Dynamic Labor Force Participation Decisions of Males in the Presence of Layoffs and Uncertain Job Offers

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ABSTRACT

This paper presents a utility maximization model of workers who make decisions to work or not over a lifetime. The objective is to maximize the presented discounted value of utility arising from the participation decisions. In addition to duration dependence introduced through time-variant job offer and layoff probabilities, state dependence enters the model by the existence of a different risk while working, namely, the dismissal risk, than the one while not working, namely, the possibility of no job offers. A dynamic programming algorithm is solved and estimated within a maximum likelihood routine, with data from the National Longitudinal Surveys youth cohort.

I. Introduction

Labor force participation decisions of individuals have long been considered an important issue on both theoretical and empirical grounds. In this paper, a structural model is developed to estimate the probability of working at each point in time over a finite-time horizon based on the utility maximization behavior of individuals. The model

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includes job search, job acceptance, and quit behavior, and explains duration of unemployment and employment. It allows for uncertain, duration-dependent, firm-initiated job offers while unemployed, and layoffs. The dynamic structure of the model is sufficiently rich to enable one to trace the effects of age and employment experience on quits and layoffs, and of age and duration of unemployment on finding a job.

This study differs from the existing theoretical and empirical literature of dynamic labor force participation by its inclusion of layoffs in an estimable framework. In the prior literature the cause of job separations and its relationship to employment experience have been mainly dealt with in theoretical models. See, for example, Jovanovic (1979), Burdett and Mortensen (1980), and Mincer and Jovanovic (1981). The empirical work has been limited to single-event frameworks (job separations only). See, for example, Katz (1985), who estimates a hazard model of layoffs. So far, there have been no studies that incorporate layoffs in an estimable labor force participation framework.

In this paper, job search, job acceptance, and quits are modeled as outcomes of dynamic utility maximization behavior. Layoffs and job offers are the (potential) firm's decision, and depend on the (potential) worker's labor market experience.

The model differs from a job search problem with a single-episode: search is undertaken until a job is accepted which is assumed to be held forever. In contrast, this study develops a two-state model where the complete picture of movements in and out of the labor force is utilized, and the decision to work is explained in a structural framework by allowing for comparisons at each point in time between market wage and reservation wage.

Substantial progress has been made in applied econometrics in the estimation of structural dynamic stochastic optimization models in the last decade. Topics that have been explored so far are job matching (Miller 1984), retention of air force officers (Gotz and McCall 1984), fertility (Wolpin 1984), labor market models of search (Stern 1985, Wolpin 1987), when to replace vehicles (Rust 1987), when to stop renewing patents (Pakes 1986), labor force participation decisions of married women (Eckstein and Wolpin 1987), and fertility and female labor supply (Hotz and Miller 1988). These models apply basic optimization theory to longitudinal micro data sets using dynamic programming methods. The estimates obtained from these models enable one to draw policy implications in a framework where all the restrictions imposed by the theory are satisfied. Increased care in collecting longitudinal data, and accessible, fast, and efficient computer systems have also been important factors in encouraging such work. This paper uses the discrete-time, discrete-choice, finite horizon dynamic programming technique introduced by Wolpin (1984, 1987).

The model is estimated for white males using data from the NLS youth cohort. It is tested against the raw data and not rejected on the basis that the predicted transition probabilities are found to differ insignificantly from actual transition probabilities. The model, although consisting of a few parameters, satisfactorily predicts a variety of labor market conditions. Using the estimated values of structural parameters we calculate impacts of the layoff possibility, the wage distribution parameters, and job offers on the expected duration of work and joblessness. The empirical findings in this study are consistent with those in the prior empirical and theoretical literature.

The main results are those which show falling quit and layoff rates with tenure, and falling job offer probabilities with the duration of nonemployment. The impacts of changes in forcing variables are such that, on average, a high mean wage, a low layoff probability or a high wage variance prolongs employment and shortens nonemployment while a high job offer probability shortens both durations.

II. The Model

The individual in this model is assumed to maximize the present discounted value of utility arising from his labor force participation decisions. When he works he earns wage income; when he does not work he has leisure time but earns no income. The objective is to maximize the present value of utility:

$$\text{(1)} \quad \max \sum_{t=0}^{T} \delta^t U(P_t, X_t)$$

where $U(P_t, X_t)$ is the utility derived from the participation decisions, $P_t = 0$ (no participation) or $P_t = 1$ (participation), X_t is consumption in period t, δ is the subjective discount factor, and T marks the end of life.

This is a two-state, multi-episode problem where the value of working is compared with the value of not working at each point in time. At times, however, the decision is not entirely up to the individual. For example, when layoffs occur workers are assumed to be unemployed for at least one period.[1] Since the firm side is not studied, a layoff possibility is

1. The event of layoff is taken to include both temporary and permanent layoffs, i.e., those with and without the possibility of recall.

Origin State	Exogenous Events in the Labor Market	Destination State
Employed (E)	No layoff ——	Remain employed or quit (E) or (N)
	Layoff ——	Laid off (N)
Not employed (N)	Job offer ——	Accept or reject the offer (E) or (N)
	No job offer ——	Remain unemployed (N)

Figure 1
The Transition Process Between Labor Force States

considered exogenous like no job offer possibility. Figure 1 provides guidance to the dynamic process.

Individuals can voluntarily quit their jobs or be involuntarily laid off; they search and may accept a job offer while out of work and become employed, or turn down job offers and consume leisure.[2] Workers may receive job offers from other firms while employed and switch to other jobs without any intervening nonemployment spells.[3] Wages are drawn randomly in each period, conditional on receiving a job offer while out of work and not being laid off while employed. If a worker continues to be employed given that he is not laid off this implies that the outcome of the wage-reservation wage comparison favors remaining to be employed rather than quitting.

The individual faces a choice of working or not working in each time period and decides in favor of one of these if the outcome provides higher life time utility than the alternative. In an environment where there is uncertainty surrounding wage and job offers, and a nonzero layoff probability, a worker who is not laid off makes optimal decisions to quit and look for a job (consume leisure) or to continue employment, and a non-

2. This is a two-state model where no distinction between unemployment and out of the labor force is made. Therefore, casual substitutions in terminology, such as unemployment for nonemployment and nonparticipation for not working will be made.

3. The model does not differentiate between employment at different firms as long as work is continuous. This follows from assuming a single wage distribution for all jobs. We refrain from developing a more general structure solely to keep computational costs within reasonable limits.

worker who has either quit or been laid off waits to receive job offers and then decides whether or not to accept a job opportunity when one arises.

State dependence arises in the model because a layoff-related event can occur only when the origin state is employment and an offer-related event can occur only when the origin state is nonemployment, even though a layoff leads to the same destination as a lack of job offer and a nonlayoff results in the same choice set as a job offer. This difference causes state dependence as long as the layoff rate and the job-offer arrival rate differ.

In the specific formulation of the model, the utility function (denoted by U_t for short-hand notation) and the budget constraint for period t are:

(2) $U_t = s(1 - P_t) + X_t$

(3) $X_t = w_t P_t + Y_t$

where w_t is the wage rate at t, s is the time-invariant positive value of leisure and Y_t is nonearned income in period t. All income is assumed to be consumed in the same period it is received, i.e., no savings.

The absence of savings from the model is unimportant given the assumed linearity of the utility function in X_t. More explicitly, let

$$\sum_{t=0}^{T} \delta^t X_t$$

be the objective (wealth) function to be maximized with $X_t = (w_t - c_t)P_t + Y_t$ where c_t denotes some real cost of working. If X_t is not observed, the two models cannot be distinguished from each other. Hence, calling this a utility maximization model without savings or a wealth maximization model is a matter of taste alone.

The job offer probability, p_{ne}, is modeled to vary with the duration of the last unemployment spell (k_t) and the layoff probability, p_{en}, with the last employment spell (l_t). To allow duration dependence in these probabilities the following functional forms are adopted:

(4) $$p_{ne}(k_t) = \frac{1}{1 + \exp(-(a_{ne} + b_{ne} \cdot k_t))}$$

(5) $$p_{en}(l_t) = \frac{1}{1 + \exp(-(a_{en} + b_{en} \cdot l_t))}$$

The subscripts denote the origin state and the destination state; "n" denotes nonemployment and "e" denotes employment. With this logit specification the probabilities are restricted to lie between zero and unity. The effects of duration on the probabilities are determined by the coefficients b_{ne} and b_{en}. It is helpful to illustrate the relationship to k_t and l_t (duration) to t (time) with a time line.

$$0 \cdots \underset{t_1}{N} \,|\!\longleftarrow E \longrightarrow\!|\!\longleftarrow N \longrightarrow\!| \cdots T$$
$$\qquad t_1 + t_2 \qquad t_1 + t_2 + t_3$$

For example, if $t = t_1 + t_2$ then $l_t = t_2 - 1, k_t = 0$; if $t = t_1 + t_2 + t_3, l_t = 0, k_t = t_3 - 1$. Duration variables refer to the duration of the immediately preceding spell and make up the state space.

These probabilities may be duration-dependent for several plausible reasons: the layoff (job offer) probability may fall with the duration of employment (unemployment) if, for instance, employers believe that previous employment (unemployment) experience proxies for unobserved (un)desirable traits about the (potential) worker (this type of phenomena is characterized as occurrence dependence by Heckman and Borjas 1980), or, the job offer probability may rise if, for instance, potential workers learn about the job market. In addition, a layoff may become less likely with tenure due to seniority rules or on-the-job training investments in the firm.

The discounted maximum lifetime utility is denoted by V, the valuation function:

$$(6) \quad V(\Omega_0) = E_0 \max \sum_{t=0}^{T} \delta^t U(P_t, X_t)$$

where Ω_t is the information set at t which consists of the state variables, i.e., past decisions on P_t. A solution to the labor force participation problem is provided by backwards recursion using Bellman's principle (1957). By incorporating the choices depicted in Figure 1 and substituting for the utility function, value functions, V_t, can be obtained for all t as follows, beginning with T. Since nonearned income (Y_t) accrues in both labor force states it has no net effect on the decision making process. Henceforth, Y_t is dropped from the equations. The value functions for each state and time period are:

$$(7) \quad V_T(P_T = 1) = w_T$$

$$(8) \quad V_T(P_T = 0) = s$$

$$\begin{aligned}(9) \quad V_t(P_t = 1; l_t) = w_t + \delta\{[1 - p_{en}(l_t)] \\ \cdot E_t \max[V_{t+1}(P_{t+1} = 1; l_{t+1} = l_t + 1), \\ V_{t+1}(P_{t+1} = 0; k_{t+1} = 0)] \\ + p_{en}(l_t) E_t V_{t+1}(P_{t+1} = 0; k_{t+1} = 0)\} \\ = w_t + \delta FE_t(l_t) \qquad \text{for } t < T\end{aligned}$$

$$
\begin{aligned}
(10)\quad V_t(P_t = 0; k_t) &= s + \delta\{p_{ne}(k_t) \\
&\qquad \cdot E_t \max[V_{t+1}(P_{t+1} = 1; l_t = 0), \\
&\qquad\qquad V_{t+1}(P_{t+1} = 0; k_{t+1} = k_t + 1)] \\
&\qquad + [1 - p_{ne}(k_t)]E_t V_{t+1} \\
&\qquad \cdot (P_{t+1} = 0; k_{t+1} = k_t + 1)\} \\
&= s + \delta FN_t(k_t) \qquad\qquad \text{for } t < T
\end{aligned}
$$

Equations (7) and (8) apply to the last period for participation (work) and nonparticipation (no work), respectively. Equations (9) and (10) apply to periods $t < T$, $E_t(\cdot)$ is the expectations operator with respect to the wage given the existing information set at t, and $FE_t(l_t)$, $FN_t(k_t)$ are collections of terms representing the future components of the value function beginning with current employment and nonemployment respectively. These equations are solved separately for all possible values of the state space, i.e., for k_t, $l_t = 0, \ldots, t - 1$, and for all t.

The dynamic structure of the model is motivated as follows. If the individual is out of work at t, and remains out of work at $t + 1$, then the stock of nonemployment is increased by one period, as expressed in $k_{t+1} = k_t + 1$. If, instead, he becomes unemployed at $t + 1$ after having been employed for l_t periods then $k_{t+1} = 0$ since job search has just commenced. Similarly, the stock of the most recent employment spell, l_t, is either augmented by one if employment is continued, or equal to zero if employment follows unemployment. These "equations of motion" appear in parentheses on the right-hand side of Equations (9) and (10).[4]

The age- and duration-specific transition probabilities between working and not working can now be written.[5]

$$
\begin{aligned}
(11)\quad Pr(P_t = 1|P_{t-1} = 0) &\equiv Pr(N \text{ to } E)_t \\
&= p_{ne}(k_t)Pr[V_t(P_t = 1; l_t = 0) \\
&\qquad > V_t(P_t = 0; k_t = k_{t-1} + 1)]
\end{aligned}
$$

$$
\begin{aligned}
(12)\quad Pr(P_t = 1|P_{t-1} = 1) &\equiv Pr(E \text{ to } E)_t \\
&= (1 - p_{en}(l_t))Pr[V_t(P_t = 1; l_t = l_{t-1} + 1) \\
&\qquad > V_t(P_t = 0; k_t = 0)]
\end{aligned}
$$

4. The equation of motion is sometimes referred to as the "plant equation," for example, Whittle (1982).

5. The model and results in the rest of the paper are stated in terms of these two probabilities only as a matter of convention. The remaining two probabilities are simply complements

In switching from nonemployment to employment (Equation 11) the worker receives a job offer and accepts it, i.e., conditional on receiving a job offer the value of becoming employed exceeds the value of continuing to remain unemployed, having done so for k_t periods already. Likewise, the probability of deciding to remain employed (Equation 12) requires that the value of being employed with experience l_t exceeds the value of nonparticipation and that the worker is not laid off from his job. $Pr(P_t = 0|P_{t-1} = 0) \equiv Pr(N \text{ to } N)_t$ and $Pr(P_t = 0|P_{t-1} = 1) \equiv Pr(E \text{ to } N)_t$ are the complements of the probabilities shown in Equations (11) and (12), for given k_t and l_t, respectively.

In order to convert the probability statements into manageable terms, Equations (9) and (10) have to be solved. To do this one needs a stochastic specification of the wages. Let $w_t = w_o \exp(e_t)$ be i.i.d. where e_t is normally distributed $(0, \sigma_e^2)$ and w_o is a positive constant. Prior work has found the lognormal distribution to be a reasonable approximation to wages (Heckman and Polachek 1974). The lognormal distribution has a positive domain and is skewed to right. Individuals are assumed to know the distribution of wages, but they do not know the realization of w_t until they make a draw. The constant s includes the dollar worth of nonmarket time, unemployment insurance, and is net of search costs.

The expectation operators in Equations (9) and (10) are expanded as follows. Rewrite $E_{\max}(x, a) = E(x|x > a)Pr(x > a) + aPr(x < a)$ for stochastic x and nonstochastic a, then use $E(x|x > a)Pr(x > a) = \exp(\tfrac{1}{2}\sigma_x^2)(1 - F[\ln a - \sigma_x^2)/\sigma_x])$ for $\ln x$ distributed normal $(0, \sigma_x^2)$ and where $F(\cdot)$ stands for the standard normal cumulative distribution function. Use the reservation wage to simplify notation. The reservation wage, R_t, is solved as the wage that satisfies $V_t(P_t = 1) = V_t(P_t = 0)$ to yield $R_t = s + \delta FN_t(k_t) - \delta FE_t(l_t)$ for $t < T$, and $R_T = s$. There are in fact two different reservation wage sequences depending on the current state a person is in. They are

(13) R_t(Employment in the previous period)

$$= s + \delta(FN_t(0) - FE_t(l_t)) = R_t(l_t)$$

(14) R_t(Nonemployment in the previous period)

$$= s + \delta(FN_t(k_t) - FE_t(0)) = R_t(k_t)$$

The first reservation wage may also be called the "resignation wage" following Lippman and McCall (1976). The two reservation wages would be equal if it were not for duration dependence in the job offer and layoff

of the former ones. Also, duration dependence is suppressed in notation, i.e., all probabilities depend on k_t or l_t but this is not made explicit for the sake of brevity.

probabilities. When obvious, no distinction is made between the two to avoid notational clutter.

Then the future components are

$$(15)\quad FE_T(l_T) = 0$$

$$(16)\quad FN_T(k_T) = 0$$

$$\begin{aligned}(17)\quad FE_t(l_t) = {} & [1 - p_{en}(l_t)] \\ & \{w_o \exp(.5\,\sigma_e^2)[1 - F([\ln(R_{t+1}(l_{t+1})) - \ln w_o - \sigma_e^2]/\sigma_e)] \\ & - R_{t+1}(l_{t+1})[1 - F([\ln(R_{t+1}(l_{t+1})) - \ln w_o]/\sigma_e)]\} \\ & + s + \delta FN_{t+1}(0) \qquad \text{for } t < T\end{aligned}$$

$$\begin{aligned}(18)\quad FN_t(k_t) = {} & p_{ne}(k_t) \\ & \cdot \{w_o \exp(.5\,\sigma_e^2)[1 - F([\ln(R_{t+1}(k_{t+1})) \\ & \qquad - \ln w_o - \sigma_e^2]/\sigma_e)] \\ & - R_{t+1}(k_{t+1})[1 - F([\ln(R_{t+1}(k_{t+1})) - \ln w_o)]/\sigma_e)]\} \\ & + s + \delta FN_{t+1}(k_t + 1) \qquad \text{for } t < T\end{aligned}$$

The arguments of the future components, k_t and l_t in (17) and (18), reflect that an individual has to consider all possible values of the state space when making a decision. This amounts to solving Equations (17) and (18) for all possible values of k_t, $l_t = 1, \ldots, t - 1$, for $t = 1, \ldots, T$.

The transition probabilities can be restated in terms of the reservation wage:

$$\begin{aligned}(19)\quad Pr(N \text{ to } E)_t &= p_{ne}(k_t)Pr(w_t > R_t(k_t)) \\ &= p_{ne}(k_t)Pr(e_t > \ln(R_t(k_t)/w_o))\end{aligned}$$

and

$$\begin{aligned}(20)\quad Pr(E \text{ to } E)_t &= [1 - p_{en}(l_t)]Pr(w_t > R_t(l_t)) \\ &= [1 - p_{en}(l_t)]Pr(e_t > \ln(R_t(l_t)/w_o)\end{aligned}$$

Hence, the labor force participation probabilities are generated from the optimizing model. While astructural models are easier to compute than a structural model the gain in estimating the latter is in accounting for endogeneities in human behavior with only a few parameters and in being able to perform policy experiments which require knowledge of the structure.[6] Suppose, for example, there is an increase in the layoff probability.

6. See Flinn and Heckman (1982, Appendix B) where the authors discuss identification issues that arise in formulations of multi-state labor force participation models.

Then the job acceptance probability is expected to fall since, everything else held constant, employment becomes less desirable. To give another example, the model predicts that quit rates increase with an increase in the job offer probability.

After some algebraic manipulation the reservation wage can be rewritten in recursive form as follows:

$$(21)\quad R_t = s + \delta \cdot [p_{ne}(k_t) - (1 - p_{en}(l_t))] \cdot \{w_o \exp(.5\,\sigma_e^2)[1 - F[(\ln(R_{t+1}/w_o) - \sigma_e^2)/\sigma_e]] - R_{t+1}[1 - F[\ln(R_{t+1}/w_o)/\sigma_e]]\}$$

Due to the discrete nature of the model, analytic interpretations like those in conventional comparative-static exercises are particularly intractable and one has to use numerical simulation methods to analyze the properties of the reservation age. Unlike the standard finite-horizon job search model (see, for example, Lippman and McCall 1976), reservation wages in this model do not necessarily decline. (Mortensen 1986 presents an up-to-date review of job search models.) Reservation wages may rise or fall depending on the magnitude of the layoff probability relative to the job offer probability, the initial term in brackets in Equation (21). For example, numerical simulations reveal that they are not even monotonic if the layoff probability is (unrealistically) high so as to yield a positive sign for the term in brackets.

To develop intuition further it is useful to take a closer look at the reservation wages. Other things held constant, as R_t rises, the employment probability falls and the nonemployment probability rises. Other things held constant, an increase in the offer probability raises the probability of obtaining a job, and a decrease in the layoff probability raises the probability of keeping a job. The quit probability is part of the employment separation probability, $Pr(E \text{ to } N)_t$, which rises with the reservation (resignation) wage, other things held constant.

$$(22)\quad Pr(E \text{ to } N)_t = [1 - p_{en}(l_t)]Pr(w_t < R_t(l_t)) + p_{en}(l_t)$$

and

$$(23)\quad Pr(\text{Quit})_t = Pr(w_t < R_t(l_t))$$

To develop a final point consider the conditions under which the reservation wage becomes static. There are two ways to eliminate the dynamic components of the problem: set $\delta = 0$ so that people discount the future infinitely and attach no significance to it, or set the job offer probability equal to the probability of no-layoff to eliminate state dependence (see Equation 21). In the first case, when $\delta = 0$, the future loses its importance and the model collapses to a simple time-homogeneous (static) problem. In the second case, when there is no difference between the job offer probability and the no-layoff probability, participation and nonparticipation states look equally attractive (or equally unattractive) in all future periods (see Equation 21). A no-layoff probability is the probability of an offer to remain employed. Only current per period earnings in each state differ, consequently, no decision remains to be made on the choice of the participation sequence that enhances lifetime utility more than any other. In both cases reservation wages stabilize over time ($R_t = s$) and the decisions about accepting a job offer or quitting can be expressed in the form of simple probabilities.

III. The Data

The duration and cause of job separation data are from the weekly labor force activities of the NLS youth cohort. The analysis is conducted for white, male, 1979 terminal high-school graduates who were between the ages of 14 and 22 when first interviewed in 1979. Although race and sex may have a significant impact on the composition of the transition rates, to include variables reflecting exogenous characteristics such as race or sex increases the number of times the dynamic programming problem is solved by six. (There are three racial categories in the NLS.)

Whites are chosen in order to have a sample of meaningful size, for whites are the largest NLS subsample. The resulting sample consists of 155 young white males who have completed their high-school education in 1979. Opting to work with a nonschooling sample avoids the problem of initial conditions as long as schooling is exogenous. Young males who had their terminal contact with high school in 1979 are selected so as to have the longest horizon available. The average observed duration for a youth is approximately 200 weeks, i.e., from the 1979 graduation date through the 1983 survey. During this period, the 155 men in the sample switch between nonemployment and employment six times on average.

With all individuals combined 418 nonemployment and 499 employment spells are observed. Thirty-three of the nonemployment and 122 of the employment spells are censored at the end of the observation period. On average, a nonemployment spell lasts 17 weeks, and an employment spell lasts 46 weeks, including censored spells. Twenty percent of the completed employment spells terminate involuntarily. In the sample examined, half of the time spent not working is spent out of the labor force.

To clear the duration statistics of censoring bias, mean durations from a simple exponential model are presented. Although the exponential model assumes away time-specific switch probabilities it should be adequate to serve the purpose of obtaining consistent mean duration statistics. The formula to compute expected duration is (sum of durations/number of complete spells) for each state. The expected duration of a nonparticipation spell is 20 weeks (4.5 months) and of a participation spell is 71 weeks (1.4 years). Based on this simple model, in the long-run, the average fraction of time spent working is 78 percent and time spent not working is 22 percent. This behavior is typical of white males.

IV. Parameter Estimates and Tests of the Model

The likelihood equation for a person is the product of conditional probabilities in Equations (19) and (20) in chronological order beginning with leaving high school and ending with the last survey.

The sample log-likelihood function consists of sums of logarithms of individual likelihood equations. The log-likelihood function is maximized using NMSIMP and GRADX programs of the Goldfeld-Quandt optimization package. At each evaluation of the function, the dynamic programming problem is solved using the new set of parameter values. This gives rise to a technical problem when T is large. To circumvent this problem the value functions are simulated for various values of T to find the smallest T that does not significantly alter the estimated probabilities. It is observed that at $T = 225$ weeks, i.e., four years after graduating from high school, the participation probabilities have the same pattern as in the simulations with longer T except toward the very end of the horizon. One can argue that the youth heavily discount the future and, presumably, what may take place beyond some distant date like 225 has negligible value. The results that follow are based on this specification.

Table 1 presents the parameter estimates of the model. The mean wage is estimated to be higher than the payoff from not being employed. The magnitude of the subjective discount factor is high and significantly different than zero, the lower bound for a discount factor. It yields 384 percent as the annual rate of time preferences. These estimates reflect a high regard of young men for the present. Interest rates outside the theoretically plausible ranges have been encountered before in the empirical literature. [Hall and Mishkin (1982) find 40 percent and higher annual interest rates that lead them to conclude that marginal propensity to consume out of transitory income is substantially high.]

Job offer and layoff probabilities are found to continuously and significantly decline, the former more steeply and higher than the latter at all durations. Constant layoff and job offer probabilities are rejected be-

Table 1
Parameter Estimates

Parameter	Point Estimate	Asymptotic Normal Statistic	Formula
Wage offer			
w_o	4.78	(182.07)	
σ_e	0.55	(40.29)	
Mean wage	5.56		$w_o \exp(\frac{1}{2}\,\sigma_e^2)$
Standard error in wage	3.29		$w_o\{\exp(\sigma_e^2)[\exp(\sigma_e^2) - 1]\}^{1/2}$
Discount factor δ	0.93	(138.01)	
job offer probability			
Constant (a_{ne})	-2.63	(-46.38)	
Slope (b_{ne})	-0.02	(-7.91)	
Range in (0, T)	$(6 \times 10^{-2}, 7 \times 10^{-4})$		$\{1 + \exp[-(a_{ne} + b_{ne}k)]\}^{-1}$
Layoff probability			
Constant (a_{en})	-4.25	(-51.49)	
Slope (b_{en})	-0.02	(-6.43)	
Range in (0, T)	$(1 \times 10^{-2}, 3 \times 10^{-4})$		$\{1 + \exp[-(a_{en} + b_{en}l)]\}^{-1}$
$\log L = -3{,}541.81$			

Note: The single-period payoff from not being employed, s, is not separately identified and fixed at a value of 5.00 in estimation.

cause slope coefficients are significant.[7] A test of dynamic behavior is conducted using the discount factor. The discount factor is significantly different than zero as its t-statistic shows. Hence, the static model is rejected. [See the discussion following Equation (21) in Section II.]

At this point, it is useful to compare these results with the results of Wolpin (1987) who uses wage on the first (and only) job and no other employment data in his structural search model where employment is an absorbing state. In contrast, in this multi-spell model, transition and duration data on employment are included, but observed wages are left out for computational reasons.[8] Despite these differences the two models yield

7. A likelihood ratio test between this model and a more restrictive one where both the job offer and layoff probabilities are time-invariant also rejects constancy.

8. Observed wages are not included in the likelihood function for computational reasons. Incorporating them would require estimating joint probabilities of wages and transitions instead of transition probabilities only. While omitting the wage data causes nonidentification of one of the parameters, s, there are substantial gains in terms of computational costs.

remarkably similar results. For example, the estimate of the standard error of log-wage is 0.50 in the former study and 0.55 in the latter. Moreover, the pattern of the estimated job offer probabilities are alike even though functional form assumptions are different for these probabilities, i.e., normal in the former study, and logistic in the latter. Hence, the two papers arrive at similar conclusions regarding labor market behavior of the youth even though they differ in sample design and model construction.

A likelihood-ratio test is conducted to judge the overall performance of the model. The test that is used is asymptotically equivalent to a standard goodness-of-fit test that compares frequencies of actual and predicted outcomes. In this test, the sum of the logarithms of actual transition frequencies constitute the unrestricted model, and the log likelihood function estimated in this paper, which is the sum of the logarithms of predicted probabilities, is the restricted model. One can envision a suitable nesting relation between the models under investigation to facilitate the likelihood ratio test. For example, assume that a constant term in the model, e.g., w_o, differs in each period, ensuring a different reservation wage and, hence, a different switch probability for all participation histories. The resulting (unrestricted) model nests the model of this paper.

The corresponding χ^2 statistic $= -2\ln$ (restricted model likelihood) $-$ ln (unrestricted model likelihood) $= -2[-3542 - (-2256)]$ is not used in a χ^2 test. Instead $((\chi^2/n)^{1/3} - 1 + (2/9n))(9n/2)^{1/2}$ approximation is used because n = degrees of freedom is large.[9] This is the Wilson-Hilferty transformation distributed standard normal, and is more accurate than the Fisher standard normal transformation, $(2\chi^2)^{1/2} - (2n - 1)^{1/2}$ (Harris 1966). The model is not rejected on the basis that the actual transition frequencies do not significantly differ from the predicted transition probabilities.[10]

9. It should be noted that this test has a tendency to commit type II error because of the large degrees of freedom. Degrees of freedom are high because the unrestricted model essentially assigns a different hazard rate to each movement in the data for each distinct experience, and virtually has as many parameters as there are different experience and status change combinations in the raw data. To be specific, d.f. = 48,613.

10. Another unrestricted model is sought that is more restricted than the unrestricted model mentioned in the text to lower the degrees of freedom in the test. The most natural choice is to estimate a model that computes a different empirical hazard rate in each period but ignores differences in unemployment and employment histories. This model is nested in the first unrestricted model with exclusionary restrictions on the implicit duration components of the hazard rates. The two unrestricted models are found to be statistically insignificant from each other. The principal structural model with duration dependence cannot be tested against the second unrestricted model because it is not appropriately nested. A second structural model with no duration dependence is estimated (see Footnote 7). Then this

V. Predictions of the Model

Based on the parameter estimates, the predicted dynamic labor force behavior of individuals; the effects of changes in forcing variables on the expected duration of working and joblessness; and how the dynamic behavior of individuals changes with variations in the parameters are analyzed in the following three sections.

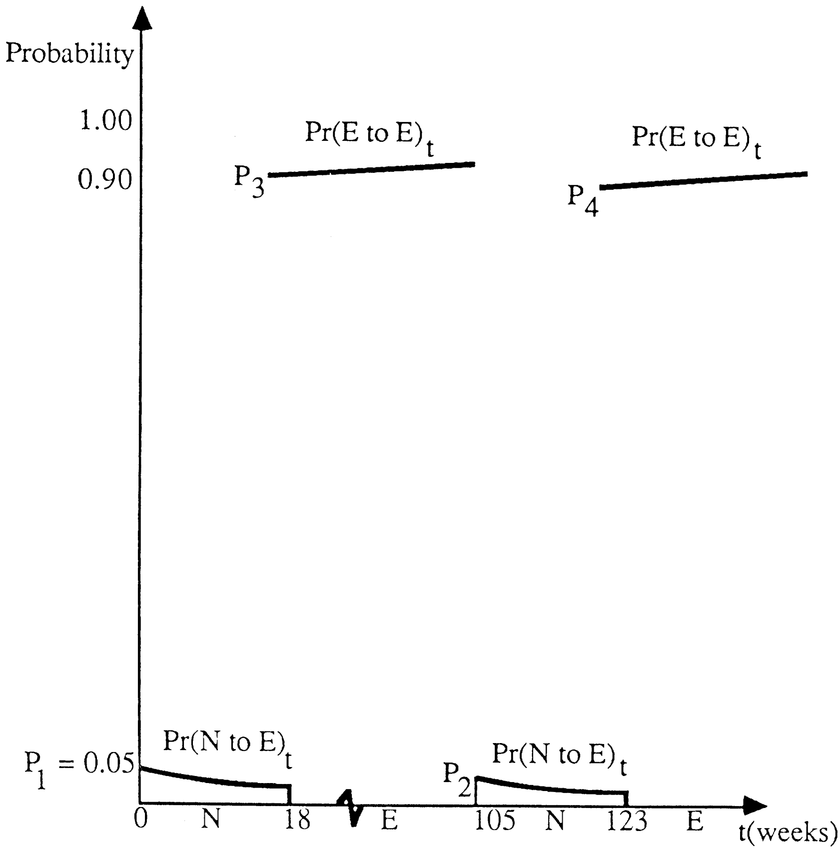
A. The Dynamic Labor Force Behavior

The estimation results are such that reservation wages when not working decline as the number of periods spent unemployed increase and reservation wages when working go down as tenure (employment) stock grows. For given duration (experience) levels reservation wages increase over time. Combining the time (age) effect with the effect of duration implies that after each labor market experience the youth raise their reservation wages higher than they were at the beginning of the previous spell (the time effect) and then moderate it during the course of the current spell (the effect of duration). This applies to both unemployment and employment spells. Rising reservation wages from one spell to the next, i.e., over time, can at best be explained by increased valuation of own productivity after having had exposure in the labor market.

Figure 2 illustrates the transition behavior over time predicted by the model for average durations in each state. In the sample as well $Pr(N \text{ to } E)_t$ falls and $Pr(E \text{ to } E)_t$ is relatively flat over time: both of these behavioral patterns are satisfactorily predicted by the model as shown in the figure.

In the situation of obtaining a job, the probability of receiving a job offer from firms declines with elapsed unemployment faster than the reservation wage. This produces a decreased likelihood of finding work with accumulating unemployment (declining $Pr(N \text{ to } E)_t$ in Figure 2 refers). Furthermore, together with declining probabilities of firm-initiated separations with the duration of employment, declining reservations wages with experience lead to an increased likelihood of remaining on the job as employment experience increases (rising $Pr(E \text{ to } E)_t$ in Figure 2 refers). As a corollary of this finding, quit rates fall with tenure on the job.

model is tested against the second unrestricted model, both of which have age dependence and no duration dependence (d.f. = 435). The result of this test also indicates that a structural model of the same genre as the model of the paper performs well against an unrestricted model of comparable nature.



Note: $P_2 < P_1$ and $P_4 < P_3$

Figure 2
Predicted Transition Behavior

B. Simulations Based on Parameter Estimates

In this subsection the effects of shifts in the parameters on expected spell durations using the estimated values are demonstrated, and the results are compared with previous findings in the literature. Expected duration formulas are

$$(24)\quad E(t_n) = \sum_{t_n=1}^{T} \prod_{j=1}^{t_n} Pr(N \text{ to } N)_j$$

$$(25)\quad E(t_e) = \sum_{t_e=1}^{T} \prod_{j=1}^{t_e} Pr(E \text{ to } E)_j$$

where the switch probabilities are, as before,

$$Pr(N \text{ to } E)_t = p_{ne}(k_t)Pr(e_t > \ln(R_t/w_o))$$

$$Pr(E \text{ to } E)_t = (1 - p_{en}(l_t))Pr(e_t > \ln(R_t/w_o))$$

and where expected duration of nonemployment, $E(t_n)$, is inversely related to the former probability and that of employment, $E(t_e)$, is positively related to the latter probability.

The first line in Table 2 shows the sample means of nonemployment and employment durations, the second line shows a simple exponential model's predictions (as discussed at the end of Section 3), and the third line shows the model's prediction to be used as a threshold value in the second half of the table. The predicted means of both models are higher than the sample means because they take into account censoring unlike the sample means. This is more pronounced in the case of working spells, since most employment spells tend to be longer than unemployment spells, and are more likely to be subject to censoring at the end of the observation period. The mean duration measures predicted by both models reflect a commonly observed fact that males spend more time working than otherwise; 73 percent of the time according to our model.

Table 2
Simulated Changes in Expected Durations

	Expected Duration of Nonemployment	Expected Duration of Employment
Sample mean (in weeks)	16.70	46.04
Exponential model mean	19.60	71.12
Model prediction	18.41	87.36
Percentage Change in the Parameter Value	**Percentage Change in Expected Duration of Nonemployment**	**Percentage Change in Expected Duration of Employment**
+10% Constant in wage	−0.4%	+42.0%
+10% Variance in log wage	−0.4%	+42.0%
+10% Constant in offer probability	−19.0%	−66.0%
−10% Constant in layoff probability	−0.2%	+28.0%

Note: Parameter values are from Table 1.

The rest of the table indicates percentage changes in expected durations with respect to a change in the listed parameter.[11] First, consider the effect of an improvement in w_o, the constant component of the wage. This induces a decrease in the reservation wage. As a result, the term R_t/w_o decreases and the probability that wage exceeds the reservation wage rises. Since this probability governs the probability of both choosing employment over nonemployment and remaining on the job, expected duration of nonemployment falls and expected duration of employment rises. Conversely, a decrease in w_o increases the reservation (resignation) wage since an employed worker may quit in response to a lower wage.

This finding is consistent with Toikka (1976) in the previous literature who describes a Markov model with three labor force states and finds that the transition probability from employment to unemployment or out of the labor force is adversely affected with the wage. Furthermore, in job search models like Wolpin (1987) and Burdett et al. (1985) the reservation wage is found to increase in response to an increase in the constant component of the wage (the mean wage in these papers) but be dominated by a larger increase in the wage itself, resulting in an overall decrease in the unemployment probability. The result of this paper is consistent with these findings.

If the payoff from nonemployment (s) were to go up instead of w_o, the results would be reversed, since s/w_o is the identified component in the model. Mortensen (1986) argues that as cost of search goes down (or as the payoff from nonemployment goes up) the unemployment spells tend to get longer in a standard search model. This is the result achieved in the labor force participation framework of this model. Thus, if the cost of search is increased, people will search less and stay employed longer.

Increasing the variance in the wage induced by an increase in σ_e lowers the reservation wage, as in the case of an increase in the constant component of the wage. The chance of very high wages makes staying on the job or attaining a job worthwhile; therefore, expected duration of nonemployment is shorter and of employment is longer. In general, the effect on duration could go in either direction if $0 < R_t/w_o < 1$ because of the negative augmentation in the cumulative normal distribution function argument in the expected duration equation. In this case $0 < R_t/w_o < 1$ and increasing σ_e makes the whole argument, $\ln(R_t/w_o)/\sigma_e$, more negative, consequently, the working probability rises, and shorter nonemployment spells, longer employment spells follow.[12]

11. Experimenting with lower or higher perturbations than the ones listed in Table 2 does not change the qualitative conclusions. Reversing the directions of the changes in parameter values simply reverses the sign of the change in expected duration.

12. In standard search models, as the variance in the wage rises the reservation wage also

Next, consider a favorable shift in the job offer probability brought on by an increase in the constant term. In response to this, workers can afford to be selective and the reservation wage rises. A higher offer probability implies that continuing to work in the presence of a positive layoff probability is less valuable while there is an opportunity to explore outside possibilities; therefore, shorter durations on a job follow. The process of finding suitable jobs is sped up, despite the rise in the reservation wage; hence shorter durations on search follow. This finding is consistent with the standard job search models as well, see, for example, Wolpin (1987) or Mortensen (1986).

The direct effect of the layoff probability on expected durations is reinforced by its indirect effect on the reservation wages. A downward shift in the layoff probability at all durations lowers the reservation wage of workers. In addition to a lower average duration of nonemployment and a higher average duration of employment induced by a drop in the layoff rate, a lower reservation wage causes workers to be more willing to remain on a job or accept a job offer, since the negative traits of working such as involuntary dismissals, firings, and layoffs are less likely. Expected duration of nonemployment is shorter, and that of employment is longer, as layoffs decrease.

C. Dynamic Responses to Changes in the Forcing Variables

The simulations of this section show changes in dynamic labor force behavior of the youth when parameter values are changed. The results are displayed in Table 3. For the sake of exposition, the behavior of the youth one month (four weeks) after graduation is presented with minimum and maximum duration levels. These correspond to zero and three weeks respectively. Table 3, Row 1 shows the model estimate while the remaining rows show changes with respect to a change in the listed parameter.

In each row, reservation wages are seen to be very low (Columns 1 and 2), and this is reflected in high job acceptance and low quit probabilities (Columns 3 and 4). However, the probability of finding a job (Column 7) is low because job offer probabilities are minuscule (Column 5).[13] Probability of remaining employed is high because of a low layoff probability (Column 6) combined with a low quit probability.

rises, leaving the net effect on duration of unemployment generally ambiguous. However, in a simple search model, prolonged unemployment is more plausible because it pays to shop around longer for jobs when high wages are probable.

13. Wolpin (1987) finds the same pattern, i.e., low reservation wages and low offer probabilities, in his structural job search model.

Table 3
Simulated Changes in Selected Reservation Wages, Job Acceptance, and Quit Probabilities One Month after Graduation[a]

	Reservation Wage While Unemployed (1)		Reservation Wage While Employed (2)		Job Acceptance Probability (3)		Quit Probability (4)		Job Offer Probability (5)		Layoff Probability (6)		Probability of Switching from Unemployment to Employment (7)		Probability of Remaining Employed (8)	
Duration (weeks)[b]	0 (a)	3 (b)	0 (a)	3 (b)	0 (a)	3 (b)	0 (a)	3 (b)	0 (a)	3 (b)	0 (a)	3 (b)	0 3a × 5a	3 3b × 5b	0 (1–4a) × (1–6a)	3 (1–4b) × (1–6b)
Model estimate[c]	1.39	1.28	1.39	1.37	0.89	0.91	0.110	0.108	0.07	0.06	0.014	0.013	0.06	0.06	0.878	0.881
+ 10% Constant in wage	0.00	0.00	0.00	0.00	1.00	1.00	0.000	0.000	0.07	0.06	0.014	0.013	0.07	0.06	0.986	0.987
+ 10% Variance in log wage	0.11	0.00	0.11	0.09	0.99	1.00	0.010	0.000	0.07	0.06	0.014	0.013	0.07	0.06	0.976	0.987

+10% Constant in offer probability	1.80	1.68	1.80	1.78	0.84	0.86	0.164	0.161	0.09	0.08	0.014	0.013	0.07	0.07	0.825	0.828
−10% Constant in layoff probability	1.28	1.16	1.28	1.26	0.91	0.92	0.100	0.093	0.07	0.06	0.009	0.009	0.06	0.06	0.892	0.899

a. The variables in Columns (1) through (8) are computed by the following formulae:

(1) $R_t(k_t) = s + \delta(FN_t(k_t) - FE_t(0))$
(2) $R_t(l_t) = s + \delta(FN_t(0) - FE_t(l_t))$
(3) Probability of accepting a job $= Pr(w_t > R_t(k_t))$
(4) Probability of quitting $= Pr(w_t < R_t(l_t))$
(5) Job Offer Probability $= p_{ne}(k_t)$
(6) Layoff Probability $= p_{en}(l_t)$
(7) $Pr(N \text{ to } E)_t = (3) \times (5)$
(8) $Pr(E \text{ to } E)_t = (1-(4)) \times (1-(6))$

b. Duration refers to the number of weeks unemployed, k_t, in Columns (1), (3), (5), and (7), and weeks employed, l_t, in Columns (2), (4), (6), and (8).

c. The estimates are from Table 1.

Effects of parameter changes are consistent with expected duration simulations in Table 2. Only a summary of results is given here for the sake of brevity. An increase in the mean wage or wage variance, or a decrease in the layoff rate increases the job acceptance probability and decreases the quit probability thereby increasing the employment probability. An increase in the job offer probability decreases the job acceptance probability, increases the quit probability and hence decreases the probability of employment.

Effects of duration are preserved when these parameters change, i.e., if a probability increases or decreases with experience then it does so in each row. (Rows denote parameter changes and Columns (a) and (b) denote different duration levels.) This is equivalent to saying that parameter changes result in shifts in the transition probabilities at fixed experience levels.

The duration effects themselves are interesting. For example, quit probability falls by 2 percent with the duration of employment (Columns 4a and 4b, first row), and the decline becomes steeper, 7 percent, if the layoff probability decreases (Columns 4a and 4b, last row). The job acceptance probability rises with duration of nonemployment since reservation wages fall. In Columns (3a) and (3b) of the first row this is reflected as a 13 percent increase. The increase is less, 3 percent, when job offer probabilities rise (the fourth row). Other similar experiments are shown in the remaining columns and rows of Table 3.

We will conclude with a final remark about prediction. Average labor force participation rates cannot be computed from this model because transition probabilities are time-specific. If it were a stationary model with unchanging probabilities over time then the average non-participation rate, Π_N, and participation rate, Π_E, would be computed as follows:

$$(26) \quad \Pi_N = \frac{1 - Pr(E \text{ to } E)}{1 - Pr(E \text{ to } E) + Pr(N \text{ to } E)}$$

$$(27) \quad \Pi_E = \frac{Pr(N \text{ to } E)}{1 - Pr(E \text{ to } E) + Pr(N \text{ to } E)}$$

In this model, however, the probabilities of state occupancy in each period, $\Pi_N(t)$ and $\Pi_E(t)$, obtain recursively as

$$\Pi_N(t) = \Pi_N(t-1)(1 - Pr(N \text{ to } E)_t) + \Pi_E(t-1)Pr(E \text{ to } N)_t$$

$$\Pi_E(t) = 1 - \Pi_N(t)$$

where some assumption has to be made about initial (or terminal) state occupancy probability.

VI. Conclusion

In this paper a dynamic labor force participation model with layoffs is developed and estimated. The model is a discrete-time, finite-horizon, discounted utility maximization model where individuals make labor force participation decisions in an environment with uncertain job offers and layoffs. In addition to duration dependence introduced through time-varying job offer and layoff probabilities, state dependence enters the model by the existence of a different risk while working, namely, the dismissal risk, than the one while not working, namely, the possibility of no job offers.

The data are from the National Longitudinal Surveys of Labor Market Experience youth cohort. Job offer and layoff probabilities are allowed to vary with the duration of recent labor market experience, generating a duration effect in addition to the age effect caused by the finite horizon, on the probability of working and not working. The duration effects are found to be negative and significant. The model's predictions are not rejected in a goodness-of-fit test where they are compared with observed transition frequencies.

Based on the structural parameter estimates, simulations are performed to assess the impact of changes in forcing variables on nonemployment and employment duration. When confronted with a high mean wage, a high variance in the wage or a low layoff probability, workers, on average, tend to go through shorter durations of nonemployment and longer durations of employment, and when the frequency of job offers is raised both durations tend to be lower on average.

The dynamic predictions are rising working probabilities, falling quit and falling layoff rates with duration of employment or tenure; and, falling job offer probabilities and falling working probabilities with the duration of nonemployment. The results reported in this paper support the theory pertaining to job separations, which has not been estimated before in comparable frameworks, and the remaining results are in agreement with prior findings in the empirical job search and labor force participation literature.

Appendix

Identification of the Model

Identification of all but one of the parameters is achieved by variations in the transition data, nonlinearities in the model, and the finite-horizon assumption. In each period, one observes the fraction of people working or not working. The people differ with respect to their recent participation histories, that is, with respect to k_t and l_t. The model matches the observed fractions with the probabilities in the likelihood function. That is,

(A.1) (Fraction of people who work at t who have searched for k_t periods before t) $= p_{ne}(k_t)Pr(w_t > R_t(k_t)) = Pr(N \text{ to } E)_t$

(A.2) (Fraction of people who continue working at t having worked for l_t periods before t) $= (1 - p_{en}(l_t))Pr(w_t > R_t(l_t)) = Pr(E \text{ to } E)_t$

The constant and duration coefficients of the layoff probability are identified directly from the cause of job separations data given sufficient variation in the duration of employment stocks of people who are laid off.

Because of the lognormal distribution assumption the variance of e_t is identified. The variance does not enter like a scale variable as in a probit model: variance of the wage $= w_o^2 \exp(\sigma_e^2)[\exp(\sigma_e^2) - 1]$.

It is helpful for the rest of the discussion to rewrite R_t, the reservation wage at t, as a function of R_{t+1} by substituting in expressions for $FE_t(l_t)$ and $FN_t(k_t)$ from Equations (15) and (16) given in the text.

$$\begin{aligned}
R_t &= s + \delta[FN_t(k_t) - FE_t(l_t)] \\
&= s + \delta\{p_{ne}(k_t)[w_o \exp(.5\,\sigma_e^2)[1 - F[(\ln(R_{t+1}/w_o) - \sigma_e^2)/\sigma_e]] \\
&\qquad\qquad - R_{t+1}(1 - F(\ln(R_{t+1}1/w_o)/\sigma_e))] \\
&\qquad + s + \delta FN_{t+1}(k_{t+1}) - [1 - p_{en}(l_t)] \\
&\qquad \cdot [w_o \exp(.5\,\sigma_e^2)[1 - F(\ln(R_{t+1}/w_o) - \sigma_e^2)/\sigma_e]) \\
&\qquad\quad - R_{t+1}(1 - F(\ln(R_{t+1}/w_o)/\sigma_e))] \\
&\qquad - s - \delta FN_{t+1}(k_{t+1})\} \qquad \text{for } t < T
\end{aligned}$$

After deleting similar terms and dividing both sides by w_o one obtains

$$\begin{aligned}
\text{(A.3)}\quad \frac{R_t}{w_o} &= \frac{s}{w_o} + \delta[p_{ne}(k_t) - (1 - p_{en}(l_t))] \\
&\qquad \cdot \{\exp(.5\,\sigma_e^2)[1 - F[(\ln(R_{t+1}/w_o) - \sigma_e^2)/\sigma_e]] \\
&\qquad - \frac{R_{t+1}}{w_o}[1 - F[\ln(R_{t+1}/w_o)/\sigma_e]]\} \qquad \text{for } t < T
\end{aligned}$$

Also from $V_T(P_T = 1) = V_T(P_T = 0)$

$$\text{(A.4)}\quad \frac{R_T}{w_o} = \frac{s}{w_o}$$

The finite horizon assigns a terminal value to R_T as s, the one-period value of nonmarket time. We will show later that s and w_o are not separately identified. For now, treat s/w_o as a composite parameter. This parameter and the remaining unknowns, the offer probability, $p_{ne}(k_t)$, and the discount factor, δ, are identified from equations (A.1)–(A.3) given the nonlinearities in the model. The identification of the duration coefficient of the job offer probability requires variation in the duration of unemployment stocks.

Because of the lognormality assumption s and w_o always enter the model as a ratio. If normality were assumed then they would enter as a difference, $s - w_o$. In the absence of measurement errors, the lowest observed wage can be used as a consistent estimator of s. In this application s is fixed at a positive value and w_o is estimated. The model is flexible enough to allow for exogenous regressors such as age, education, sex, race, family background, local market conditions, and others in, say, the log-wage function. The added coefficients are identified through variation in the relevant variables across individuals so long as they are excluded from the utility function. But, in this work, only a constant term for the wage, w_o, is estimated in order to keep the state space at manageable dimensions.

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