use reduced form empirical analysis and those that use structural models. Using the first methodology, Mincer and Jovanovic (1979), Schönberg (2005), and Dustmann and Meghir (2005), among others, focus on using econometric methods to control the endogeneity of job mobility and unobserved heterogeneity. In general, they find that general human capital is the most important source of wage growth. The return to firm-specific human capital is mixed and differentiated across countries and skill groups. Job search accounts for 20 to 30% of total wage growth.

Within the structural model literature, the papers can be divided into 2 groups: papers that incorporate deterministic human capital accumulation into exogenous search models and those that allow for endogenous human capital accumulation in exogenous search models. Bunzel et al. (1999), Bagger et al. (2007), Barlevy (2005), Omer (2004), Yamaguchi (2006), and Pavan (2007) are included in the first group. Bunzel et al. (1999) allow for a linear human capital production function within Burdett and Mortensen (1998)'s wage-posting framework where wages are allowed to grow on the job linearly. They find that there is almost no human capital accumulation, especially for high school graduates using Danish data. Bagger et al. (2007) allow for a piece-wise linear human capital production function to examine how earnings dynamics are related to interfirm competition due to search, human capital accumulation, and idiosyncratic production shock within Postel-Vinay and Robin (2002)'s counter-offer framework. They find that human capital accumulation is more important than job search early in the career for medium and high skilled workers. Omer (2004) allows for a linear human capital accumulation within a partial search model and finds that on-the-job search contributes 4 times less than general experience to total wage growth. Yamaguchi (2006) allows for a polynomial human capital accumulation process and focuses on wage bargaining between firms and workers. He finds that human capital accumulation is more important and accounts for around 60% of the total wage growth over the first 10 years.

Compared to these papers, my paper differs in the following dimensions. First, these papers only allow for deterministic human capital accumulation and job offers arrive exogenously.[3] In my paper, both human capital investment and search intensity are endogenized thus allowing for endogenous job arrival rates. Second, most of these papers treat human capital accumulation and job search separately with no interactions. Omer (2004) and Yamaguchi (2006) do discuss the interactions but their models are restrictive in how human capital accumulation affects job search behavior. With human capital accumulation, the reservation wage (or match quality in Yamaguchi (2006) is lower than without. However, in my model, the interactions in both directions can be studied since both forces are endogenized. In particular, not only is the reservation rental rate lower, but the job arrival rate is higher with human capital accumulation than without. Third, these papers only focus on the wage growth over the first half of the life cycle within frameworks where workers live infinitely. My paper focuses on the earnings dynamics over the full life cycle within a life cycle framework.

Rubinstein and Weiss (2005) is included in the second group where only human capital investment is endogenized. My paper takes a further step by explicitly modeling both human capital investment and search intensity decisions within a relatively simple search framework to examine the interactions between human capital investment and job search. Jovanovic (1979) endogenizes both human capital investment and search intensity. However, he primarily focuses on the relationship between the firm-specific human capital and job separation within a matching framework.

In the model, workers face a non-degenerate distribution of the human capital rental rate in the presence of labor market imperfections.[4] Workers can improve their

[3] Pavan (2007) is an exception in the sense that he allows for the job arrival and job destruction rates to depend on a series of observable and unobservable characteristics.

[4] In this paper, I do not consider the firm's problem, i.e., how the rental rate distribution is determined. However, this question is important and will be investigated in the future.

earnings over the life cycle by accumulating human capital and searching for better rental rates. The expectation of rising rental rates through searching in the future gives workers more incentive to invest in human capital. In the meantime, workers tend to spend more effort on searching for better jobs due to the reinforcement from human capital accumulation. My preliminary results show that human capital investment and job search working together are able to produce a concave life cycle earnings profile. Workers are willing to accept lower rental rates at the beginning of life cycle in order to facilitate human capital formation. As more human capital is accumulated, job search becomes more beneficial. These interactions between human capital investment and job search cause a dramatic increase in earnings at the beginning of the life cycle. As the life cycle progresses, both job search and human capital accumulation slow down and so does earnings growth.

The structural model is estimated through indirect inference using synthetic cohorts constructed from the National Longitudinal Survey of Youth (NLSY) and the Survey of Income and Program Participation (SIPP). I show that the search and human capital production function parameters can be identified using both earnings information and information on job-to-job transitions and unemployment-to-job transitions over the full life cycle. Preliminary results show that human capital accumulation is more important in shaping the life cycle earnings profile, accounting for 67-80% of the total earnings growth. Job search also plays a substantial role, accounting for 20-33% of the total growth.

The rest of the paper is organized as follows. The model is presented in Section 2. Section 3 discusses the identification and estimation strategies. Details on sample selection and construction of labor market histories are presented in Section 4. Section 5 discusses estimation results and quantifies the relative contributions of human capital accumulation and job search to life cycle earnings dynamics. Section 6 concludes.

2 Model

2.1 The Environment

The model is built in the spirit of a Burdett and Mortensen (1998) search model and a Ben-Porath (1967) human capital production model. Workers enter the labor market unemployed at period 1, remain in the market until period T, and retire after period T. They maximize their expected earnings over T periods in the labor market by choosing how much market time to invest in human capital and how much effort to spend on search. At each period, they can be either unemployed or employed.

They may transit between unemployment and employment as well as from job to job. Workers face a non-degenerate distribution of the rental rate of human capital, $F(R)$, which is log-normally distributed. That is, $\ln(R) \sim N(\mu, \sigma^2)$. Time is discrete. Workers discount the future at a rate β.

2.2 Human Capital Production Technology

Workers are endowed with an initial stock of human capital, h_0, when they enter the labor market. Human capital is assumed to be homogeneous and transferrable across jobs. Workers can only invest in human capital while on the job. Here human capital refers to skills that workers can only acquire through working. Human capital does not change during the course of unemployment. Following Heckman et al. (1998), human capital does not depreciate.

Assume a simplified Ben-Porath human capital production function $Q(h, i)$, where h is the current human capital stock and i is the fraction of market time allocated to human capital investment. Assume the production function $Q(\cdot, \cdot)$ is concave in both h and i and takes the following specification

$$Q(h, i) = a(hi)^{\alpha},$$

where $0 < \alpha < 1$ is a curvature parameter and $a > 0$ is a scale parameter which represents learning ability. I assume learning ability is constant over time. Hence the law of motion for human capital for employed workers at period t is

$$h_{t+1} = h_t + a(h_t i_t)^{\alpha}.$$

2.3 Search Technology

In the search literature, there are several ways of measuring search intensity: fraction of time devoted to job search (Seater (1977) and Jovanovic (1979)), number of applications filled out or the number of job search methods used by a worker (Benhabib and Bull (1983) and Shimer (2004)), and search effort (Mortensen (2003), Christensen et al. (2005), Lise (2005)). Search effort can include time and resources spent on search as well as anything else that affects the job offer arrival rate. In this paper, I follow Mortensen (2003) and Christensen et al. (2005) and use search effort as the measure of search intensity.

Let $\lambda(s)$ denote the job offer arrival rate, an increasing and concave function of search effort s, with boundary conditions $\lambda(0) = 0$ and $\lambda'_{s \longrightarrow 0} = +\infty$. Assume a linear production function for the job offer arrival rate, i.e. $\lambda(s) = \lambda s$, where λ is a search efficiency parameter. Let $c(s)$ be the search cost function, increasing, strictly convex and twice differentiable, with boundary condition $c(0) = c'_{s \longrightarrow 0} = 0$. Following Mortensen (2003) and Christensen et al. (2005), the search cost function takes the following power form

$$c(s) = \frac{c_0 s^{1+\gamma}}{1+\gamma},$$

where $c_0 > 0$ is a scale parameter and $1+\gamma$ ($\gamma > 0$) is the elasticity of search cost with respect to search effort. Here the search cost refers to the pecuniary disutility associated with job search, not the opportunity cost of market time.

2.4 Worker's Problem

The state variables upon which workers make decisions include the employment state, the current stock of human capital, and the current rental rate. Let $U_t(h)$ denote the value of being unemployed at period t and with human capital h. Let $V_t(h, R)$ be the value of working at a firm offering a rental rate R at period t with human capital h. The worker's problem can be characterized recursively by two Bellman equations. The Bellman equation for an unemployed worker is

$$\begin{aligned} U_t(h) &= \max_{s_t^0} bh - c(s_t^0) + \beta\lambda s_t^0 \int \max\{U_{t+1}(h), V_{t+1}(h, R)\} dF(R) \\ &\quad + \beta(1 - \lambda s_t^0) U_{t+1}(h) \\ s.t \\ &\quad 0 \leq \lambda s_t^0 \leq 1 \end{aligned} \tag{1}$$

At period t, an unemployed worker receives some amount of compensation, bh which depends on his stock of human capital at that period. I assume b, the rental rate equivalent for the unemployed, is constant over time and independent of h. At the beginning of period t, given his human capital, h, the worker must decide how much effort, s_t^0, to expend on job search which in turn determines the job offer arrival rate at the end of period t. At the end of period t, with probability λs_t^0, he receives a job offer R from the offer distribution $F(R)$. He has to immediately decide whether to accept that offer by comparing the value of working at period $t+1$ if accepts to the value of staying unemployed at period $t+1$. With probability $1 - \lambda s_t^0$, he receives no offer and hence stays unemployed at period $t+1$.

The Bellman equation for an employed worker who works at a firm offering R

with human capital h at period t is

$$\begin{aligned}
V_t(h,R) &= \max_{\{s_t^1,i_t\}} Rh(1-i_t) - c(s_t^1) + \beta(1-\delta)(1-\lambda s_t^1)V_{t+1}(h',R) \\
&\quad +\beta(1-\delta)\lambda s_t^1 \int \max\{V_{t+1}(h',R'), V_{t+1}(h',R)\} dF(R') \\
&\quad +\beta\delta U_{t+1}(h') \\
s.t & \\
&\quad 0 \le i_t \le 1, \\
&\quad 0 \le \lambda s_t^1 \le 1 \\
&\quad h' = h + a(hi_t)^\alpha. \qquad (2)
\end{aligned}$$

At the beginning of period t, given his human capital stock h and rental rate R, an employed worker has to decide not only how much effort s_t^1 to spend on searching for a better job but also how much time i_t to invest in human capital and thus earnings to forego. The worker receives earnings $Rh(1-i_t)$ for period t and production, both commodity and human capital, then takes place. At the end of period t, the job can be destroyed with probability δ in which case the worker returns to unemployment at period $t+1$. With probability $(1-\delta)\lambda s_t^1$, the job is not destroyed and the worker receives a new job offer R' at the end of period t. The worker then must decide whether to accept the new job offer R' by comparing the value of working at the new job at period $t+1$ to that of staying with the current job at period $t+1$ with the new human capital h'. With probability $(1-\delta)(1-\lambda s_t^1)$, the job is not destroyed and the worker receives no offers and stays with the current job at period $t+1$.[5] Human capital grows due to investment and human capital at period $t+1$ is determined by the law of motion.

It can be shown from backward induction that $U_t(h)$ is increasing in h and $V_t(h,R)$ is increasing in both h and R. Given these properties of the value functions, unemployed workers adopt the following reservation rental rate strategy: only offers that are at least as good as the reservation rental rate, denoted by $\phi_t(h)$ and determined by $U_t(h) = V_t(h, \phi_t(h))$, are accepted. For employed workers, the reservation rental rate, at which workers are indifferent between accepting the new offer and staying with the current job, is the current rental rate, since human capital is general and transferable between jobs. Using the reservation rental rate strategies, the Bellman

[5]Since the model is non-stationary, it is possible that workers may find that quitting to unemployment is worthwhile in some cases. However, I find that they barely choose to do so after allowing voluntary quit to unemployment. Hence I abstract that choice here for simplicity.

equations (1) and (2) can be simplified as follows.

$$
\begin{aligned}
U_t(h) \quad = \quad & \max_{s_t^0} bh - c(s_t^0) + \beta\lambda s_t^0 \int_{\phi_{t+1}(h)} (V_{t+1}(h,R') - U_{t+1}(h))\, dF(R') \\
& + \beta U_{t+1}(h) \\
s.t.\quad & \\
& 0 \leq \lambda s_t^0 \leq 1. \qquad (3)
\end{aligned}
$$

$$
\begin{aligned}
V_t(h,R) \quad = \quad & \max_{\{s_t^1, i_t\}} Rh(1-i_t) - c(s_t^1) + \beta(1-\delta)V_{t+1}(h',R) + \beta\delta U_{t+1}(h') \\
& + \beta(1-\delta)\lambda s_t^1 \int_R (V_{t+1}(h',R') - V_{t+1}(h',R))\, dF(R') \\
s.t.\quad & \\
& 0 \leq i_t \leq 1, \\
& 0 \leq \lambda s_t^1 \leq 1 \\
& h' = h + a(hi_t)^\alpha. \qquad (4)
\end{aligned}
$$

2.5 Analysis

Assuming interior solutions, the following three first order conditions characterize the solutions to the model:

$$
c'(s_t^0) = \beta\lambda \int_{\phi_{t+1}(h)} (V_{t+1}(h,R') - U_{t+1}(h))\, dF(R'), \qquad (5)
$$

$$
c'(s_t^1) = \beta(1-\delta)\lambda \int_R (V_{t+1}(h',R') - V_{t+1}(h',R))\, dF(R'), \qquad (6)
$$

$$
\begin{aligned}
Rh \quad = \quad & \beta \frac{\partial h'}{\partial i_t} \left(\delta \frac{\partial U_{t+1}(h')}{\partial h'} + (1-\delta) \frac{\partial V_{t+1}(h',R)}{\partial h'} \right. \\
& \left. + (1-\delta)\lambda s_t^1 \int_R \left(\frac{\partial V_{t+1}(h',R')}{\partial h'} - \frac{\partial V_{t+1}(h',R)}{\partial h'} \right) dF(R') \right). \qquad (7)
\end{aligned}
$$

Equation (5) characterizes the optimal search intensity for the unemployed. The left hand side of the equation is the marginal cost of search and the right hand side is the marginal return to search. The interactions between human capital investment and job search lie in that unemployed workers tend to spend more effort on search and lower their reservation rates with human capital accumulation than without. The intuition is simple. Working is more attractive than staying unemployed, if human capital accumulation is allowed. On the one hand, workers receive constant compensation bh and see no growth in human capital while unemployed. On the other hand, they may augment their human capital and locate better outside offers while working. This encourages unemployed workers to exit unemployment as quickly as possible by searching more intensively and lowering their reservation rates. Hence s_t^0 is higher and the reservation rate $\phi_{t+1}(h)$ is lower than they would be without human capital growth. s_t^0 is increasing in h, because the marginal returns to search are higher for workers with more human capital.[6]

Equation (6) characterizes the optimal search intensity for the employed workers. The on-the-job search intensity with human capital growth is higher than without since the marginal return to search is higher than it would be with no human capital growth.[7] s_t^1 is increasing in h because search is more valuable for individuals with more human capital as the right hand side is increasing in h' which in turn is increasing in h. As R increases, the marginal return to search decreases since the probability of reaping the gains due to search becomes smaller. Hence s_t^1 is decreasing in R.

Equation (7) characterizes the optimal investment in human capital. The investment is decreasing in h due to the concavity of the human capital production function. The right hand side is the expected marginal return to human capital investment. It includes 3 parts. The first term is the marginal return to investment if workers end up unemployed next period. The second term is the marginal return to investment if workers stay with the same job. The last term is a "bonus" due to search, which is the expected marginal return to investment if workers switch jobs. To see how human capital investment interacts with job search, set δ equal to 0 for a moment. In a pure human capital world where there is no job search, the third term drops out and R does not matter for the investment decision. This is because what workers forego today per unit of human capital is the same as what they receive tomorrow. However, with job search, the marginal return to human capital investment now includes both the second and the third terms. Hence the investment in human capital is greater with job search than without. Meanwhile with job search, the investment in human capital is decreasing in R. This is because the "bonus" term is a decreasing function of R. The higher the R is, the less likely workers receive the "bonus". This is general as long as δ is small and b is relatively low compared to the distribution of the rental rate.

[6] This can be easily proved for period $T-1$. I assume without loss of generality that $U_{T+1} = V_{T+1} = 0$. In this case, $U_T(h) = bh$, $V_T(h,R) = Rh$, and $\phi_T(h) = b$. After substituting these into equation (5), the right hand side becomes $\beta\lambda h \int_b (R'-b)dF(R')$ which is increasing in h, as long as some of the rental rates are higher than b.

[7] This is clear for period $T-1$, since $U_T(h) = bh$ and $V_T(h,R) = Rh$. The marginal return to search with human capital accumulation is $\beta(1-\delta)\lambda h' \int_R (R'-R)dF(R')$ which is greater than the counterpart without human capital growth, $\beta(1-\delta)\lambda h \int_R (R'-R)dF(R')$ since $h' > h$.

2.6 Numerical Illustration

Due to the intractability of the analytical solutions to the structural model, I present a numerical example in this section to demonstrate how the model works and how human capital accumulation interacts with job search over the life cycle. To do this, I solve a 40-period model for a set of parameters listed in Table 1. The model is then simulated to generate a random sample of size of 20,000. Life cycle profiles of search intensities and human capital investment and those of wages and transitions are plotted in Figures 2 and 3.

Generally speaking, the search intensities, both for the unemployed and employed, decrease as workers age. Search intensity, plotted in panel (a) of Figure 2, for the unemployed is relatively flat. This is mainly because human capital only accumulates on the job. As long as investment in human capital is still beneficial, unemployed workers would like to work rather than stay unemployed. The search intensity on the job, plotted in panel (b) of Figure 2, is smaller than the counterpart for the unemployed. This implies the job arrival rate on the job is lower than that for the unemployed workers, which is consistent with the findings in the search literature. The search intensity on the job is decreasing over time because the values of outside options decrease as workers move from low-paying to high-paying jobs. Human capital investment, plotted in panel (c) of Figure 2, is also declining over time. At the end of the life cycle, workers barely invest in human capital. The curvature of the human capital investment depends on α. The larger α is, the more investment in human capital occurs at the beginning of the life cycle.

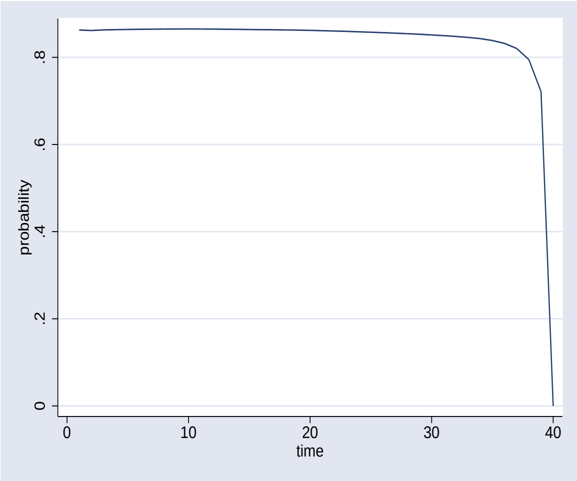
The reservation rate for the unemployed workers is generally increasing over time, as shown in panel (a) of Figure 3. At the beginning of the life cycle, workers would like to accept any rental rate and set their reservation rates equal to the minimum rental rate in the distribution under the current parameterization. This is because investment in human capital at the beginning of the life cycle is so valuable that workers would like to accept any job to start accumulating human capital. As human capital accumulates over time, the value of being unemployed increases and the incentive to invest in human capital declines. This causes the reservation rate to increase. The reservation rate decreases slightly when the life cycle comes to the end, equal to b at the last period. The rental rate, plotted in panel (b) of Figure 3, rises over time with a dramatic increase at the beginning of the life cycle and then stabilizes. This causes a big drop in the job-to-job transition rate at the beginning of the life cycle, as shown in panel (d) of Figure 3, along with the declining search intensity on the job. The unemployment-to-job transition rate, plotted in panel (c) of Figure 3, is also decreasing over time. Most of the decline is due to the increase of the reservation rate since the search intensity for the unemployed is relatively flat over time. As a result of both human capital accumulation and job search, as shown in panel (e) of Figure 3, wages increase over time and with a concave-shape.

The interactions between human capital investment and job search can be shown by examining how human capital investment responds to changes in the search parameters on the one hand and how search behavior responds to changes in the human capital production parameters. A high λ results in more investment in human capital and more human capital accumulated over time, as shown in panel (a) of Figure 4. This is because a high λ results in more unemployment-to-job and job-to-to job transitions increasing the expectation of an increase in the rental rate over the life cycle, holding everything else constant. For γ the pattern is reversed. A high γ means high search costs that discourage workers from searching for better outside options. Therefore workers make fewer unemployment-to-job and job-to-job transitions and less investment in human capital results, as shown in panel (b) of Figure 4. The parameters b and δ work the same way as γ. A high b increases the value of being unemployed and discourages workers from exiting unemployment. A high δ increases the probability of workers going back to unemployment and lowers the return to human capital investment. In both cases, less human capital accumulation results, as plotted in panels (c) and (d) of Figure 4, respectively.

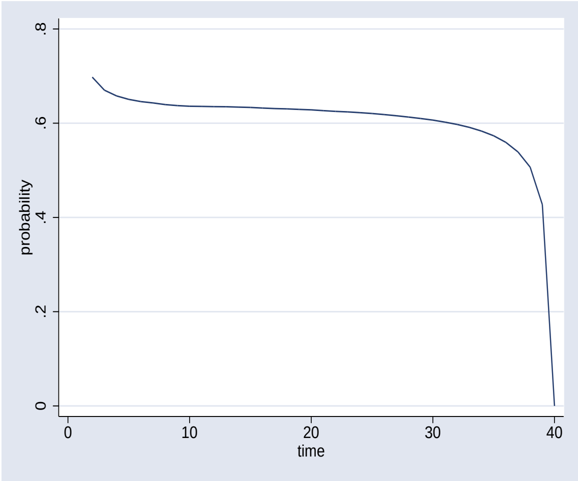
Changes in the human capital production parameters also affect search behavior over the life cycle. A high value for learning ability, a, induces workers to invest more in human capital. This causes workers to spend more effort in searching while unemployed to exit unemployment as quickly as possible, as plotted in panel (a) of Figure 5. It is interesting that with a high a the search intensity on the job becomes lower at the beginning of the life cycle and then higher than that with a low a. This is mainly because a high a also induces more investment in human capital at the beginning of the life cycle. Workers choose to substitute search intensity for human capital investment because they can not afford to increase both at the same time. As workers accumulate more human capital, the search intensity on the job surpasses that with a low a due to the positive interactions between search and human capital accumulation, as shown in panel (b) of Figure 5. The reservation rate with a high a is lower than that with a low a and is at the lower bound of the rental rates for longer period of time. This is due to more investment in human capital associated with a high a. At the end of the life cycle, with a high a, more human capital accumulates and the reservation rate becomes higher than that with a low a.Finally, with a high a, the average rental rate is lower during the first half of the life cycle and then overtakes that with a low a at the end of life cycle. This is a result of both the reservation rate and search intensity on the job exhibiting similar patterns over the life cycle. The parameter α works the same way as a does. A high α induces more investment in human capital at the beginning of the life cycle. Thus, in order to take advantage of this, workers want to exit unemployment as quickly as possible by increasing search intensity and lowering the reservation rate, and to substitute search intensity for human capital investment while working early in the life cycle.

λ	c	γ	b	δ	a	α	h_0	μ	σ	β	T
0.57	1.0	4.0	1.5	0.2	0.08	0.6	6.0	0.7	0.3	0.96	40

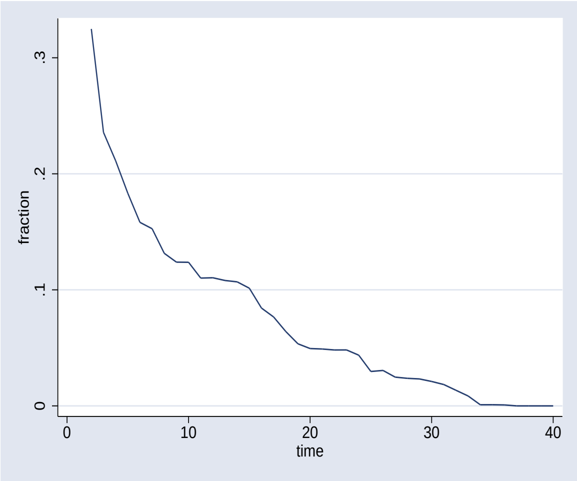
Table 1: Parameters Used for Numerical Illustrations



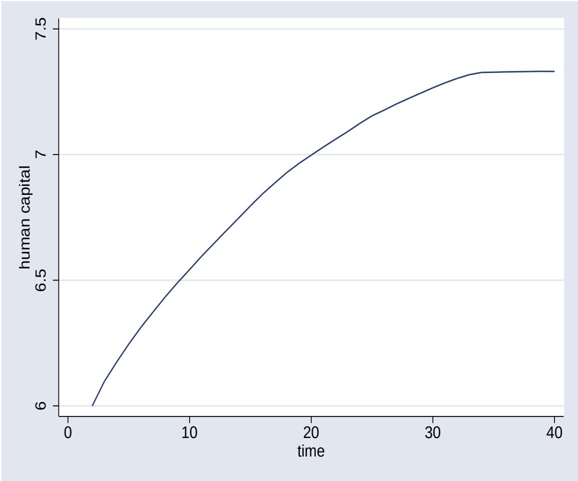
(a) search intensity while unemployed



(b) on-the-job search intensity

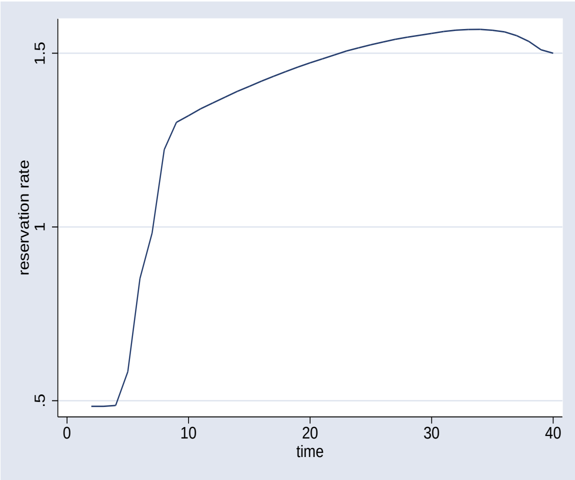


(c) human capital investment

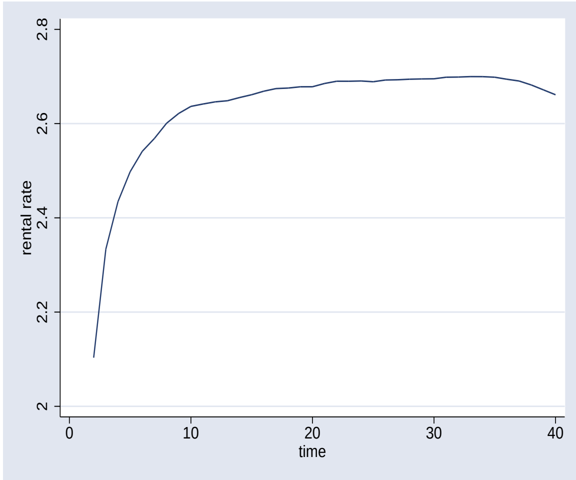


(d) human capital accumulation

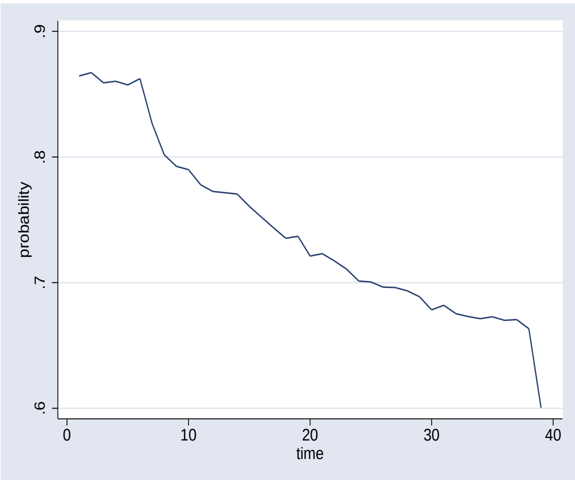
Figure 2: Life Cycle Profiles 1



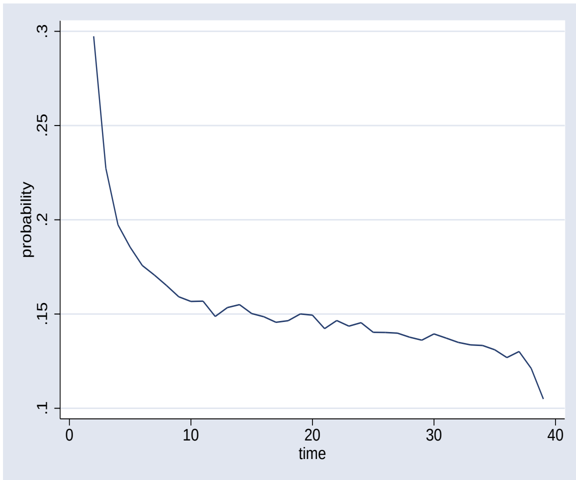
(a) reservation rates



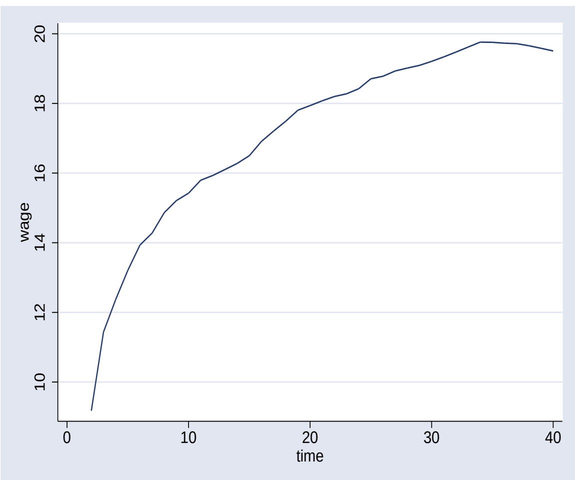
(b) rental rates



(c) unemployment-to-job transitions

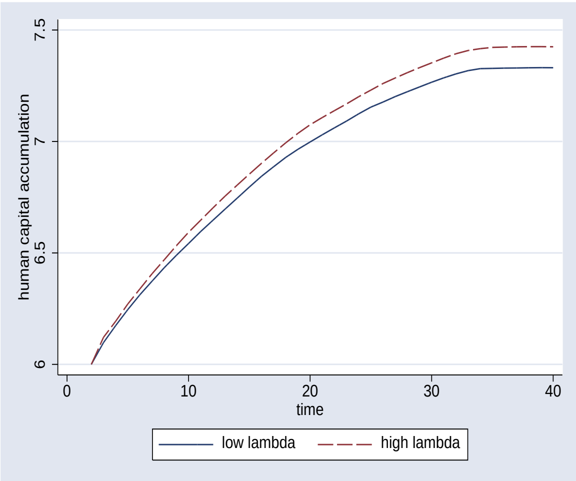


(d) job-to-job transitions

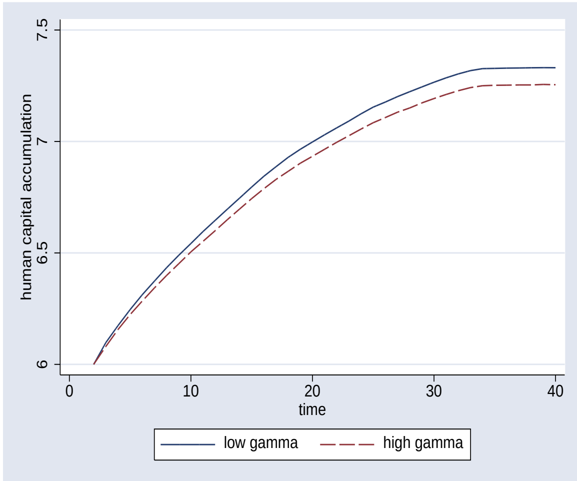


(e) wages

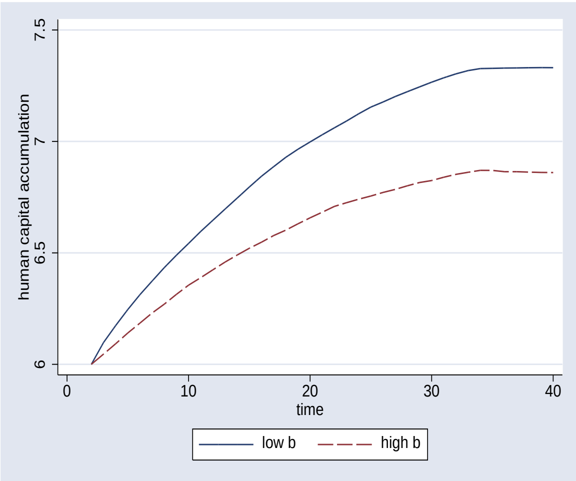
Figure 3: Life Cycle Profiles 2



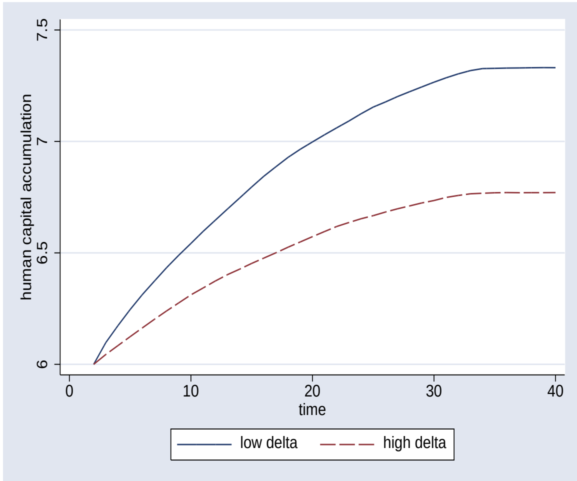
(a) responses of h to λ



(b) responses of h to γ

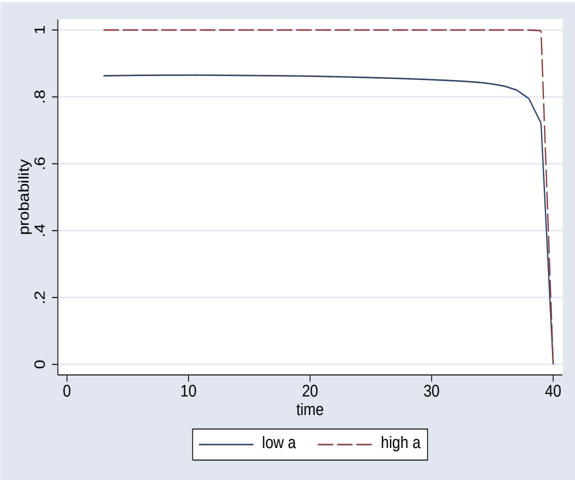


(c) responses of h to b

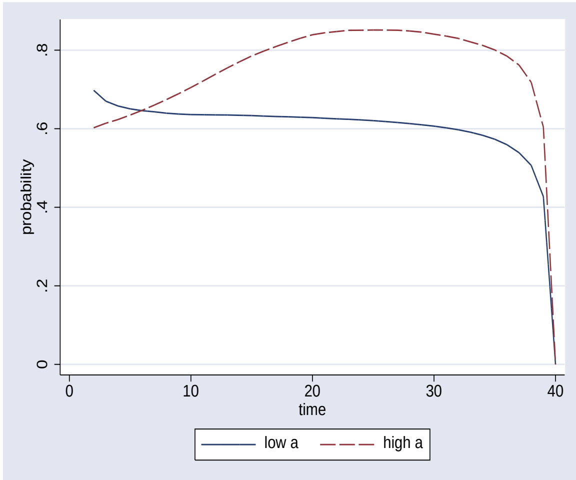


(d) responses of h to δ

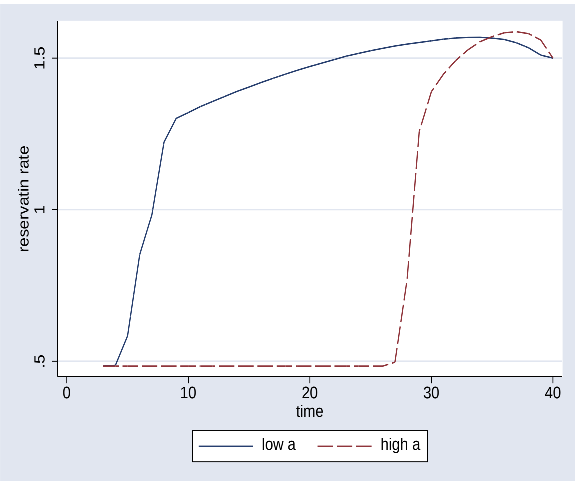
Figure 4: Responses of Human Capital to Search Parameters



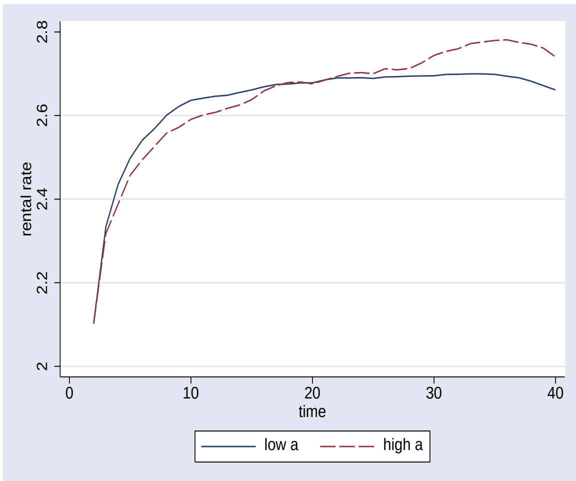
(a) responses of s^0 to a



(b) responses of s^1 to a

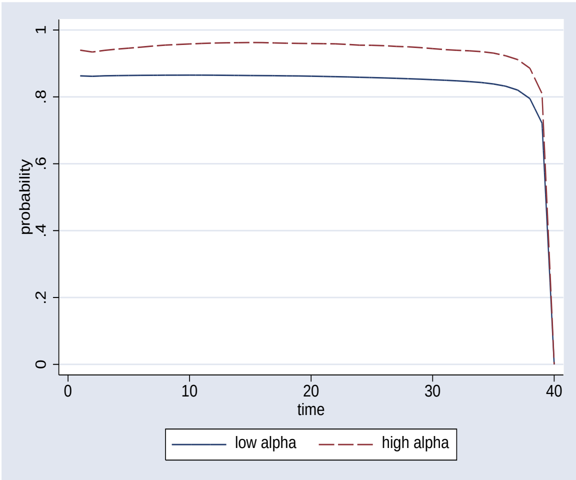


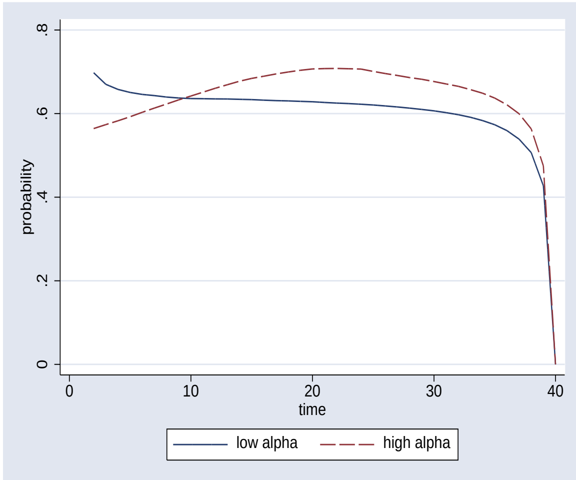
(c) responses of reservation rates to a



(d) responses of rental rates to a

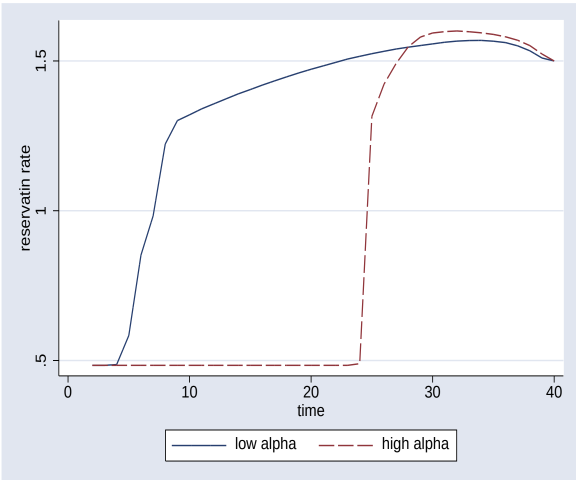
Figure 5: Responses of Search behavior to a

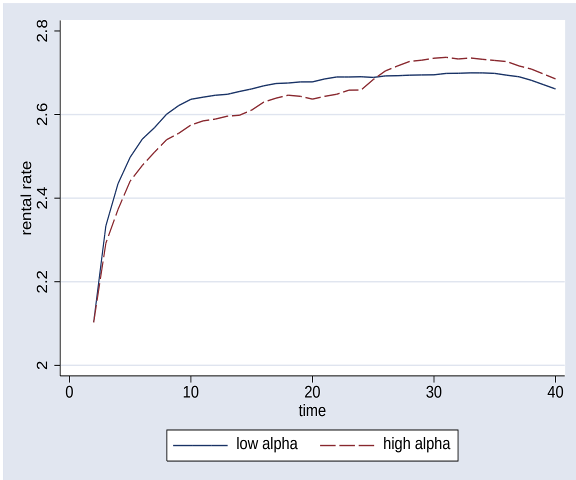




(a) responses of s^0 to α

(b) responses of s^1 to α





(c) responses of reservation rates to α

(d) responses of rental rates to α

Figure 6: Responses of Search behavior to α

3 Identification and Estimation

The structural parameters of interest include 5 parameters related to search friction (λ, δ, b, c, and γ), 2 human capital production function parameters (a and α), the initial human capital level (h_0), and 2 distribution parameters for the rental rate (μ and σ). For this version, I assume workers are ex ante homogeneous in terms of the initial stock of human capital h_0 and learning ability a. This is mainly because the goal of this paper is to examine the evolution of earnings over the life cycle for a relatively homogeneous group, white male high school graduates.

3.1 Identification

One of the key issues for the estimation is how to separately identify the search and human capital production function parameters, since these two forces interact with each other over the life cycle. In the search literature, the search parameters usually are identified using wage information, information on unemployment durations and job durations, and information on job-to-job transitions. The key idea of this paper in estimating search parameters is to use the information on unemployment-to-job transitions and job-to-job transitions over the full life cycle, especially the information of older workers. The idea is as follows. The model predicts that the investment in human capital decreases as workers age. Older workers experience almost no human capital growth. However, they still make job-to-job transitions especially when their current jobs have a low rental rate. Hence, the search parameters can be identified by examining how the job-to-job transitions, especially for the older workers, responds to observed characteristics, for example, experience, job tenure, and wages. Since search intensity is not observed in data, λ, c, and γ can only be identified up to scale unless c is normalized (Christensen et al. (2005)). Here in this paper I normalize c to 1 for identification purposes.

In the human capital literature, the human capital production function parameters are estimated using information on wage growth, because wage growth only comes from human capital investment in human capital models.[8] However, wage growth in my model is a result of both human capital accumulation and job search through job-to-job transitions. Nevertheless, on the same job, wages grow solely due to human capital accumulation. Hence the information on within-job wage growth can help to identify the human capital production function parameters, a and α. It is well known in the human capital literature that one cannot separately identify the level of initial human capital from the rental rate. Usually the rental rate is normalized to some particular value so that it is possible to interpret human capital in a pecuniary sense.

[8]For example, see Heckman et al. (1998), Hugget et al. (2004), Heckman (1976), and Brown (1976).

The integration of job search and human capital accumulation in this paper does not resolve this issue either. In fact, in addition to the non-separation between h_0 and μ, b and a can not be separated from h_0 either, as shown in the following proposition.

Proposition 1 *Given λ, γ, α, and σ, for any $\kappa > 0$,*

$$h'_0 = h_0\kappa \quad , \quad \mu' = \mu - \ln(\kappa)$$

$$b' = b/\kappa \quad , \quad a' = a\kappa^{1-\alpha}$$

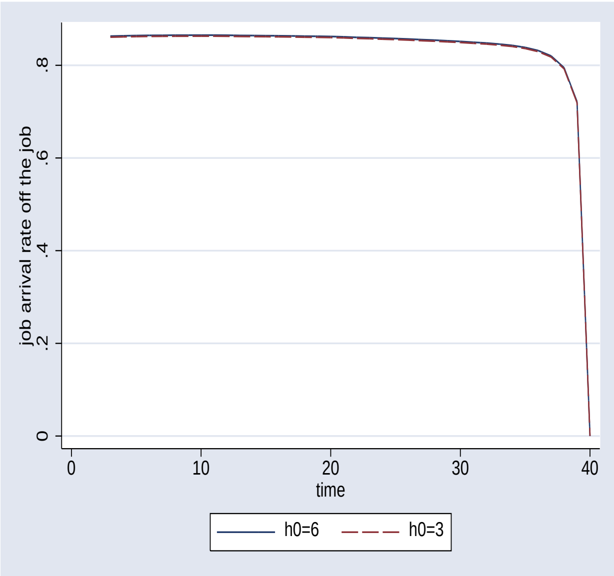
the two sets of parameters $\{h_0, \mu, b, a\}$ and $\{h'_0, \mu', b', a'\}$ yield the same behavior (search intensities and human capital investment) with $T = 2$.

Proof. See the Appendix.

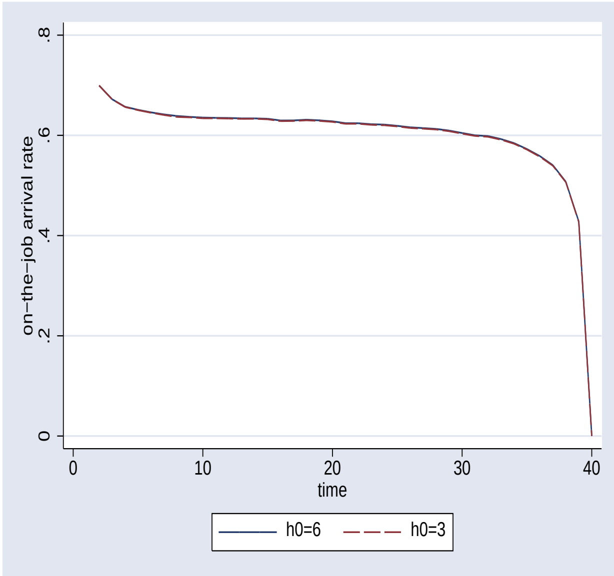
The non-separation between h_0 and μ and between h_0 and b results from the multiplicative period earnings functions, $hR(1-i)$ and hb, and the fact that h is not observed. For decisions on search intensity, what really matters is the relative location in the rental rate distribution, which is not affected by the scaling. Recall that within-job wage growth is used to identify the human capital production function where a acts as the intercept and α acts as the slope of wage growth. Taking the difference of wages drops the intercept term a, which leads to the identification for α but not for a. Hence a has to adjust relative to h_0.

To confirm that the scaling is also true in a more general setting, I solve and simulate a 40-period model based on two sets of parameters that have the properties described in the above proposition. The results (in Figures 7 and 8) show that human capital investment and search intensity, as well as the transition and wage profiles, are almost identical under these two sets of parameters. Parameterizations are list in Table 2.

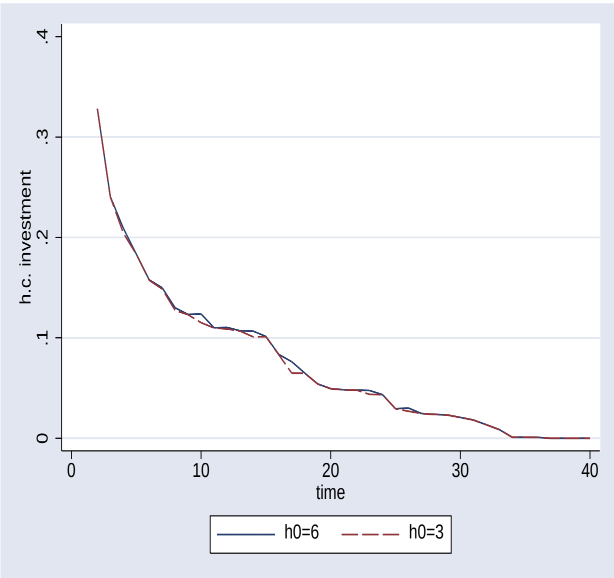
In this paper, the initial human capital h_0 is normalized to 100. The model period is set to a quarter (13 weeks). The discount factor β is then fixed following the convention in the literature such that $\beta = 1/(1+r)$ where r is the quarterly risk-free interest rate. The quarterly interest rate is derived from an annual interest rate of 4%. The rest of the parameters are then estimated via indirect inference (Gourieroux et al. (1993)). Indirect inference is a generalization of the method of simulated moments. The main idea is to find a set of structural parameters that minimize the distance between a set of moments from the real data and the model-predicted counterparts of these moments based on simulated data from the structural model. The set of moments that are matched can be viewed as a set of auxiliary parameters from a set of auxiliary models. These auxiliary models can be structural or just reduced forms and they should capture the main features of the original structural model.



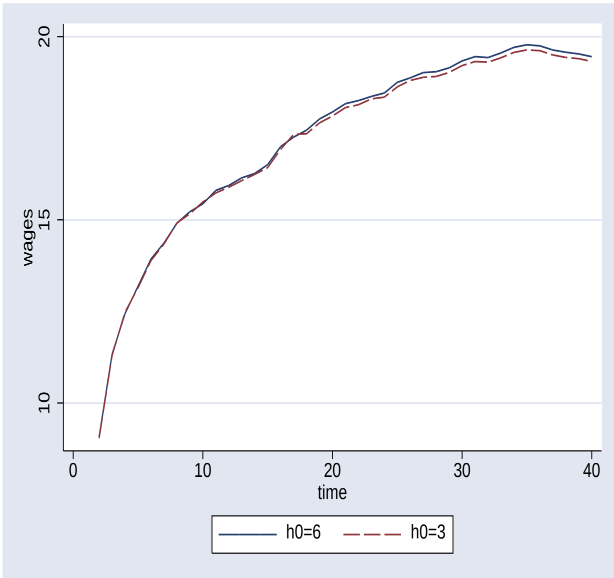
(a) search intensity while unemployed



(b) on-the-job search intensity



(c) human capital investment

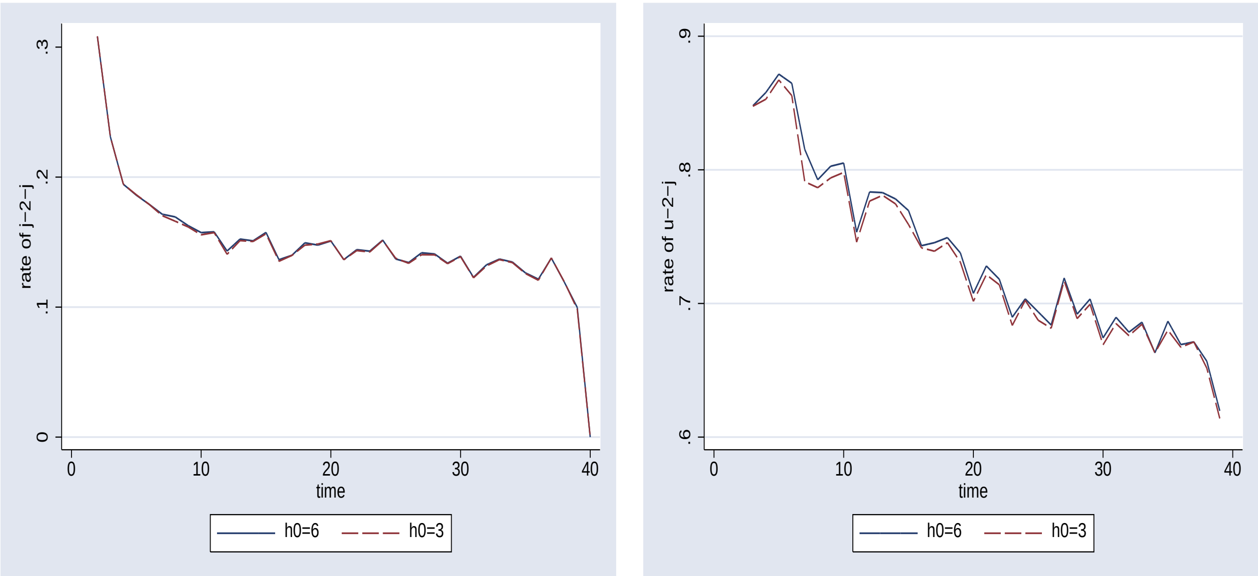


(d) wages

Figure 7: Decisions and Profiles under 2 Parameterizations

	h_0	b	μ	a	λ	γ	α	σ	β	c	δ	T
Set 1	6.0	1.5	0.7	0.08	0.57	4.0	0.6	0.3	0.96	1.0	0.2	40
Set 2	3.0	3.0	1.39	0.06	0.57	4.0	0.6	0.3	0.96	1.0	0.2	40

Table 2: Parameterizations: Test for Scaling



(a) job-to-job transition rates

(b) unemployment to job transition rates

Figure 8: Decisions and Profiles under 2 Parameterizations, cont.

3.2 Auxiliary Model

The choice of auxiliary model is crucial in the sense that it determines if the structural parameters can be identified and the efficiency of the indirect inference estimators. Based on the identification strategies discussed in the previous section, my auxiliary models consist of regression models of discrete choices on job-to-job transitions and unemployment-to-job transitions, a regression model of within-job log wage growth, and Mincerian log wage regression models.

Regressions of discrete choices on transitions. Recall in the model that the hazard rate out of an unemployment spell at period t is $\lambda s_t(h_t)(1 - F(\psi_t(h_t)))$ and the job-to-job hazard rate is equal to $(1 - \delta)\lambda s_t(h_t, R_t)(1 - F(R_t))$. Examining how outcomes of unemployment-to-employment transitions and of job-to-job transitions responds to the variations in h and R can help reveal the underlying search parameters, λ and γ. Although h and R are not observable in the data, they can approximated by work experience, job tenure, and wages. Let $Y_{i,k,t}$ be a binary choice variable for individual i at unemployment spell k and period t, with 1 for exit and 0 otherwise. Let $x_{i,t}$ denote the actual working experience, total market experience net of unemployment durations, for individual i at period t. Hence the linear probability regression for unemployment-to-job transitions is

$$Y_{i,k,t} = \beta_0 + \beta_1 x_{i,t} + \beta_2 x_{i,t}^2 + u_{i,k,t}, \tag{8}$$

where $u_{i,k,t}$ is the error term. Similarly, let $Y_{i,j,t}$ denote a binary choice variable for individual i at job spell j and period t, with 1 for a job-to-job transition and 0 otherwise. Let $T_{i,j,t}$ and $w_{i,j,t}$ be the tenure and wage, respectively, at job j and period t for individual i. The linear probability regression for job-to-job transitions is

$$Y_{i,j,t} = \beta_3 + \beta_4 x_{i,t} + \beta_5 x_{i,t}^2 + \beta_6 T_{i,j,t} + \beta_7 T_{i,j,t}^2 + \beta_8 w_{i,j,t} + \beta_9 w_{i,j,t}^2 + u_{i,j,t}, \tag{9}$$

where $u_{i,j,t}$ is another error term.

Regression of within-job wage growth. As discussed in the previous section, wage growth on a job is solely due to human capital accumulation. Hence regressing within-job wage variations against actual experience and job tenure can help reveal the curvature parameter of the human capital production function, α. Let $\ln w_{i,j,t}$ be the log wage of individual i on job j at period t. Define $\Delta \ln w_{i,j,t} = \ln w_{i,j,t+1} - \ln w_{i,j,t}$. Therefore,

$$\Delta \ln w_{i,j,t} = \beta_{10} + \beta_{11} x_{i,t} + \beta_{12} x_{i,t}^2 + \beta_{13} T_{i,j,t} + \beta_{14} T_{i,j,t}^2 + \epsilon_{i,j,t}, \tag{10}$$

where $\epsilon_{i,j,t}$ is the corresponding error term.

Mincerian wage regression. A Mincerian wage regression can help to identify the distribution parameters of the rental rate, μ and σ. In addition to actual experience, job tenure, I also include a dummy variable, djj as a regressor, with value equal to 1 if the state prior to the current job is another job and 0 if unemployment prior to the current job. The model predicts that on average wages following job-to-job transitions are higher than those following unemployment. Let $\ln w_{i,j,t}$ be the log wage at period t for individual i at job j. Hence,

$$\ln w_{i,j,t} = \beta_{15} + \beta_{16}x_{i,t} + \beta_{17}x_{i,t}^2 + \beta_{18}T_{i,j,t} + \beta_{19}T_{i,j,t}^2 + \beta_{20}djj_{i,j,t} + \nu_{i,j,t}. \qquad (11)$$

Regressions of initial wages and initial job-to-job transitions. Given the assumption of the common initial human capital among the same cohort, variations of the initial wages and initial job-to-job transitions of the first job at period 2 solely come from the variation of R and can help to identify the dispersion of the rental rate distribution, σ. The initial wages of the first jobs at period 2 are also helpful to identify the mean of the rental rate distribution, μ. Let $\ln w_{i,2}$ be the logarithm of the wage of the first job at period 2 for individual i.[9] Let $Y_{i,2}$ be a binary variable indicating a job-to-job transition from the first job at period 2 for individual i. Let $T_{i,1}$ be the total tenure of the first job for individual i. Therefore,

$$\ln w_{i,2} = \beta_{21} + \beta_{22}T_{i,1} + \beta_{23}T_{i,1}^2 + \varepsilon_i^1 \qquad (12)$$

$$Y_{i,2} = \beta_{24} + \beta_{25}T_{i,1} + \beta_{26}T_{i,1}^2 + \beta_{27}w_{i,2} + \beta_{28}w_{i,2}^2 + \varepsilon_i^2 \qquad (13)$$

Additional moments. The job destruction rate, δ, is assumed in the model to be the same for everyone and constant over time. Hence a consistent estimator of δ is the average fraction of workers who are laid off over time. The rental rate equivalent for the unemployed, b, affects the individual reservation rental rate and is equal to the reservation rental rate at period T. Hence the minimum wage at period T, $\underline{w}_T$, among those who just come out of unemployment can help to identify b.

Summary. Denote θ as the set of parameters of interest that need to be estimated. That is $\theta = \{\lambda, b, \gamma, a, \alpha, \mu, \sigma\}$.[10] Denote ρ as the vector of auxiliary parameters, whose consistent estimator based on the real data is $\hat{\rho}$. Here ρ includes all the regression coefficients β_0 to β_{28} from equations (8) to (13) plus one additional moment, $\underline{w}_T$. In total, there are 30 moments that I seek to match using the structural model. Let $\hat{\rho}(\theta)_s$ be the consistent estimator of ρ from the artificial data generated from one simulation of the structural model, indexed by s. Let $\hat{\rho}(\theta)$ be the average of S simulations, $\hat{\rho}(\theta) = (1/S)\Sigma_{s=1}^{S}\hat{\rho}(\theta)_s$. Then the consistent estimator of θ, via indirect inference, is given by

$$\hat{\theta} = \arg\min(\hat{\rho}(\theta) - \hat{\rho})' W^* (\hat{\rho}(\theta) - \hat{\rho}), \qquad (14)$$

where W^* is the optimal weighting matrix, which is equal to the inverse of the covariance matrix of $\hat{\rho}$, $Var(\hat{\rho})^{-1}$. The minimization is implemented using simulated

[9] Every one in the model starts from unemployment at the first period. The initial wages are available from the second period, if any.

[10] The job destruction rate δ is set to match the empirical counterpart and not included in the estimation routine.

	true values	full life cycle	first 25 years	20+20
λ	0.57	0.57	0.92	0.59
b	1.5	1.51	1.64	1.51
γ	4.0	4.09	5.97	4.63
a	0.08	0.08	0.08	0.08
α	0.6	0.60	0.57	0.6
h_0	6.0	fixed	fixed	fixed
μ	0.7	0.70	0.60	0.69
σ	0.3	0.30	0.33	0.3

Table 3: Tests of Estimation Strategy

annealing (Goffe et al. (1994)) and the optimal weighting matrix is obtained through bootstrapping.

A small exercise is conducted to test whether the proposed estimation strategy works. First, I specify the true model as $r = 0.04$, $c_0 = 1.0$, $T = 40$, $\lambda = 0.57$, $\delta = 0.2$, $b = 1.5$, $\gamma = 4.0$, $a = 0.08$, $\alpha = 0.6$, $h_0 = 6.0$, $\mu = 0.7$, and $\sigma = 0.3$. Second, I solve and simulate the model to generate 10 artificial samples of size 500. For each artificial sample, the consistent estimates of the auxiliary parameters and the optimal weighting matrix are obtained. The averages over the 10 samples are then used as the set of moments and the optimal weighting matrix for the true model, $\hat{\rho}$ and W^*. Third, the indirect inference procedure based on the proposed auxiliary models is implemented to see if the true parameters can be recovered, holding h_0 fixed. As shown in column 3 of Table 3, the true parameters can be recovered using the proposed estimation protocol, given the information in equations (8) to (13) is available for the full life cycle.

3.3 Data Restrictions

My primary choice of data for the analysis is the NLSY from 1979 to 2004.[11] It provides information on the job market history for around 20 to 25 years. One interesting question is whether the proposed estimation strategy still works, given information on only the first half of the life cycle is available as in the NLSY. To see this, I conduct another exercise where only the information from the first 25 years is used in the estimation. The model specification is the same as the previous one. As we can see from column 4 in Table 2, not all of the parameters are recovered, especially the search parameters, λ, b, and γ. This confirms that information for older workers is important to identify the search parameters as discussed in the previous section. The human capital production parameters, a and α, are almost recovered. This is mainly because younger workers undergo most of the investment in human capital.

To address this issue, I augment the NLSY with another panel data set, the SIPP. The most recent panel for the SIPP runs from 1996 to 2000. It provides detailed information for every job held by respondents age 15 and over as of 1996 over the survey period. I augment the auxiliary models with two extra regressions, the counterparts of regressions (9) and (11) for older workers. However, since the SIPP panel is a stock sample and short, job tenure and actual working experience can not be constructed. Hence, I replace actual working experience with potential experience and drop the job tenure in the these two regressions. The two regressions for the old workers are

$$Y_{i,j,t} = \beta_{29} + \beta_{30} ex_{i,t} + \beta_{31} ex_{i,t}^2 + \beta_{32} w_{i,j,t} + \beta_{33} w_{i,j,t}^2 + u_{i,j,t}, \tag{15}$$

and

$$\ln w_{i,j,t} = \beta_{34} + \beta_{35} ex_{i,t} + \beta_{36} ex_{i,t}^2 + \nu_{i,j,t}. \tag{16}$$

where $ex_{i,t}$ is the potential experience of individual i at period t.

To summarize, my final auxiliary models for the indirect inference includes regressions for two age groups, regressions (8) to (13) for the first half of the life cycle (the first 20 years in the NLSY), and regressions (15) and (16) for the second half of the life cycle (age 40 to 60 in the SIPP). I conduct another exercise to test if the revised estimation strategy works due to the data limitations. The results are shown in column 5 of Table 3. Almost all of the parameters can be recovered except γ. At this stage, I can not tell if this is an upward bias due to the limited information used in the regressions for the older group or just one randomization. Full sets of Monte-Carlo exercises will be conducted to examine the properties of the estimator under 3 different scenarios: the full life cycle, only the first half, and the first half plus limited information from the second half.

[11] See the data section for details on data issues.

4 Data

As discussed in the Estimation section, the identification strategy depends on having both wage information and information on unemployment-to-job transitions and job-to-job transitions over the full life cycle. There is not a single existing data set that provides all this information. My strategy is then to construct a synthetic cohort as consistent as possible from more than one panel data set. The two panel data sets I use are the NLSY and the SIPP. The NLSY consists of 12,686 individuals who were 14 to 21 years old as of January 1979. It contains a nationally representative core random sample, an oversample of blacks and Hispanics, and a special military oversample. Respondents have been interviewed since 1979 roughly once a year until 1994 and once every two years after 1994. Detailed information on employment and schooling has been collected.

The SIPP survey is a continuous series of national panels with the first panel starting from 1984. For the 1984-1993 period, a new panel of households was introduced each year in February. A 4-year panel was introduced in April 1996. The redesign abandoned the overlapping panel structure of the earlier SIPP, but maintained a larger sample size, with an initial sample size of 40,188 households. The 1996 panel is used for the analysis in this paper. The SIPP sample is a multistage-stratified sample of the U.S. civilian non-institutionalized population. All household members 15 years old and over are interviewed by self-response or proxy response every 4 months. Core information on labor force, program participation and income for the past 4 months is asked at each interview. Both data sets provide instruments with which jobs can be linked across interviews and thus individual labor market histories can be constructed.

4.1 Sample Selection

In both data sets, I select only white males who are high school graduates and do not pursue further schooling. In the NLSY, I select only those who graduated from high school after 1978, since reconstructing employment histories prior to 1978 is not possible in the NLSY, and before 1984 in order to have more homogeneous cohorts. In the SIPP, I restrict the sample to those who were high school graduates as of January 1996.

In both samples, a job is defined as an employment relationship that consists of at least 35 hours a week[12] and lasts longer than 4 weeks. In the NLSY, these full-time jobs have to start within three years after high school graduation to guarantee the

[12]The focus on full-time jobs is standard in the literature. See, for example, Bowlus et al. (2001), Eckstein and Wolpin (1995), Wolpin (1992), Yamaguchi (2006), Topel and Ward (1992), Rendon (2006).

school-to-work transition.[13] If the first full-time job happens to surround the graduation date, it is used as the first spell only if it is held at least 2 months longer after graduation. This eliminates temporary or summer jobs held while still in school. To deal with overlapping jobs, I drop those jobs that are covered entirely by other longer jobs. For those jobs that only overlap in part, I replace the starting dates of the later jobs with the stopping dates of the earlier jobs. In both samples, if a job is indicated as still ongoing at the last interview, the job is right-censored. In the NLSY sample, the censoring rate is quite low, about 7.7% due to the long panel. The censoring rate for the SIPP sample is around 67%.

Weekly wages are used as earnings and converted to 2000 dollars in both samples. In the NLSY, respondents are asked the time unit of rate of pay and corresponding rate of pay. If an individual is not paid weekly, the rate of pay is then converted to a weekly wage using hours information. In the SIPP, a monthly wage is recorded. Hence, a weekly wage is then equal to the monthly wage divided by the actual weeks worked for that particular month. In both samples, wages are trimmed 1% at the top and bottom of the distributions.

Those who had ever been self-employed, family workers, served in military, or retired are excluded in both samples. The final sample of analysis includes 552 individuals and 2974 full-time jobs from the NLSY and 5109 individuals and 7575 full-time jobs from the SIPP.

4.2 Quarterly Histories

The model period is a quarter (13 weeks). The quarterly labor market histories since high school graduation are constructed for the two samples. The quarterly histories are constructed according to the following rules.

First, I set the calendar quarter that contains the high school graduation date as the first quarter in the labor market. This is in line with Wolpin (1992) and Eckstein and Wolpin (1995). Second, employment states are determined based on the major activity occurring during a particular calendar quarter. In the literature, there are generally two ways to construct quarterly histories. One is to use the information at the first week of a particular quarter. The other is to use the major activity of a particular quarter.[14] I follow the latter in this paper. A worker is classified as employed, if he works most of the time, greater than 7 weeks, during a particular quarter. Otherwise, he is unemployed. Third, the job of the quarter is defined as the one that a worker stays with the longest during that quarter, given he is employed during that quarter. The wage on this job during that quarter is then defined as the

[13] See Bowlus et al. (2001) for details.

[14] Yamaguchi (2006) and Rendon (2006) use the former. Topel and Ward (1992) and Wolpin (1992) use the latter.

wage for the quarter. Fourth, the quarterly transitions are determined based on the employment states and jobs held during two consecutive quarters. A worker makes an unemployment-to-job transition if he is unemployed at the current quarter and employed at the next quarter. A worker makes a job-to-job transition if he changes jobs between two quarters.

4.3 Sample of Analysis

Suppose individuals expect to work in the labor market for 40 years (160 quarters). The sample of analysis is a synthetic cohort which is composed of the NLSY cohort (the first 20 years) and the SIPP cohort which includes individuals who are 40 to 60 between 1996 and 2000. The combined quarterly market histories from these two cohorts are then used for the estimation and analysis.

Table 4 shows some main sample statistics for the synthetic cohort of analysis. Columns 2 to 5 show statistics for the NLSY cohort and columns 6 and 7 for the SIPP cohort. Full-time work experience increases from 8.5 quarters over the first 5 years to 61 quarters if one has been in the labor market for 16 to 20 years. Job seniority increases from around 6 quarter (1.5 years) over the first 5 years to around 28 quarters (7 years) if one has been in the market for 16 to 20 years. As experience and job seniority increase, the average weekly wage increases from \$443 to \$685 over the same period of time. The wage grows at a decreasing rate. From year 5 to year 10, the wage increases by more than \$120, then \$70 from years 10 to 15 and \$50 from years 15 to 20. No wage growth is seen from year 20 to year 30 and only a slight increase, about \$34, from year 30 to year 40. On average, a high school graduate can expect wage growth of 2% per quarter on the job over the first 5 years. This amounts to about 8% per year. This growth declines over time, down to 0.3% per quarter if one has been in the market for 16 to 20 years. Job switching results in wage growth of 3.5% per quarter over the first 5 years, which is almost twice as high as the growth on the job over the same period of time. The between-job wage growth does not decrease as much as the within-job wage growth, at 2.4% per quarter over the last 10 years. The job-to-job transition rate decreases over time and as the wage increases, from 6% per quarter over the first 5 years to about 2% over the last 10 years. The unemployment-to-job transition rate also decreases over time from 27.5% per quarter over the first 5 years in the labor market to 7% if one has been in the market for 16 to 20 years. The unemployment-to-job transition rate in the SIPP cohort is relatively higher than and does not decrease as much as that in the NLSY cohort.

One potential problem with using a synthetic cohort is that of cohort and time effects. The estimation and analysis based on the synthetic cohort would be inappropriate if the NLSY cohort and the SIPP cohort were too different. To see how different these two cohorts are, Figure 9 plots the job-to-job transition rates and weekly wages

	NLSY				SIPP	
	<= 5 years	6-10 years	11-15 years	16-20 years	21-30 years	31-40 years
actual experience(quarters)	8.45	24.62	42.32	60.79		
job tenure (quarters)	5.92	12.52	19.79	27.94		
total no. of jobs	1.78	3.20	4.31	5.10		
weekly wage	443.60	566.74	637.10	685.38	682.32	716.26
within-job wage growth per quarter	0.018	0.008	0.004	0.003	0.002	0.0002
between-job wage growth per quarter	0.035	0.034	0.044	0.009	0.055	0.024
j-j transition rate per quarter	0.063	0.049	0.033	0.028	0.024	0.018
u-j transition rate per quarter	0.275	0.164	0.117	0.070	0.260	0.202

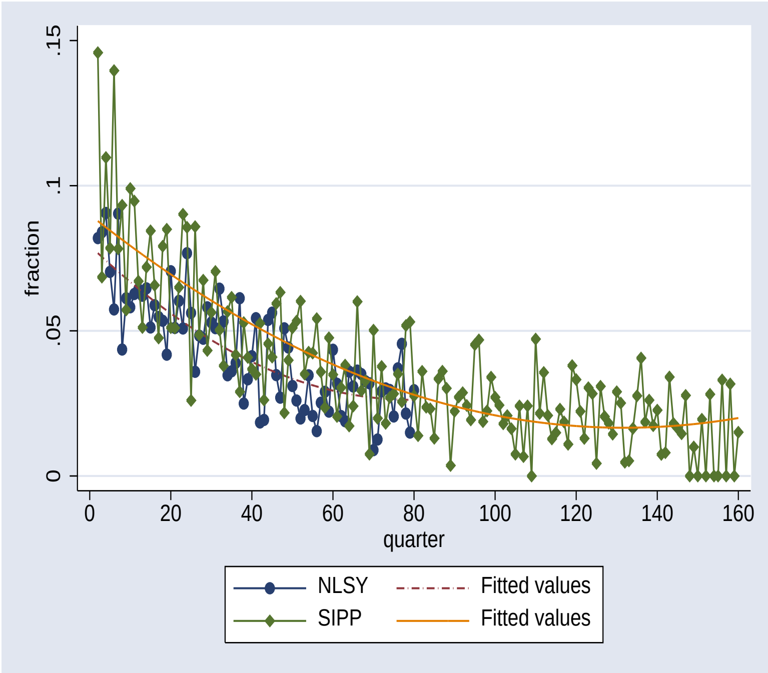
Table 4: Sample Statistics for the Synthetic Cohort of Analysis

over the life cycle for these two cohorts. These two pieces of information are essential in the estimation. Surprisingly, these two cohorts show very similar patterns in these two dimensions with small differences. The job-to-job transition rate is slightly lower in the NLSY cohort than in the SIPP cohort, while the weekly wage in the NLSY cohort is lower at the beginning and then surpasses its counterpart in the SIPP cohort.

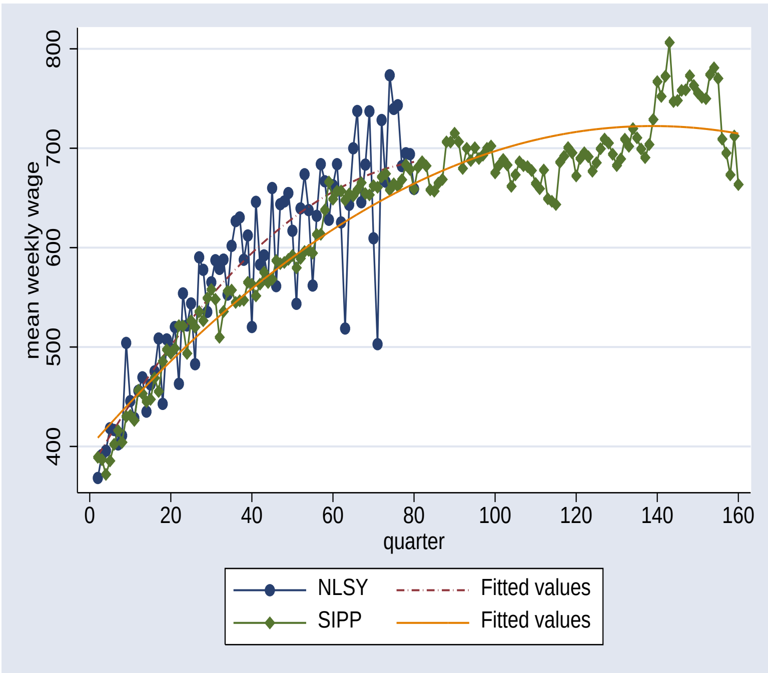
4.4 Implementation of Auxiliary Regressions

One key issue when implementing indirect inference is sampling from the model simulated data in exactly the same way as the actual data were sampled. Due to the nature of the data, several problems deserve special attention.

Initial conditions. In the NLSY sample, around 33% (182/552) of white male high school graduates start full-time jobs immediately after high school graduation. Recall that I set the calendar quarter that contains the high school graduation date as the first quarter in the labor market. By doing this, I produce the appearance of duration dependence in the unemployment-to-job transition even when none is present. This generates a spike in the unemployment-to-job transition rate at the first quarter, of 57%, which then drops to 20% in the following quarter. To address this, those jobs that start immediately after high school graduation are left-censored and the information on unemployment-to-job transitions at the first quarter is not used in the auxiliary regressions for both the real data and the simulated data from the model.



(a) job-to-job transition rates



(b) weekly wages

Figure 9: Comparisons of the NLSY Cohort and the SIPP Cohort

Wages in the NLSY. In the NLSY, during each interview, respondents are asked a wage for each job held since the last interview. If a job is ongoing at the interview week, the reported wage is treated as the wage as of the interview week for that job. If a job ends before the interview week, the reported wage is treated as the wage as of the last week for that job. Meanwhile, respondents are interviewed once a year before 1994 and once every two years after 1994. Hence wages are not available for every quarter, only for those quarters that contain the interview weeks and the last weeks of jobs. This poses two issues when implementing the auxiliary regressions, selection and timing of the wages. The inclusion of wage as a regressor in equations (9) and (13) leads to a selection problem. This is because wages are only observed during quarters that contain the last weeks of jobs and the interview weeks. Hence the probability of a job-to-job transition is higher for those quarters with wage observations than that for every quarter. In fact, the mean job-to-job transition probability for all quarters is around 4% per quarter and the mean job-to-job transition probability is much higher around 17% for those quarters with wage observations. To address this, I exclude wages from regressions (9) and (13) for both the data and the model.

The other selection problem occurs for the initial wage regression in the NLSY, regression (12). Recall that I only select those high school graduates who graduated between 1978 and 1984. Most of the interviews from 1978 to 1984 happen from January to July, which are in the first and second calendar quarter. The most common calendar quarter for high school graduation is the second (April-June). Recall again that I set the calendar quarter that contains high school graduation date as the first quarter in the labor market. Therefore, the first job most likely starts from the third calendar quarter, if any, which is not the interview quarter. Therefore, in order to have a wage observation for the first job at the third calendar quarter, the job has to be short to get a stopping wage at next interview. This results in a selection of short jobs conditional on having wage observations. In fact, the average duration of the first jobs in the NLSY sample is 13.4 quarters while the counterpart for first jobs conditional on having a wage in quarter 2 is only 1.6 quarters. The estimates of the distribution of the rental rate are likely downward biased if only the wages of these short jobs are used since short jobs usually have low wages. To address this, I use the first available wage within the first year in the labor market from the first jobs in the auxiliary regression for the NLSY sample. By doing this, I ignore the wage growth over the first year on the first job and hence may bias the human capital investment downward at the beginning.

The wage timing problem occurs because in the NLSY wages are not available for every quarter. Meanwhile, interviews are conducted roughly once a year before 1994 and every two years after 1994. In the NLSY sample, the average distance between two quarters that have wage observations on the same job is about 4 quarters before 1994 and about 7.4 quarters after 1994. To make the model consistent with the data when implementing indirect inference, I apply an interviewing scheme to the simulated data where interviews start from quarter 2 and run for every 4 quarters before quarter 58, and every 8 quarters after that. The quarter 58 corresponds to the year of 1994 in the NLSY. I use only those wages that fall in the interview quarters and stopping quarters of jobs for the simulated data when estimating regressions (10) and (11). In addition to this, the log wage growth in regression (10) is transformed into quarterly log wage growth by dividing the wage growth by the tenure differences in both the real data and the simulated data.

Wages of older workers in the SIPP. Recall that the rental rate equivalent for the unemployed, b, is identified through the minimum wage among those post-displaced workers at the last period. However, due to the short panel of the SIPP and the retirement of most older workers, there are too few post-displaced wage observations. Using these few observations could bias the estimate of b. Hence instead of using only the post-displaced wages at the last period, I use all the wages at the last period. For this version of the paper, I calibrate b to 1.2, which is derived by dividing \$120, the minimum wage in the last period in the SIPP, by 100, the initial human capital, rather than estimate it through the indirect inference.

5 Preliminary Results

A set of preliminary parameter estimates are presented in Table 5.[15] The estimate of the search efficiency parameter, λ, is 0.056, which means that the job offer arrival probability for one unit of search effort is 5.6% per quarter. This estimate is smaller than those found by the search literature that also endogenizes search intensity. Lise (2005) finds that λ is 0.65 per quarter using the NLSY. Christensen et al. (2005) using Danish data find that λ is about 0.14 per quarter. The estimate for the search cost, γ is around 20. This is much higher than that in Christensen et al. (2005), around 2. The estimate for the learning ability parameter in the human capital production function is around 0.5, which is higher than those in the human capital literature. For example, Heckman et al. (1998) find that a is around 0.08. However, a is related to the initial human capital level. The initial human capital in my paper is almost 10 times bigger than that in their paper. Thus a needs to be bigger in order to generate the same amount of human capital investment.[16] The curvature parameter, α, in the human capital production function is 0.14 and is smaller than that in Heckman et al. (1998), around 0.8. Partly this is because their analysis is based on annual wages while in my paper I assume human capital production takes place every quarter. The mean of the log of the rental rate distribution is 1.3 and the standard deviation is 0.3.

[15] Standard errors of these estimates are not available for this version.

[16] Human capital investment is a decreasing function of human capital stock. If a were the same as in their paper, my model would generate less human capital investment. Thus, the estimate of a in my paper is larger than that in their paper in order to generate the same amount of the investment.

	parameter	estimate
search efficiency	λ	0.056
search cost curvature	γ	19.530
learning ability	a	0.513
curvature in human capital production function	α	0.144
mean of rental rate distribution	μ	1.311
s.d. of the rental rate distribution	σ	0.329
initial human capital	h_0	100
job destruction	δ	0.03
rental rate equivalency for the unemployed	b	1.2

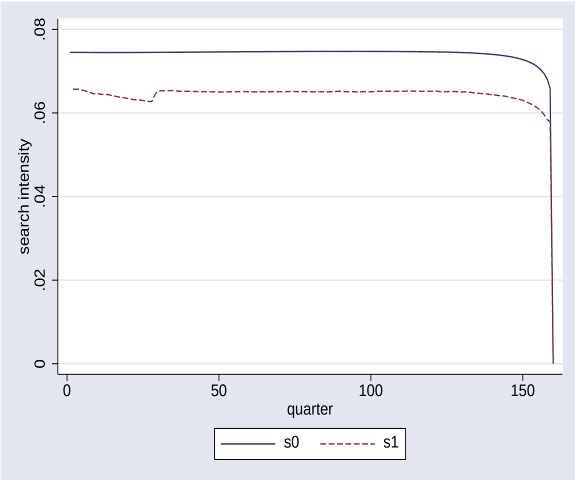
Table 5: Preliminary Parameter Estimates

This translates into a mean rental rate of 3.9 and with a standard deviation of 1.3. Thus for one unit of human capital, the mean rental rate is about $3.90 per week. The implied rental rate distribution, as plotted in panel (b) of Figure 11, is disperse, ranging from 1 to 10, and skewed to the right with a long right tail. Compared to the rental rate distribution, b is almost at the low end. Hence the rental rate distribution is fully uncovered. The parameters b is calibrated to match the minimum wage at the last period in the SIPP. The minimum wage generated by the model based on these estimates at the last period is about $127, which is quite close to the empirical counterpart in the SIPP, $120.

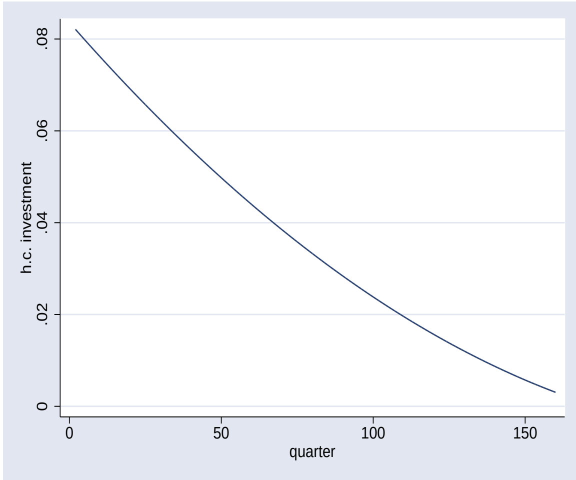
Under these estimates, the model predicts that human capital investment is decreasing over time and leads an average increase in human capital over the life cycle of 65%, as shown in panels (b) and (c) of Figure 10. Panel (a) in Figure 11 plots the kernel density for the distribution of human capital at the end of the life cycle. We can see that the distribution is very disperse, ranging from 100 to 200. In the model, workers start with the same amount of human capital. However they experience very different labor market trajectories over the life cycle resulting in different paths of human capital investment and search behavior. These two forces working together make even ex-ante identical workers very different at the end of the life cycle. With regard to search, the model predicts that the job arrival rate for the unemployed workers is higher than that on the job, as shown in panel (a) of Figure 10. This is consistent with most findings in the search literature. The reservation rate, plotted in panel (d) of Figure 10, is increasing over time and equal to the lowest rental rate in the distribution at the beginning of the life cycle to take advantage of human capital investment. The average rental rate, plotted in panel (e) of Figure 10, increases over time from an average of 3.9 initially to 4.8 at the end of the life cycle. Panel (c) in Figure 11 plots two wage distributions, one for wages at the beginning of the life cycle and the other at the end of the life cycle. At the beginning of the life cycle, workers have the same amount of human capital, they are willing to accept any rental rate to start accumulating human capital. Hence the initial wage distribution centers around the mean of the rental rate multiplied by the initial human capital. The wage dispersion at the beginning comes from the dispersion of the rental rate and associated variation in human capital investment. The wage distribution at the end of life cycle shifts to the right and is much more dispersed than the initial wage distribution. This is because both the rental rate and human capital grow over time. The dispersion not only comes from the dispersion in the rental rates but also from that in human capital levels at the end of the life cycle.

To examine the interactions between human capital accumulation and job search, I conduct two counterfactual experiments. In the first experiment, I turn off search on the job but allow for exogenous unemployment-to-job transitions and job destruction. Everyone at the beginning of the life cycle takes a random draw from the rental rate distribution and keeps it until the end of the life cycle. Compared to the model that has both human capital accumulation and job search, this situation yields a lower average investment in human capital at the beginning of the life cycle and higher average investment in the middle, as shown in panel (a) of Figure 12. At the beginning of the life cycle, workers in these two models start with the same amount of human capital and the same rental rate. However, workers in the model with on-the-job search expect their rental rates to rise over the life cycle and thus invest more at the beginning. In contrast, workers in the model without on-the-job search know their rental rates will stay the same and therefore their human capital investment decision is independent of their rental rates. Over time, workers in the model with job search have higher rental rates than their counterparts in the model without job search thus reducing the investment. Overall, workers in these two models accumulate almost the same amount of human capital on average over the life cycle. However, there is no dispersion in human capital in the model without on-the-job search.

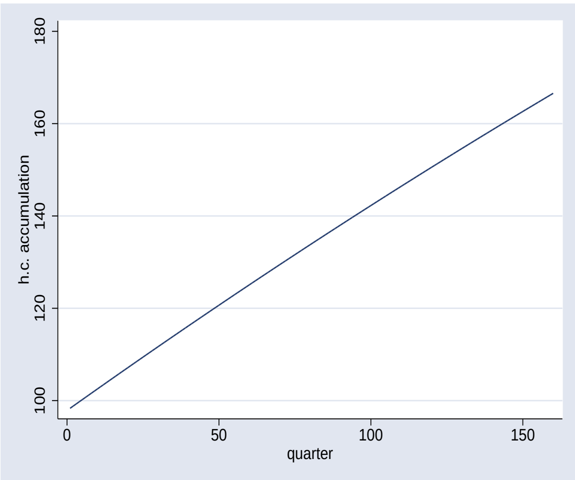
In the second experiment, I turn off human capital accumulation and only allow for job search. Compared to the model with human capital accumulation, workers in the search only model search less intensively while unemployed and raise their reservation rates, as plotted in panels (c) and (e) of Figure 12. Search intensity on the job is also lower than with human capital accumulation, as shown in panel (d) of Figure 12. Panel (f) in Figure 12 plots life cycle wage profiles for 3 scenarios: model with both human capital accumulation and job search, model with human capital accumu-



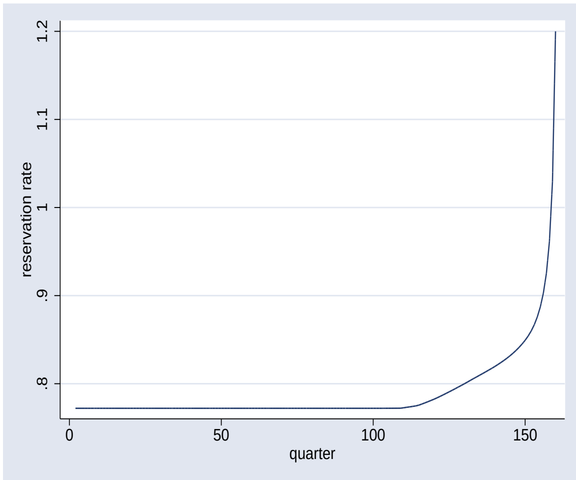
(a) search intensity



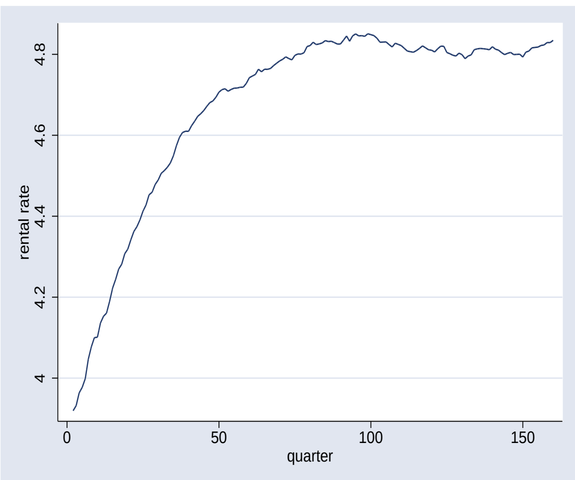
(b) human capital investment



(c) human capital accumulation

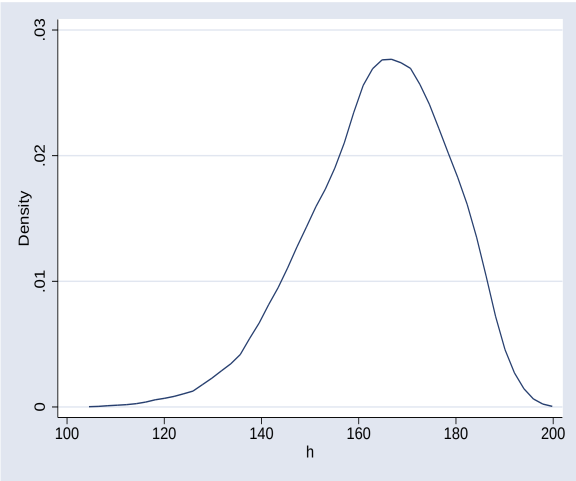


(d) reservation rates

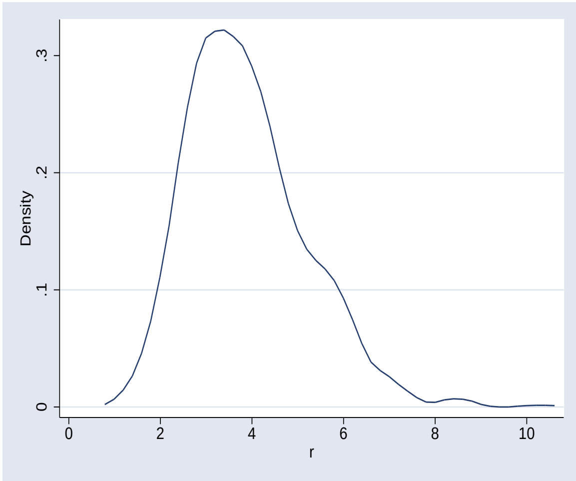


(e) rental rates

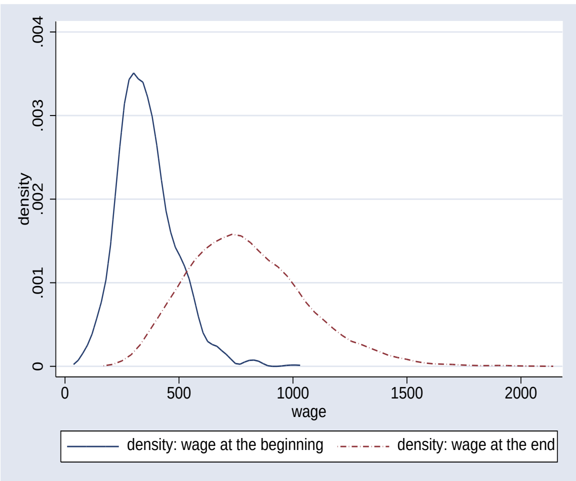
Figure 10: Model Predictions



(a) distribution of h



(b) distribution of rental rate



(c) wage distributions

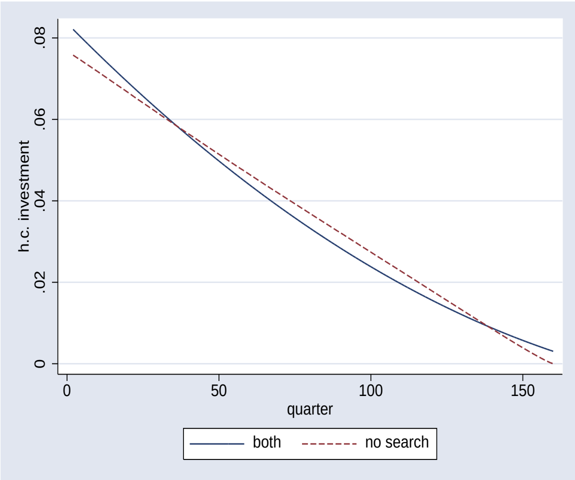
Figure 11: Distributions of Human Capital, Rental Rates, and Wages

lation only, and model with search only. As we can see, the average wage increases by \$440 over the life cycle in the model with both human capital accumulation and job search. The model with human capital accumulation generates a wage increase of \$295. The model with job search can only generate a wage increase of \$90. Thus, human capital accumulation is more important and accounts for 67-80% of the total wage growth and job search accounts for 20-33%.

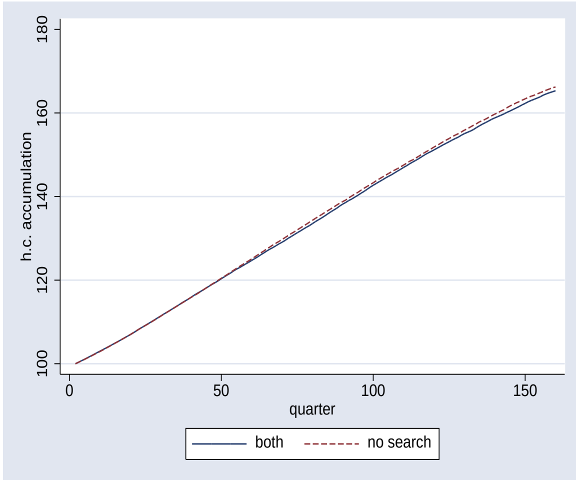
Tables 6 to 8 compare the auxiliary parameters from the data and the model. The model does a fairly good job in predicting the correct signs for most of the auxiliary parameters. In particular, the model does well in matching the job-to-job transitions for the older workers, as shown in column 9 of Table 6, the initial job-to-job transitions, as shown in column 7 of Table 6, and the total wage growth, as shown in column 3 of Table 7. However, the model also has some difficulties matching the data in other dimensions.

First, the model under-predicts the unemployment-to job transitions and job-to-job transitions, as shown in Table 6 and panels (b) and (c) in Figure 13. Partly this may be because the wage information is not used in the auxiliary regressions related to job-to-job transitions. Wage information is an important piece of identification information for the search parameters. However, due to the selection problem discussed in the previous section, wages are excluded from the regressions. This may cause the model to have difficulty in pinning down the right search parameters. A possible solution is to impute the wage for each quarter in the NLSY and in the model. This way the selection problem can be avoided and more variation can be introduced into the regressions by including the wage as a regressor. Another possible reason for the poor fit is that the model has only one search cost function for both unemployed and employed workers. This may make it difficult for the model to match both unemployment-to-job transitions and job-to-job transitions. To match the relatively low transitions on the job in the data, the model imposes a low λ and a high γ. However, at the same time, this generates low unemployment-to-job transitions. There are more observations in the data on job-to-job transitions than on unemployment-to-job transitions. This puts more weight on the job-to-job transitions in the weighting matrix, making that a priority to match. Hence under-prediction of unemployment-to-job transition results.

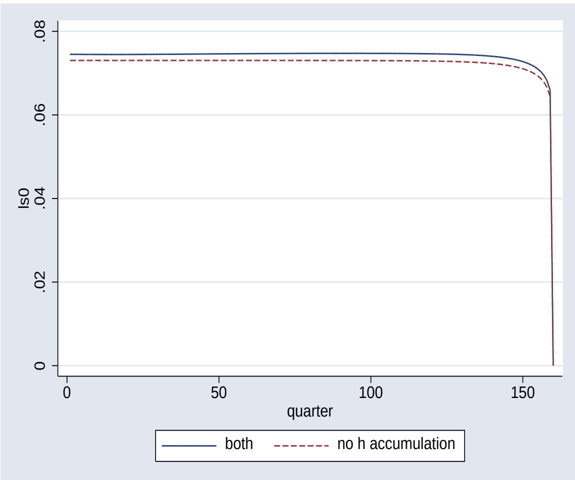
Second, the model does not generate as much curvature for wage growth as in the data, as seen in panel (a) of Figure 13. The estimate of the curvature parameter in the human capital production function is smaller than those in the human capital literature. Partly this is because the model under-predicts the job-to-job transitions. Thus in order to match the overall wage growth in the data, the curvature in the human capital production function has to be smaller and the ability parameter a has to be bigger to induce substantial wage growth due to human capital accumulation.



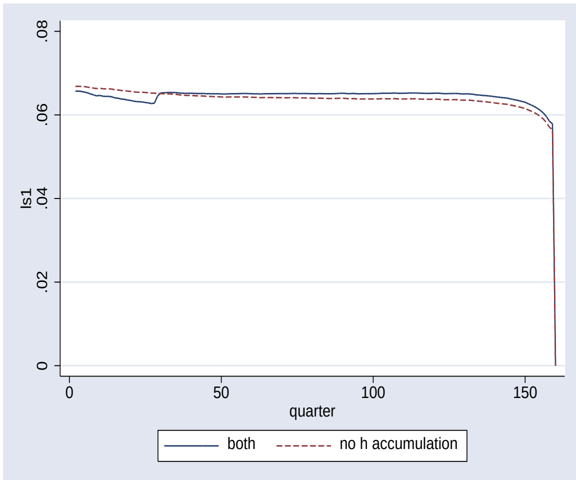
(a) human capital investment



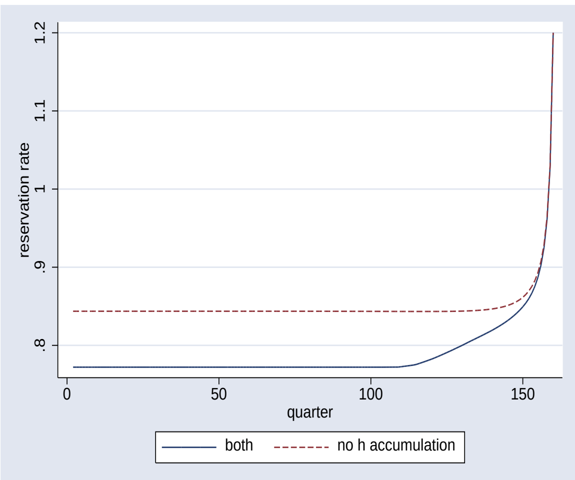
(b) human capital accumulation



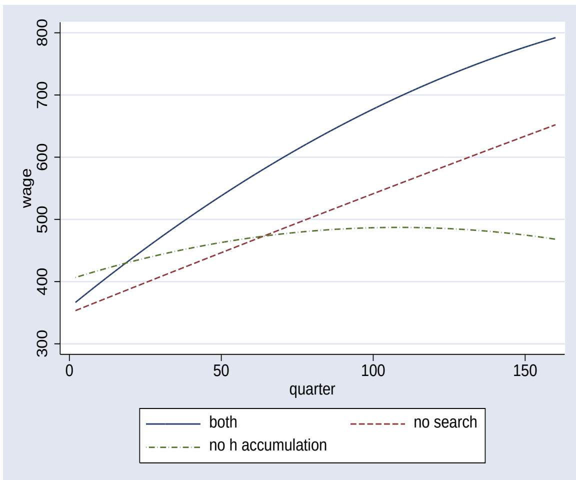
(c) search intensity for the unemployed



(d) search intensity on the job

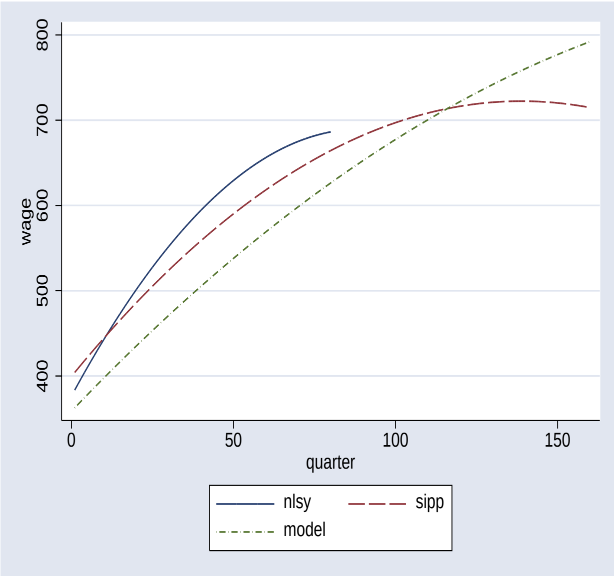


(e) reservation rates

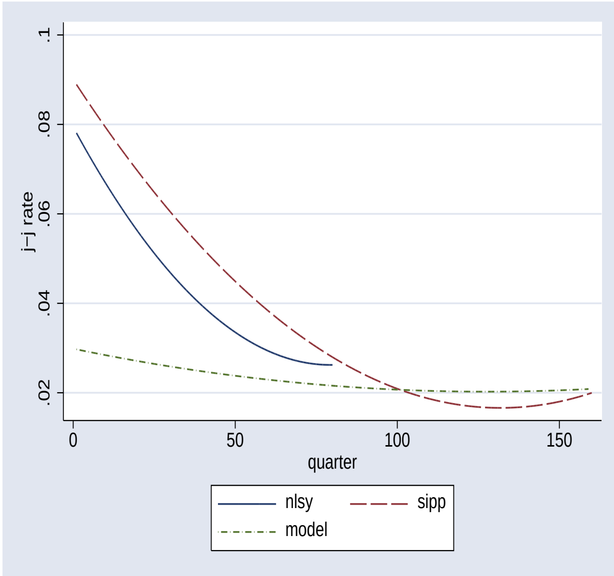


(f) wages

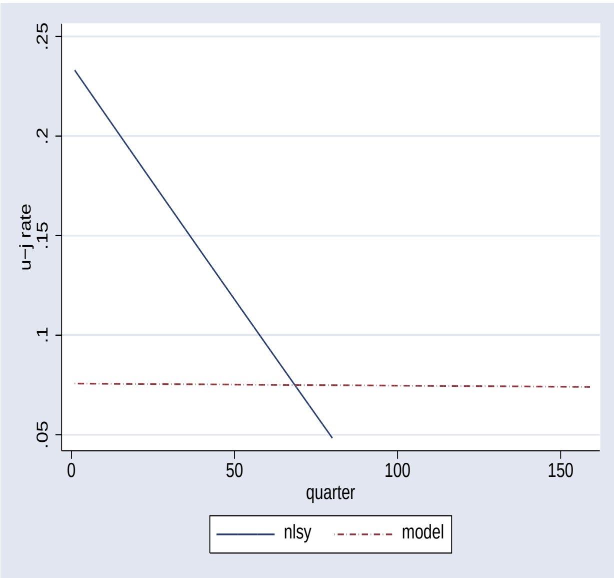
Figure 12: Counterfactual Experiments



(a) weekly wages



(b) job-to-job transitions



(c) unemployment-to-job transitions

Figure 13: Model Fits

	u-to-j transition		j-to-j transition					
	NLSY (<= quarter 80)	Model	NLSY (<= quarter 80)	Model	NLSY (quarter 2)	Model	SIPP (quarters 81-160)	Model
$exp/100$	**-0.251**	0.003	**-0.048**	-0.045			**-0.019**	0.014
$exp^2/10000$	**0.266**	-0.015	0.032	0.044				
$tenure/100$			**-0.250**	-0.027	**-1.031**	-0.712		
$tenure^2/10000$			**0.273**	0.019	**0.97**	1.067		
$w/100$							**-0.011**	-0.019
$w^2/10000$							**0.001**	0.001
cons	**0.180**	0.074	**0.081**	0.036	**0.165**	0.093	**0.089**	0.098

Note: number in bold are statistically significant from zero.

Table 6: Auxiliary Parameters from the Data and the Model-Transition Regressions

	log wage					
	NLSY (<= quarter 80)	Model	NLSY (quarter 2)	Model	SIPP (quarters 81-160)	Model
$exp/100$	**1.309**	0.975			**-0.703**	0.769
$exp^2/10000$	**-1.032**	-0.494			**0.345**	-0.184
$tenure/100$	**0.940**	0.498	0.054	1.509		
$tenure^2/10000$	**-0.751**	-0.013	0.134	-1.660		
$dju/100$	**10.132**	22.247				
cons	**5.834**	5.790	**5.862**	5.642	**6.773**	5.874

Note: number in bold are statistically significant from zero.

Table 7: Auxiliary Parameters from the Data and the Model-Wage Regressions

	within-job log wage growth	
	NLSY(<= quarter 80)	Model
$exp/100$	-0.043	-0.000
$exp^2/10000$	0.021	-0.009
$tenure/100$	**-0.069**	-0.001
$tenure^2/10000$	**0.117**	0.003
cons	**0.024**	0.007

Note: number in bold are statistically significant from zero.

Table 8: Auxiliary Parameters from the Data and the Model-Wage Growth Regression

6 Conclusion

This paper presents a life cycle model that endogenizes both human capital investment and job search to examine the interactions between human capital accumulation and job search over the life cycle. The expectation of rising rental rates over the life cycle induces more investment in human capital at the beginning of the life cycle. To take advantage of human capital accumulation, workers spend more effort on searching while unemployed and lower their reservation rates. Due to human capital accumulation, workers also search more intensively on the job. Preliminary results show the rental rate distribution is disperse with a long right tail. This is different from the human capital literature where there is only one rental rate. Ex-ante identical workers can accumulate different amounts of human capital over the life cycle due to different labor market histories. Wage dispersion increases over the life cycle due to both human capital accumulation and job search. Human capital accumulation is the most important force for earnings growth over the life cycle, accounting for 67-80% of the total earnings growth. Job search also plays a substantial role, accounting for 20-33% of the total growth.

To improve the goodness of fit of the model, future effort will be spent on several dimensions. The nature of wages in the NLSY makes it difficult for the model to be consistent with the data in implementing indirect inference. To address this issue, I plan, first, to introduce to the simulated data generated by the model an interview sampling scheme that is similar to the NLSY to make the model more consistent with the data. Second, I plan to impute quarterly wages in both the NLSY and the model to aid in identification of the search parameters. The same search cost function for both unemployed and employed workers may make it difficult for the model to match both unemployment-to-job transitions and job-to-job transitions. To address this, I plan to introduce heterogeneity in terms of search technology or human capital production to improve the flexibility of the model.

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