# Reemployment Patterns of Displaced Older Workers*

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**Abstract**

In the past two decades, the incidence of involuntary job loss among workers over the age of 50 has increased relative to that of their younger counterparts. This age group experiences particularly severe displacement effects, including long unemployment durations and large earnings losses upon reemployment. While several recent studies have focused on dynamic models of employment and retirement behavior, these analyses have ignored displacement and its consequences. This paper investigates these phenomena by providing structural estimates of a dynamic job search model applied to a sample of displaced workers in the Health and Retirement Study. The estimates imply that reservation wages are low in comparison to the distribution of observed wages, particularly for full-time jobs. Simulations indicate that both market opportunities and age-related preferences for leisure are responsible for the observed unemployment durations, but that older workers would still have relatively long post-displacement jobless spells if preferences for leisure did not vary with age.

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# 1 Introduction

Since 1980, the incidence of job displacement among workers over the age of 50 has increased relative to that of their younger counterparts. Prior research indicates that this group experiences substantial costs of dislocation, in the form of low reemployment rates and large earnings losses upon reemployment[1]. In spite of these findings, most research on the effects of displacement has focused on younger cohorts[2]. This study assesses the economic impacts of late-career job loss on employment and earnings. In particular, it attempts to quantify the extent to which the observed earnings losses and low reemployment rates are due to voluntary nonemployment due to preferences for leisure and the availability of non-labor income, or involuntary unemployment due to poor labor market opportunities.

The labor force patterns of older workers have received much attention recently, motivated by the aging of America's population and the resulting increased significance of policies aimed at older adults. Authors such as Gustman and Steinmeier (1986) and Berkovec and Stern (1991) have modeled the labor force decisions of those nearing retirement age in the context of life-cycle models of labor supply. These models explicitly assume that individuals are able to assess their labor market prospects costlessly, instantaneously, and with certainty, and that they can freely choose the amount of labor to supply at a given market wage. These assumptions are inconsistent with the descriptive findings of several other studies such as Hurd (1996), who observes that older workers experience substantial labor market rigidities, as well as imperfect information about the wages they could earn. Furthermore, life-cycle models are silent concerning involuntary unemployment, and therefore cannot explain the labor market experiences of an increasingly large portion of the population of those nearing retirement age.

To address this shortcoming, this study models the labor supply decisions of older men and women in the context of a discrete-time job search model. Using monthly employment data from the Health and Retirement Study (HRS), a structural model of the labor market transitions of displaced older men and women is estimated, incorporating all of the restrictions implied by job search theory. Because of the importance of preferences for leisure in determining labor market outcomes among this population, the standard income-maximization version of the search model is not a sufficiently close approximation to reality

[1] See Farber (1997, 2001, and 2003) for extensive accounts of the incidence and costs of displacement.

[2] Chan and Huff Stevens (1998) and Couch (1998), discussed below, are notable exceptions that use data from the Health and Retirement Study.

in this setting. Therefore, I allow for a worker's utility, including the value of leisure, to depend on whether an individual is not employed, working part-time, or working full-time.

The salient features of this model closely follow those of standard job search theory: the probability of receiving an offer in a period of fixed length is possibly less than unity, and may be dependent on the duration of the search, the type of offer in question (either full-time or part-time), and other observable factors; wage offers represent draws from a stochastic distribution known to the searcher; and if an offer is refused it cannot be recalled. Additionally, the search horizon is assumed to be finite, after which search is terminated and no offers are accepted.[3]

It is worth reemphasizing that the lower reemployment rates and associated earnings losses of older workers may not be indicative of poor job prospects relative to the population as a whole. Preferences for leisure and the availability of non-labor income such as private pensions and Social Security benefits could induce workers to remain nonemployed regardless of the arrival rate of offers. Distinguishing between these chance and choice components of reemployment rates is often referred to as "the" identification problem in duration studies, and disentangling these components is only possible within a structural search framework. Furthermore, evaluating the impact of changes in policies or other relevant variables in the economic environment necessitates identifying endogenous behavioral responses separately from (exogenous) chance components of reemployment rates.

The estimated models imply that choice plays some part in the long unemployment durations of displaced older workers, but only in the form of rejections of part-time job offers. Even if all full-time offers were accepted, full-time monthly reemployment rates would increase only marginally. The estimated mean duration until a full-time job offer arrives is roughly two years, and is significantly longer for minorities and the oldest displaced workers. While these results are striking, they must be interpreted with care, since the structural models are only identified with the aid of parametric assumptions regarding the distribution of wage offers. With this caveat in mind, I present simulations which do not rely as heavily on functional form restrictions. In particular, I simulate unemployment durations assuming no population variation in preferences for leisure. The results indicate that both preferences and constraints explain the within-sample negative correlation between age and reemployment rates, and tentatively confirm that some of the differences

[3] An infinite search horizon would be a poor approximation to reality for the HRS sample, as many respondents express a desire to exit the labor market within a few years.

between post-displacement outcomes of older and younger workers is due to opportunities rather than preferences for leisure or the availability of non-labor income. Finally, specification tests indicate that the model fits the data reasonably well, and that slight misspecifications would likely not alter the central findings.

The remainder of the paper is organized as follows: the HRS sample to be used in the empirical work will be presented in more detail in Section 3, followed by a more detailed discussion of the model briefly outlined above in Section 4. Section 5 details identification and other estimation issues, and Section 6 presents estimation results, inferences, and specification tests of the model. Section 7 provides further evidence on the relative importance of preferences and market opportunities in explaining the data, and Section 8 concludes. Initially, we turn to a review of the relevant literature.

## 2 Previous Literature on Job Loss

Although no previous study has examined the labor market behavior of older individuals in a search environment, this paper builds upon a long line of research that focuses on the economic impacts of displacement. Swaim and Podgursky (1991) find that, among displaced workers, an additional year of tenure on one's last job is associated with a 2 to 5 per cent longer period of joblessness.[4] It is not clear whether the loss of firm-specific human capital is a cause of low reemployment rates of those over 50, or if older (high-tenure) workers are simply more choosy about their employment opportunities following displacement. Farber (2001), in a comprehensive account of the incidence of displacement for the U. S. population as a whole, finds that the probability of an involuntary job loss for those aged 55-64 increased from under 4% in the period 1980-1982 to over 5% in 1990-1992.

Chan and Huff Stevens (1998) analyze displaced men from the HRS, finding that approximately 10% of their total sample had experienced a job loss between 1990 and 1996. In addition to observing greater rates of displacement than previously believed, the authors also find that although many of these individuals did return to work, monthly reemployment rates were sufficiently low that this group's employment rates did not converge to that of their non-displaced counterparts until seven years later. While Chan and Huff Stevens' preliminary findings do not provide definitive evidence regarding the ability of jobless older

[4] Fallick (1996) provides a more detailed review of Swaim and Podgursky (1991) and several other empirical studies of job displacement.

men to return to work, they do suggest that these men wish to return to work but have difficulties doing so. In the only other study of late-career job loss using the HRS, Couch (1998) finds that the average displaced worker in the 1992 Wave of the HRS experiences an earnings loss of 39% two years after displacement[5], and confirms Farber's (1997) findings that approximately 5% of those who were employed in 1989 experienced an involuntary job loss in the period 1990-1992. These results suggest that search frictions are important, and that people cannot simply choose hours worked at a predetermined wage or freely choose whether or not they will work each period.

The findings of these literatures imply several salient features of the labor market facing older adults. Specifically, many workers near retirement age face severe hours rigidities within jobs—those working in jobs which are primarily part-time do not usually have the option of working full time without switching jobs, and vice versa. Secondly, the rate of involuntary job loss has increased among older workers in the previous two decades. Finally, the unemployed possibly have difficulty obtaining job offers, particularly for full-time work, and jobless spells are more persistent for this group than for many others in the U.S. population. These features, as well as the lack of efforts to model post-displacement outcomes, motivate the specifications described below.

# 3 Data

The Health and Retirement Study (HRS) is a longitudinal survey targeted at those aged 51-61 in the first wave of data collection, 1992. A nationally representative cross-section was selected for interview, as well as an oversample of non-whites and Florida residents. Spouses and domestic partners of the targeted group were also interviewed, resulting in a total of 12,652 individuals included in Wave 1. The ongoing survey is administered every two years to all base year respondents who can be located, resulting in sample sizes of 11,596 in Wave 2 (1994) and 10,970 in Wave 3 (1996).

The HRS is the first wide scale longitudinal study of older Americans to be conducted since the Retirement History Survey of the late 1960s and early 1970s, and as such can be used to address a variety of important questions regarding the health, economic well-being, and labor market status of those nearing or at retirement age in the 1990s. A battery of

[5] Farber (1997) and other studies report population-wide average earnings losses of 10-25% two years post-displacement.

questions was designed to elicit information regarding respondents' labor market earnings and histories, availability of non-labor income such as pensions and Social Security, and subjective expectations of employment prospects and desired hours worked.

HRS respondents were also linked with federal W-2 and self-employment earnings records for every year from 1980 to 1991, and quarterly Social Security earnings and benefits data from 1951-1991.[6] For those who agreed to have their W-2 data released, earnings at every employer from 1980 to 1991, as well as the number of years worked for the employer, can be linked to their Wave 1 survey responses. Analogously, for those who agreed to have their records matched with data from the Social Security Administration, measures of Social Security wealth and future monthly benefits can be obtained in accordance with various assumptions regarding the timing of benefit receipt and post-1991 employment experience.[7] As a result, the HRS is particularly well-suited to search-theoretic analyses of the labor market outcomes of older Americans.

This study focuses on those who experienced an involuntary job loss between 1988 and 1996. In order to identify those eligible for inclusion in the estimation sample, it was necessary to consider several different cases. Among those in the first Wave of the HRS sample, to be considered displaced, a person must report losing a job after 1987 in which they had at least five years of tenure. If that respondent was employed at the time of the Wave 1 survey and indicated that the reason for leaving her previous job was due to a layoff or plant closure, her retrospective job history and W-2 records were used to determine when the displacement occurred, and when the post-displacement unemployment spell ended by a return to employment. For those unemployed in the Wave 1 survey who reported losing their most recent job due to layoff or plant closure, inclusion in the sample was dependent on whether the job ended after 1987 and whether pre-displacement tenure was greater than 5 years, as in the previous case.

The classification of Waves 2 and 3 respondents as "displaced" proceeds analogously to the method for Wave 1 respondents. For all candidates for the displacement sample, only those with valid earnings, W2, and SSA records were retained. Those below the age of 50 and those reporting that they were not currently looking for work were also excluded from the analysis, resulting in 1046 valid observations for the empirical analysis. Of these,

[6] These are restricted-use data files, and only available from the HRS by special arrangement.

[7] Mitchell, Olson, and Steinmeier (1996) provide a detailed description of the Social Security earnings and benefits file. Questions about this and other HRS datasets should be directed by e-mail to hrsquest@umich.edu.

213 came from those displaced and reemployed prior to the Wave 1 survey, 357 from those displaced but not reemployed prior to Wave 1, 217 from those whose jobless spells began after Wave 1 and ended before Wave 2, 144 from those displaced after Wave 1 and still unemployed as of Wave 2, 133 from those whose spells began after Wave 2 and ended before Wave 3, and 78 from those displaced after Wave 2 and still unemployed as of Wave 3.

In order to motivate the model and estimation strategy proposed below, Table 1 presents some evidence of the variation in employment outcomes of older workers in the HRS, as a function of whether the worker was displaced from a long-term job in the 5 years leading up to the wave 1 survey. This subsample is further broken down into 2 categories, based on whether the respondent worked full-time or part-time on a post-displacement job acquired prior to the wave 1 interview, with a job being defined as full-time if it requires an average of at least 35 hours of work per week.

Table 1–Hours Constraints Among Those Displaced Prior to Wave 1

| | All Employees (N=6040) | Displaced and working (N=213) | Displaced and working PT(N=71) |
|---|---|---|---|
| Hours worked in 1992 | 39.5 | 35.2 | 22.5 |
| % desiring more hours | 16.3 | 20.7 | 33.6 |
| % desiring fewer hours | 12.8 | 10.6 | 01.4 |

This comparison does not highlight the differences between displaced and nondisplaced workers as much as one involving more recently displaced workers. However, it does show that over one-third of those who have been displaced and are currently working part-time desire to work longer hours even though some have been working for four years in a new job. These preliminary findings suggest that heterogeneity in labor supply preferences must be considered when modeling the labor force behavior of older workers. The results also indicate that many of those who are displaced wish to increase their hours and cannot do so without lengthy intervening periods of underemployment.

As described above, the final sample consists of 1046 post-displacement unemployment spells, of which 508 ended with a transition to full-time employment, 188 ended with a transition to part-time employment, and 350 were censored. Spells were classified as "censored" for a number of reasons. First, due to sample attrition in the HRS, some sample members who appeared in Wave 1 did not fill out surveys in Waves 2 or 3. Similarly, some sample members did fill out later questionnaires, but their employment status was either missing or could not be determined. Second, many unemployment spells ended in states other than working, particularly "disabled" or "retired". Finally, 141 unemployment spells that began after 1987 were ongoing as of the Wave 3 interview date, which occurred in 1996 for the majority of sample members.

The bottom panel of Table 2 summarizes the reasons for the exiting/censoring of the 1046 unemployment spells, while the top panel presents Kaplan-Meier estimates of the hazard function, defined by the number of completed spells in a period as a percentage of the total sample members at risk in the period. Thus, for the first 3 months of the post-displacement unemployment spell, the Kaplan-Meier estimate of the hazard function is 196/1046 (= 0.187), and so forth. As is apparent from the table, 55 individuals, or over 5% of the sample, have unemployment durations which last over five years, while nearly 20% of the sample obtain employment within 3 months of being displaced. The estimate of the median unemployment duration is 17.0 months, which confirms previous findings (Couch (1998) and Chan and Huff Stevens' (1998)) of persistent nonemployment among those displaced in the HRS sample.[8]

Finally, Table 3 presents sample means and standard deviations of the observable covariates used in the estimation. The excluded education category is "high school dropout", which describes the educational level of 32.3% of the sample. All of the other variables are self-explanatory except the Social Security benefit level, which is defined as the monthly Primary Insurance Amount conditional on retirement at age 65, the current Normal Retirement Age as defined by the Social Security Administration. This value was computed based on the SSA earnings data from the years 1951-1991.[9]

# 4 Theory and Model Specification

This section will describe the process by which unemployed individuals search for both part-time and full-time job offers. The starting point is a finite-horizon job search model similar to that of Wolpin (1987), with the additional assumption that hours are perfectly inflexible within jobs. The assumptions of stationarity and an infinite search horizon,

[8] Chan and Huff Stevens estimate the median duration of unemployment *among those reemployed* to be 12 months.

[9] The benefit levels were calculated using the SSA's ANYPIA program. Earnings after 1991 could increase the benefit level if earnings in these years were higher than those in one or more of the 35 years of greatest annual earnings during the 1951-1991 period. The effect of including post-1991 earnings on benefit levels is zero or negligible for a majority of the displaced sample, and including post-1991 earnings in the calculations would lead to endogeneity of benefit amounts. For these reasons, only pre-1991 earnings are used in computing the PIA. Further details can be found in Mitchell, Olson, and Steinmeier (1998).

which are common in empirical studies of structural search models, likely do not constitute reasonable approximations to reality for many populations. The justification for imposing these assumptions on the HRS sample is even weaker. Very few Americans over the age of 70 desire to be engaged in labor market activity, and this horizon is less than 10 years away for a good deal of the HRS sample at the time of the Wave 3 interview. In the empirical application, the search horizon $T_i$ will not be taken to be a function of duration, but rather a function of age, with the final search period determined from individual responses to HRS questions which ask when sample members will stop working for pay. The value of $T$ will be modeled as the solution to the dynamic problem of choosing the optimal age of retirement.

Each period $t$, searching individuals receive net unemployment income $b_t$. Part-time job offers arrive according to a Poisson process with parameter $\lambda_p$, while full-time offer arrivals are associated with Poisson parameter $\lambda_f$. By the Poisson assumption, in a small time interval $h$, the probability of receiving an offer of either type is $\lambda_j h + o(h)$, $j \in \{f, p\}$[10], so that the probability of receiving more than one offer of either type is negligible. The indirect utility of wage offers are i.i.d. realizations from known time-independent (but age-dependent) distributions $F_f(x)$ and $F_p(x)$, where the subscripts refer to part-time or full-time work respectively. One of three possible innovations may confront the agent in a given period. First, no new part-time or full-time offers arrive, which happens with probability $(1 - \lambda_p - \lambda_f)$; second, a new part-time offer may arrive, with probability $\lambda_p$; and finally, a new full-time offer may arrive with probability $\lambda_f$.[11]

Suppose that the agent derives utility from her income and leisure streams, with her preferences separable across these goods. Formally, at each $t$ the agent maximizes the function

$$E\left[\sum_{j=0}^{T_i+\tau_i-t} \frac{u(y_j)v(l_j)}{(1+r)^j}\right], \tag{4.1}$$

where $y_j$ and $l_j$ are income and leisure, respectively, in period $t+j$, $1/(1+r)$ is the agents' (common) discount rate, and $\tau_i$ is the length of time between the end of the search horizon and the end of life[12]. For now, we will normalize units of leisure to be equal to 0 if the agent

[10] Recall that $o(h)$ is defined such that $\lim_{h \longrightarrow 0} \frac{o(h)}{h} = 0$.

[11] By the Poisson assumption, the probability of both a part-time and a full-time offer arriving per period is negligibly small.

[12] This muliplicative form of utility was chosen primarily for its computational convenience. Unlike an

is engaged in full-time work, $L \in (0,1)$ if she is working part-time, and 1 if unemployed. Given this functional form of utility, the value of unemployed search at period $t$ is given by

$$\begin{aligned} V_t &= \lambda_f E \max[Q_t, u(b_t)v(1) + \frac{V_{t+1}}{1+r}] + \lambda_p E \max[S_t, u(b_t)v(1) + \frac{V_{t+1}}{1+r}] + \\ &\quad (1-\lambda_f-\lambda_p)\cdot[u(b_t)v(1) + \frac{V_{t+1}}{1+r}], \end{aligned} \tag{4.2}$$

for all $t = 1, ..., T_i - 1$. All wage distributions, offer arrival rates, and benefit amounts are assumed to be known with certainty at the initial search period, so that the information set is unchanging over time and the expectations operator is time-invariant. The first term on the right-hand side of (4.2) is the probability of receiving a full-time offer multiplied by the expected maximum of the utility stream associated with this offer, denoted $Q_t$, and the utility stream associated with remaining in the unemployed state, given by $u(b_t)v(1) + \frac{V_{t+1}}{1+r}$. The second term on the right side of (4.2) is defined similarly as the probability of receiving a part-time offer multiplied by the expected maximum of the utility stream associated with this offer, denoted $S_t$, and the value of remaining unemployed. Finally, the third term consists of the probability of not receiving any kind of offer, multiplied by the indirect utility of remaining unemployed.

The values of $Q_t$ and $S_t$ referenced in the preceding equations can be expressed in terms of the utility streams associated with these two states. Formally, the value of holding a part-time job associated with wage $w_p$ at period $t$ is

$$S_t = \sum_{j=0}^{T_i-t} \frac{1}{(1+r)^j}[u(w_p)v(L)] + \sum_{j=T_i-t+1}^{T_i+\tau_i-t} \frac{1}{(1+r)^j}[u(b_j)v(1)]. \tag{4.3}$$

Similarly, the value of holding a full-time job associated with wage $w_f$ at period $t$ is given by:

$$Q_t = \sum_{j=0}^{T_i-t} \frac{1}{(1+r)^j}[u(w_f)v(0)] + \sum_{j=T_i-t+1}^{T_i+\tau_i-t} \frac{1}{(1+r)^j}[u(b_j)v(1)], \tag{4.4}$$

and the value of $V_T$ is defined as the discounted flow of income and leisure streams associated with nonemployment:

$$V_T = \sum_{j=T_i}^{T_i+\tau_i} \frac{1}{(1+r)^j}[u(b_j)v(1)], \tag{4.5}$$

additive (in $y$ and $l$) utility function, the marginal utility of one good is dependent on the value of the other, an appealing feature.

which is a constant not under the control of the individual at period $T$.

There are a few points worth noting regarding the simplifying assumptions underlying the model. First, from the definition of $Q_t$ it is apparent that individuals who have been dislocated from previous jobs and return to full-time employment do not partially retire by working in part-time jobs to smooth the transition from work to retirement, but instead continue to work full-time until their desired time of retirement $T_i$[13]. Although research by Blau (1994) indicates that these transitions are more common than economists once thought, one could reasonably assume that those who actively seek full-time employment near to their desired retirement age would not leave these positions once they got them, as this behavior is indicative of strong labor force attachment. Although this assumption is also supported by the presumption that these individuals have a strong desire to work, these features represent a weakness of the model and may need modification in the future.[14]

Coleman and Heckman (1981) demonstrate the formal properties of an infinite-horizon analog of the model described by equations (4.2) to (4.5), in which a reservation value is associated with each of the reasons for exit from unemployment. In our formulation, utilities within a given employment state are determined uniquely by wages, so that the reservation wage property applies. Define $rw_{ft}$ as the reservation wage which, at period $t$, causes an unemployed individual to be indifferent between continuing unemployed search next period and accepting full-time work. Similarly, $rw_{pt}$ is the reservation wage which makes one indifferent between unemployment and part-time work. These reservation wages are implicitly characterized by the following:

$$\begin{aligned} Q_t(rw_{ft}) &= u(b_t)v(1) + \frac{V_{t+1}}{1+r} \\ S_t(rw_{pt}) &= u(b_t)v(1) + \frac{V_{t+1}}{1+r} \end{aligned} \tag{4.6}$$

so that each individual's optimal strategy is characterized by as many as $2 \cdot (T_i - 1)$ reser-

[13] $T_i$ is determined *a priori*, and does not depend upon whether a person finds a part- or full-time job, or on the accepted wage. This represents an unappealing time consistency problem, in that ideally $T_i$ would evolve over time in response to changes in state variables. In particular, if a person found an unusually high paying job, *ex post* they would probably want to work beyond $T_i$. In the search model, properly modeling the evolution of $T_i$ would render this problem computationally infeasible due to the necessary expansion of the state and decision spaces. Chan and Huff Stevens (1999) find that subjective retirement distributions do not change much over time among HRS sample members displaced prior to 1990, so the time-constancy of $T_i$ appears to be a reasonable approximation to reality for much of the sample.

[14] Chan and Huff Stevens (1998) find a substantial degree of negative duration dependence in exits from newly-acquired jobs, with moderate rates of match destruction very early in tenure and a large drop-off as tenure increases. In the empirical work below, transitory jobs which last fewer than three months will not be treated as exits from unemployment.

vation wages.

In order to simplify the characterization of the optimal strategy, it is helpful to define $\xi_{ft}$ and $\xi_{pt}$ as the present value of the utility streams associated with accepting employment at the full-time and part-time reservation wages, respectively (so that $\xi_{ft} = Q_t(rw_{ft})$, and $\xi_{pt} = S_t(rw_{ft})$). Then,

$$
\begin{aligned}
\xi_{ft} &= v(1)u(b_t) + \frac{V_{t+1}}{(1+r)} \\
\xi_{pt} &= \xi_{ft} \\
\xi_{fT} &\leq \sum_{j=T_i}^{T_i+\tau_i} \frac{1}{(1+r)^j}[u(b_j)v(1)] \\
\xi_{pT} &\leq \sum_{j=T_i}^{T_i+\tau_i} \frac{1}{(1+r)^j}[u(b_j)v(1)],
\end{aligned}
\tag{4.7}
$$

where the last two lines represent the endogeneity of the retirement decision, in that they are equivalent to the condition that the value of nonparticipation at $T$ is greater than the value of continued search. Recalling that wage draws are i.i.d., the value of search at any time $t < T$ can be written as

$$
\begin{gathered}
V_t = v(0)\lambda_f[E(u(w_{ft}) \mid u(w_{ft}) \geq \xi_{ft}) + \xi_{ft}\Pr(u(w_{ft}) < \xi_{ft})]+ \\
v(L)\lambda_p[E(u(w_{pt}) \mid u(w_{pt}) \geq \xi_{pt}) + \xi_{pt}\Pr(u(w_{pt}) < \xi_{pt})]+ \\
v(0)(1-\lambda_f-\lambda_p)\xi_{ft},
\end{gathered}
\tag{4.8}
$$

where $u(w_{ft})$ is the present value of accepting a wage offer into full-time work, net of leisure valuation, and $u(w_{pt})$is defined analogously.

Substituting (4.8) into (4.7) yields a nonlinear difference equation for the present values of the reservation wages, e.g., (4.8) substituted into the first line of (4.7) produces a nonlinear difference equation in $\xi_{ft}$, with the terminal condition given by the third line of (4.7). Given a chosen distribution of observed wages, I calculate the $2 \cdot (T_i - 1)$ reservation wages using Rust's (1987) nested fixed-point algorithm, in which the dynamic program is solved for every sample member at each iteration.

With the sequence of reservation wages defined, we can turn to calculating the per-period probabilities of leaving unemployment through one of the two employment states. Define $t^{uf}$ as the *hypothetical* duration of unemployment if the only alternative were full-time employment, and define $t^{up}$ analogously in the case that the only other state were part-time employment. The associated hypothetical hazard rate for exiting unemployment to full-time employment is defined as the probability of exit in period $t$, given that the agent has not exited in period $t-1$. This conditional probability is denoted by $\theta_t^{uf}$, and is determined by the product of the offer arrival rate and the probability that the offer is greater than the reservation wage[15]:

$$\theta_t^{uf} = \lambda_f(1 - F_f(rw_{ft})). \tag{4.9}$$

Similarly, the hypothetical hazard for exiting unemployment into part-time employment is

$$\theta_t^{up} = \lambda_p(1 - F_p(rw_{pt})). \tag{4.10}$$

When unemployment spells can end in more than one possible state, the duration of these spells can be represented in a competing risks framework. The density of observed unemployment spell durations is given by the density of the minimum of $t^{uf}$ and $t^{up}$, since the agent will leave unemployment when the first of these two hypothetical durations has elapsed. If a transition to a state occurs in period $t$, the duration of the spell is treated as censored with respect to the competing state. As a result, when we write the likelihood as a function of the parameters of arrival rates, distributions, and observed wages, every observation will have some element of censoring included.

Data on durations of spells of unemployment, and the state of exit from these spells, will yield consistent estimates of the hazards for each time period: $\theta_t^{uf}$ and $\theta_t^{up}$. In the absence of prior information about the distributions of wages in both sectors, duration data alone cannot identify the offer arrival rates separately from these distributions. Identification is achieved by use of observed wages, which along with the restrictions embodied in the structural model allow estimation of the parameters of the offer distributions. Recall that wages are observed in period $t$ only if they exceed the relevant reservation wages. Accepted wages are therefore distributed as truncated random variables from the wage offer distribution, with the truncation point being $rw_{ft}$ or $rw_{pt}$:

$$f(w_{ft} \mid w_{ft} > rw_{ft}) = \frac{f_f(w_{ft})}{1 - F_f(rw_{ft})}, \quad w_{ft} \geq rw_{ft}, \tag{4.11}$$

[15] The hazard rates actually depend on the probability that the *utility* of the offer is greater than the utility of the reservation wage, but this is equivalent to the condition given by (4.10) if utility is strictly increasing in the arguments. For notational convenience, the discussion in the remainder of this Section proceeds as if utility were linear in wages, i.e., if the function $u(\cdot)$ were the identity function.

and

$$f(w_{pt} \mid w_{pt} > rw_{pt}) = \frac{f_p(w_{pt})}{1 - F_p(rw_{pt})}, \quad w_{pt} \geq rw_{pt}. \tag{4.12}$$

From the assumption of stationarity in the arrival rates, wages are distributed independently of offer arrivals. As a result, the joint density of accepted wages and elapsed unemployment durations can be written as the product of the marginal density of wages and the hazard rates for each time period up to $t$. Thus, if a spell ended in full-time employment at time $t$, the contribution to the likelihood function would be

$$LC = \prod_{j=0}^{t-1} \Pr(U_j = 1 \mid U{=}1 \text{ to } j) \times \Pr(FT_t = 1, w_{ft} \mid U{=}1 \text{ to } t) \tag{4.13}$$

$$= \prod_{j=0}^{t-1}(1-\theta_j^{uf})(1-\theta_j^{up}) \times (1-\theta_t^{up})\theta_t^{uf}\frac{f_f(w_{ft})}{1-F_f(rw_{ft})}. \tag{4.14}$$

Now that all of the relevant distributions have been specified, it is possible to write the likelihood function for a sample of incomplete and completed spells of unemployment, and the associated observed wages and states of destination. Consider a sample of $N$ individuals, observed from the date of entrance into unemployment until a final interview date, which will determine the latest possible censoring point for each individual. Assume that observations occur monthly, so that if an individual obtains employment in month $t$, she has experienced $t-1$ months of unemployment since displacement. Define $t_u$ as the duration of a completed unemployment spell, and $\bar{t}_u$ as the duration of a right censored spell. Order the data so that the first $n_1$ spells are censored with respect to the unemployment duration, the next $n_2 - n_1$ sample members have completed unemployment spells and began full-time work, and the final $n_3 - n_2$ sample members have completed unemployment spells and began part-time work. Letting $FT_j = 1$ indicate full-time employment in period $j$, and defining $PT_j$ and $U_j$ analogously for the part-time and unemployment states, the likelihood function is given by

$$\begin{aligned} L = & \prod_{i=1}^{n_1}\left[\prod_{j=1}^{\bar{t}_{ui}} \Pr(U_j^i = 1 \mid U^i{=}1 \text{ to } j)\right] \times \\ & \prod_{i=n_1+1}^{n_2}\left[\prod_{j=1}^{t_{ui}-1} \Pr(U_j^i = 1 \mid U^i{=}1 \text{ to } j) \times \Pr(FT_{t_{ui}}^i = 1, w_{ft_i} \mid U^i{=}1 \text{ to } t_{ui})\right] \times \\ & \prod_{i=n_2+1}^{n_3}\left[\prod_{j=1}^{t_{ui}-1} [\Pr(U_j^i = 1 \mid U^i{=}1 \text{ to } j) \times \Pr(PT_{t_{ui}}^i = 1, w_{pt_i} \mid U^i{=}1 \text{ to } t_i)]\right] \end{aligned} \tag{4.15}$$

In order to estimate the parameters of the structural search model of labor supply, this (admittedly lengthy) likelihood function can be written as a function of the 2 hazard functions defined in this text and the densities of the truncated wage offer distributions. Maximization of this likelihood subject to the restrictions of equations (4.7-4.8) and a nonnegativity restriction on all reservation wages produces consistent estimates of the parameters, with the caveat that parametric functional forms of wage offer distributions must be specified. Flinn and Heckman's (1982) discussion of the "recoverability condition" shows that these distributions are not identifiable by nonparametric methods. I will specify wage distributions that depend on a finite vector of parameters and satisfy the recoverability condition, so that the parameters of the distributions, offer arrival rates, and reservation wages are identified. [16]

# 5 Empirical Implementation

I have assumed to this point that there is no population dispersion in any of the parameters of the model. While this assumption was introduced for ease of presentation, there are numerous reasons to believe that substantial heterogeneity exists. Consequently, I will explain how to model the various parameters as depending on both observable and unobservable characteristics. The structural model will be estimated by maximum likelihood. I adopt a methodology analogous to Narandranathan and Nickell (1985), Wolpin (1987), and Blau (1991), in the sense that, for every iteration and every person in the sample, the optimal strategy needs to be computed.

## 5.1 Heterogeneity in Full-Time and Part-Time Offer Arrival Rates

To assure the required non-negativity of wage offer arrival rates, I parameterize each as exponential functions of a finite-dimensional vector of observed variables. Specifically, let

$$\begin{aligned}\lambda_f &= \exp(X'_{\lambda_f}\beta_{\lambda_f} + \gamma_f\mu_j), \text{ and} \\ \lambda_p &= \exp(X'_{\lambda_p}\beta_{\lambda_p} + \gamma_p\mu_j).\end{aligned}$$

The covariates comprising $X_{\lambda_f}$ and $X_{\lambda_p}$ include measures of an individual's attractiveness to potential employers (although the wage offer distributions will likely capture some of

[16] Flinn and Heckman (1982) provide a very thorough analysis of identification and distribution theory in the homogenous agent search model.

this effect as well), such as education levels, race, gender, and age.[17]

While the HRS elicits information on whether the respondent is looking for full-time or part-time work, these variables will not be included in the vector of explanatory variables due to the strong possibility that these variables are endogenous–those looking for full-time work are likely doing to because they have the best chance of finding such work. Instead, in order to account for a dimension of unobserved heterogeneity, I will include an additional covariate. The SSA data includes the number of quarters of positive earnings in the period 1951-1991, which can be interpreted as a measure of both the experience of a worker and the ease with which she obtains job offers.[18] This value, $\mu_j$, will be used as a rough representation of a worker's attractiveness to employers, as summarized by her job history.

## 5.2 Estimating Offer Distributions

Identifying the parameters of the offer distributions requires specifying parametric wage distributions which satisfy Flinn and Heckman's (1982) recoverability condition. In practice, it is prudent to re-estimate the model with several different offer distributions, since many authors, such as Wolpin (1987), have found their results highly sensitive to these functional form assumptions. Wolpin obtained very sensible results assuming log-normality of offer distributions, but *negative* reservation wages assuming normality.[19]

This study initially attempts to estimate offer distributions assuming that offers are distributed log-normally, with expectations depending on a finite vector of observable variables $Z$, and a common variance for all of the members of the sample. Specifically,

$$
\begin{aligned}
(\ln(w_f^i) \quad | \quad Z_w^i) &\sim N(Z_w^{i\prime}\Gamma_{w_f}, \sigma_{w_f}^2) \\
(\ln(w_p^i) \quad | \quad Z_w^i) &\sim N(Z_w^{i\prime}\Gamma_{w_p}, \sigma_{w_p}^2).
\end{aligned} \tag{5.16}
$$

[17] Measures of labor market tightness, such as state-, industry-, or occupation-specific unemployment rates, would also be reasonable candidates for covariates which affect offer rates. However, the HRS does not presently allow merging of any of the SSA or W-2 data with occupation or industry data, or data containing geographic identifiers (the HRS is exploring ways by which these types of data may be merged in the future). I estimated additional specifications including national unemployment rates, with no significant changes in the inferences.

[18] While the likelihood of working in a particular quarter is a function of both the acceptance probability and the arrival rate, there is some justification for using this measure as a determinant of arrival rates alone. In particular, if reservation wages and offer distributions were constant throughout the sample, variation in prior employment probabilities would perfectly mirror variation in prior arrival rates. If arrival rates are correlated over time, this variable would capture variation in current arrival rates. Analogously, in the case of heterogeneity in acceptance probabilities, the procedure would still be valid, assuming that those with "high" reservation wages in the 1951-1991 period had high reservation wages after 1991.

[19] For an excellent survey of the sensitivity of results to assumptions regarding offer distributions, see Devine and Kiefer (1991).

Restricting attention to the estimation of full-time wage offer distributions, we substitute the normal density and cumulative distribution in the likelihood function for $f_f(\cdot)$ and $F_f(\cdot)$, respectively. The density and distribution are therefore defined as (suppressing conditioning on the vector $Z$ from here on):

$$
\begin{aligned}
f_f(\ln(w_f^i)) &= \sigma_{w_f}^{-1} \cdot \phi\left(\frac{Z_w^{i\prime}\Gamma_{w_f}}{\sigma_{w_f}}\right) \\
F_f(\ln(w_f^i)) &= \Phi\left(\frac{Z_w^{i\prime}\Gamma_{w_f}}{\sigma_{w_f}}\right),
\end{aligned}
\tag{5.17}
$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ refer to the standard normal pdf and cdf, respectively. The distribution of $w_p$, and the associated terms in the likelihood function, are defined analogously.

Recovering these distributions from observed accepted wages would be the best-case scenario from an estimation point of view, but doing so requires some care. The vector $Z_w$ must be of low dimension, because only 696 of the 1046 spells of unemployment observed in the HRS from 1992-1996 end in reemployment, with only 188 of these ending in part-time employment. In order to account for a substantial proportion of heterogeneity, $Z_w$ should contain at least a measure of education, age, and race. In order to account for unobserved heterogeneity in offer distributions, yearly log wages from the W-2 earnings history data (covering the years 1980-1991) are regressed on a vector of explanatory variables including age, ethnicity, sex, and education levels. Using only those years that do not correspond to the first or last year worked on a job, each individual is assigned an individual-specific "fixed effect," computed as the mean of the residuals for each sample member from the wage regression. This fixed effect, $\mu_w$ captures variation in the locations of offer distributions that is unrelated to the other variables $Z_w$, as summarized by the earnings history.

Given the sparse number of observations on accepted wages, I am not able to estimate the distributions directly from the observed data; however, there are other options. Narandranathan and Nickell (1985) first employed the procedure of using out-of-sample data on observed wages to estimate *a priori* wage-offer distributions for the unemployed. Implementation of this strategy involved regressing observed wages from a sample of employed workers on a set of observable covariates, then using the coefficients from these regressions to predict expected wages for the jobless sample. Assuming log-normality of the offer distribution, a common variance term was estimated as the variance of the residual from these regressions. van den Berg (1990) notes that this approach was somewhat flawed, in that observed wages are drawn from a truncated distribution, i.e. wages for these workers are observed only if they exceed the reservation wage for these workers when they were unemployed.[20]

As noted above, due to the small number of exits to part-time employment, both full-time and part-time log wage distributions were estimated using methodology similar to van den Berg (1990). Formally, let $w_i^* = W_i'\Gamma + \varepsilon_i$, where $\varepsilon_i \sim N(0, \sigma^2)$. If $w_i^* > 0$, then the wage $w_i$ is observed. Thus, wage offers are observed with probability $\Phi(W_i'\Gamma)$, and the relevant wage distributions can be estimated using Heckman's two-step estimation procedure to account for sample selection bias, with spouse's disability status used as an excluded instrument. The dependent variables for these models are the log of the starting wage at the current job, for all HRS sample members who were employed in the base year. Starting wages were converted 1992 dollars using the Consumer Price Index.

Table 4 presents the estimates obtained using this procedure[21]. In both the full-time and part-time wage equations, all coefficients have the expected signs; namely, wages are monotonically increasing in education levels, and the means of the wage offer distributions are lower for non-whites and females. It should be emphasized that the interpretation of this estimation is that the dependent variable is the offered wage, so that the reported coefficients represent the effects of the covariates on offer distributions, not observed wages. Finally, the coefficient on the Mills' ratio is positive but estimated imprecisely, so that it is insignificantly different from zero. The sample selection-corrected estimates are not reported for the part-time wage distributions, due to both the smaller sample size and the fact that the excluded instruments are not *a priori* justified as strongly as in the full-time wage equations.

### 5.3 Heterogeneity in Preferences for Leisure and Non-Labor Income

The final parameters of the model to be estimated are those involving the weights given to leisure in the utility function. To see how this is implemented, recall from equation

[20] van den Berg (1990a) also notes that the approach of Kiefer and Neumann (1979) was flawed because they assume that wages are observed *if and only if* they exceed reservation wages. If the offer arrival rate is not equal to 1, the "*if*" condition does not hold. Thus, when offers arrive at a rate less than unity, this procedure has no structural interpretation.

[21] As is apparent from Table 4, sample sizes were 935 and 4107 for the estimation of the part-time and full-time wage distributions, respectively. The sample consisted of HRS Wave 1 respondents who reported starting wages at the job that they currently held. As a result, this analysis is not restricted to the displaced sample used for the later estimation.

(4.7) that each period reservation wages are functions of the parameters given above and some combination of $v(1)$, $v(L)$, and $v(0)$. Since these functions are only identified up to scale, I normalize $v(1)$ to one. As in the case of offer arrival rates, there is likely to be population heterogeneity in the values of these functions, so we assume that the ratio $\frac{v(0)}{v(1)}$ can be approximated by

$$\exp(X_v^{i\prime}\beta_v + \mu_n), \tag{5.18}$$

where the vector $X_v$ includes observed characteristics related to preferences for leisure. The parameter $\mu_n$ is an individual-specific random effect meant to capture unobserved heterogeneity in leisure valuations; $\mu_n$ is assumed to come from a distribution with a finite number of points of support.[22] The number of points of support, or "types," the sample fractions of each type, and the mass points themselves are estimated jointly with the other structural parameters.[23] Thus, the likelihood of observing an individual with a given unemployment duration would be given by the weighted average of the terms given in (4.14) conditional on an individual type, with the weights given by the sample probabilities of each of the different types, $\pi_n$:

$$L(d_i \mid X) = \sum_{n=1}^{N} L(d_i \mid X, \mu_n)\pi_n. \tag{5.19}$$

I assume that the relative weights of the elements of $X_v$ in determining the ratio of the nonemployment value of leisure to the full-time working value of leisure are the same as those comprising the ratio of nonemployment to part-time leisure values. Then $\frac{v(L)}{v(1)} = \alpha \cdot \frac{v(0)}{v(1)}$, so that $\alpha$ is a scale factor which determines the value of part-time leisure to full-time leisure as income is held constant.

As with other observable controls for heterogeneity, $X_v$ contains few elements for computational simplicity; reasonable candidates include education, family structure, and age. The parameters of the leisure values $\alpha$ and $\beta_v$ are identified, given consistent estimates of the other parameters of the model, namely $\Gamma_{w_f}$, $\Gamma_{w_p}$, $\sigma_{w_f}$, $\sigma_{w_p}$, $\beta_{\lambda_f}$, and $\beta_{\lambda_p}$.

Finally, I construct measures of non-labor income $b_t$ from two sources, the matched data from the Social Security Administration and detailed HRS survey measures of wealth from

[22]This random effect is estimated via Heckman and Singer's (1984) non-parametric maximum likelihood estimator (NPMLE) for duration analyses.

[23]In practice, I stopped adding types when the marginal change in the log-likelihood function was less than 0.0001.

various sources, including housing, financial assets, and private pensions. Some simplifying assumptions are necessary to incorporate both of these components of monthly non-labor income. First, if a respondent's desired retirement age was at least 65, the monthly benefit level is taken to be the monthly PIA given the normal retirement age, which is 65 as currently defined by the SSA. If the desired retirement age is less than 65, this amount is adjusted using SSA rules regarding the "early retirement penalty", which specifies that the PIA be reduced by 5/9 of 1% for each month before age 65 that benefits are first claimed. Next, these amounts are added to benefit levels for all months after the desired retirement date, i.e., workers are assumed not to have access to this source of income until the date of their planned retirement. The contribution of wealth to non-labor income is computed as an annuity, so that each period respondents receive a flow of income equal to the interest rate $r$ multiplied by their total stock of wealth. This assumption is not realistic, but does allow for the computation of a significant element of the variation in available income across individuals.[24]

# 6 Estimation Results

## 6.1 Parameter Estimates

The structural parameters of the dynamic search model are presented in Table 5. Looking first at full-time job offer arrival rates, the estimates appear reasonable. Full-time offers arrive with a higher probability for those with higher education levels, and the offer probability is monotonically increasing in education. The age variable, which is measured in deviations from the sample mean, is essentially zero, but the coefficient on the age-squared variable, -0.981 with standard error 0.202, merits some discussion. Since the corresponding variable is the square of de-meaned age, the coefficient implies that offer arrival rates are increasing in age up to the sample mean of 55.1, but decreasing afterward. In conjunction with the negative effects of age on the location of wage offer distributions, these estimates suggest that the oldest displaced workers suffer the worst from late-career job displacement.

Non-whites have lower estimated arrival probabilities than whites, as the coefficients for "black" and "Hispanic" are -0.598 (0.124) and -0.700 (0.153), respectively. These are

[24] This component of non-labor income is available whether the respondent is employed or not. Therefore, the distributions of monthly income for full-time and part-time workers, as well as for those not working, must incorporate this measure.

large effects, as evidenced by the similarity in magnitude of the coefficients to the one for "college graduate". The estimates imply that the difference in white and minority full-time arrival rates is roughly equivalent to the premium for being a college graduate relative to dropping out of high school, so that the "minority penalty" is substantially greater in arrival rates than in mean offer distributions.[25] As in the case of the oldest workers, minorities experience both low offer arrival rates and lower mean wage offers, so that their lower post-displacement earnings relative to whites could stem from both of these sources. Females, on the other hand, have slightly higher (although statistically insignificantly different from zero) arrival rates, partially mitigating their lower mean offers.

Finally, the number of quarters of positive earnings in the period 1951-1991 (from the SSA data), $\mu_j$, which captures both the experience of a worker and is a rough measure of previous arrival rates, has a large and significant effect on full-time arrival rates. Apparently the employment histories reflect an important source of heterogeneity, and are proxying for unobserved (to the econometrician but not to firms) factors that firms use in making job offers. Exclusion of this variable would lead to biased estimates of the effect of the other covariates on offer arrival rates. Alternatively, employment histories may be proxying for search effort or attachment to the labor force, measures which have not been explicitly included due to their likely endogeneity with respect to arrival rates and offer distributions.[26]

Turning next to the arrival rates of part-time job offers, all of the coefficients have similar signs and magnitudes to those for the full-time offers, with the exception those associated with education levels. While high school dropouts again have lower arrival rates than college attendees, from high school graduation onward, arrival rates are declining in education levels. Specifically, the coefficient for high school graduates is 0.284 (0.314), while the effects of "some college" and "college graduate" are 0.167 (0.342) and -0.067 (0.358), respectively. This result is surprising, but is likely a reflection of significantly lower part-time reemployment rates for these individuals, combined with the higher locations of their offer distributions. Keeping in mind the above discussion of the effects of search intensity,

[25] The estimates of the offer distribution given in Table 4, as well as most estimates given in most studies of wage determination, suggest that the effect of minority status is comparable to the premium for completing an additional level of schooling, i.e. graduating high school versus dropping out.

[26] I have not modeled search intensity for two reasons. First, a full solution would require solutions for search intensity for every individual and time period, greatly increasing computational costs. Second, separate identification of the parameters of search intensity, arrival rates, and leisure preferences would be tenuous, given that there are only 1046 individuals in the sample.

heterogeneity in search strategy, defined here as variation in search intensity between full-time and part-time jobs, likely plays a key role in explaining the pattern of part-time arrival rates across education levels. Those with higher education levels, who have a greater likelihood of obtaining full-time job offers, focus their search efforts in the full-time sector. Consequently, they do not receive as many part-time offers. The estimates capture both search strategy and firm offer behavior, and without explicitly modeling search intensity, I am unable to separately identify both of these effects.

Of particular interest is the magnitude of the intercept term, which is larger (smaller in absolute value) than the corresponding term for full-time arrivals. This provides a preview of Table 6, in which I examine sample means of the search model parameters and find that the mean offer arrival rate is higher for part-time jobs than for full-time ones, in agreement with prior expectations.

Turning next to the leisure valuation parameters given in column 3 of Table 5, those with higher schooling levels apparently experience lower disutility of work as compared to high school dropouts. Those who are married also have weaker preferences for leisure, as the coefficient of 0.345 (0.117) indicates less disutility from working full-time relative to single individuals. This estimate deserves some attention given the recent literature on joint labor force decisions of married couples, which indicates that workers with non-working spouses tend to value their non-market time more than those without spouses at home (see, e.g., Blau and Riphahn (1999)). In contrast, other studies have found that, among younger workers, married men work more than single men. This discrepancy suggests that a household-level analysis of the joint employment decisions of spouses would be an interesting direction for future research relating to the post-displacement outcomes of older workers. Turning to column 4, the relative value of working part-time versus full-time, $v(L)/v(0)$, is estimated at 1.209 (0.072). As expected, conditional on monthly income, HRS sample members would rather work part-time than full-time, as evidenced by the value of this parameter being significantly greater than one. Finally, Appendix Table 1 presents regressions of the underlying search model parameters as a linear function of the observable variables used in the estimation. This is intended as a summary of the correlations of these variables with the parameters and the retirement date $T_i$. Given that the correlation patterns are similar for full- and part-time jobs, only the full-time parameters are displayed.

The value of the likelihood function did not sufficiently increase with the addition of a fourth point of support of the mixing distribution of unobserved heterogeneity in leisure valuations, so the number of points was set to three. The "types" are ordered in terms of increasing tastes for work, with type two not being significantly different from type one, but type three having a significantly higher valuation of work, conditional on income, than type one. From column 5 of the Table, 14.2% of the sample was estimated to be of type two, while 46.7% was estimated to be of type three (column 6).

The sample averages of the underlying search model parameters are presented in Table 6. As was apparent in Table 5, the average valuation of log monthly income is higher in the part-time employment state than in the full-time state. Put another way, conditional on income, people prefer working part-time to working full-time, which is not surprising. In contrast, the marginal valuation of log monthly income in the part-time state is essentially equal to that of the nonemployment state, implying that conditional on income, HRS sample members are nearly indifferent between working part-time and not working at all. Perhaps this result is not too surprising, given that those who have substantial work histories and desire to continue working are likely not adept at home production.

Part-time offers are estimated to arrive each month with a lower-than-expected probability of 0.079, but only a little fewer than half of the part-time offers are accepted. Full-time arrival rates are even lower, 0.042 per month, but the probability that an offer is greater than the computed reservation wage each period is 0.977. This latter result is in accord with the previous results of Narandranathan and Nickell (1985) and van den Berg (1990), who both found that choice was not an important determinant of reemployment probabilities.

Since the offer distributions are not identified without specifying parametric functional forms, there are good reasons not to interpret these results too literally. In particular, as discussed above, a primary advantage of structural estimation lies in the ability to distinguish between low offer arrival rates and low acceptance probabilities, but these inferences rely heavily on functional form to identify the part of the distribution which is below the reservation wage. If the true log wage offer distribution is not symmetric, so that the log-normality assumption represents a misspecification, it is possible that much of the mass of the full-time offer distributions lies below the reservation wage. In this case, the estimated acceptance probabilities are biased upward, while offer arrival rates are biased downward.

Subject to these caveats and taking these results at face value, it seems that the situation facing older workers desiring full-time work is rather bleak–even if they accept every wage offer presented to them, they will still have a median duration of unemployment of approximately 2 years.

## 6.2 Evaluating the Fit of the Structural Search Model

The model presented in the previous section imposed a great deal of structure on exits from post-displacement unemployment to part-time and full-time work. A cost of imposing this structure is that the true generating process may not obey the assumptions made in developing the model, so determining whether or not the model fits the data should prove informative regarding the soundness of these assumptions. The first implication of the model that can be tested is how well the estimated durations and hazard/survival rates capture actual exits from unemployment, as measured by simple Kaplan-Meier estimates of the survivor function.[27]

Figure 1 plots the sample mean of the survivor function implied by the estimates given in Table 5 versus the Kaplan-Meier estimate given in Table 2. While the two functions track each other fairly closely, before month 15 the sample mean of the survivor function generated by the estimated search model lies above the 95% confidence interval (represented by dashed lines) of the Kaplan-Meier estimate. Between months 15 and 69, the estimate from the search model lies within the Kaplan-Meier confidence band, but after the 69th month, it significantly overpredicts exits from unemployment, as evidenced by the estimated survivor function lying below the confidence band. Some care should be taken in evaluating the fit of the model after month 60, as only 55 spells last beyond the 60th month (see Table 2). However, the poor fit before month 15, particularly in months 0-3, is indicative that the model does not capture some important elements of either unobserved heterogeneity or true state dependence. The data reveal substantial negative duration dependence, with a hazard rate of exit from unemployment of 18.7% over the first three months, but only 6.6% from months 13 to 15 (see Table 2). The model cannot account for this spike in exits in the initial 3 months following displacement, but seems to track hazard rates well (roughly measured by the slope of the survivor function) in the following months. It is unlikely that the parameters which are allowed to vary over time in the model, namely offer distributions

[27] The Kaplan-Meier estimate of the survivor function impose no structure on the actual data generating process of durations. Thus, it is appropriate to treat it as the "data".

and preferences for leisure, are more poorly estimated in months 0-3 than in other months; thus, the failure of the model to capture this element of duration dependence is likely due to unmeasured attributes of the sample or true state dependence. Nonetheless, given that the model does not account for true state dependence via a separate baseline hazard for each period $t$, it fits the data rather well in comparison to other structural search models in the literature.[28]

An additional test of the model arises from its implications for the distribution of accepted part-time and full-time wages. Recall that post-displacement wages are observed only if they lie above the relevant reservation wages, so that equations (4.11) and (4.12) give the distribution of full-time and part-time observed wages, respectively. I assume above that wage offers are distributed log-normally conditional on a set of covariates $Z^i_w$, so that $(\ln(w^i_{ft}) \mid Z^i_{wt}) \sim N(Z^{i\prime}_{wt}\Gamma_{w_f}, \sigma^2_{w_f})$, and $(\ln(w^i_{pt}) \mid Z^i_{wt}) \sim N(Z^{i\prime}_{wt}\Gamma_{w_p}, \sigma^2_{w_p})$. These assumptions require that the distributions of observed (log) wages arise from a truncated normal distribution, with the truncation point given by the reservation wage. For $j \in \{f,p\}$, the expected value of observed wages is given by (suppressing conditioning on $Z^i_{wt}$):

$$E(\ln(w^i_{jt}) \mid \ln(w^i_{jt}) > \ln(rw^i_{jt})) = Z^{i\prime}_{wt}\Gamma_{w_j} + \frac{\sigma_j \cdot \phi\left[\frac{\ln(w^i_{jt}) - Z^{i\prime}_{wt}\Gamma_{w_j}}{\sigma_j}\right]}{1 - \Phi\left[\frac{\ln(rw^i_{jt}) - Z^{i\prime}_{wt}\Gamma_{w_j}}{\sigma_j}\right]}, \tag{6.20}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal pdf and cdf, respectively. A fundamental test of the fit of the search model comes from comparing the sample averages of expected accepted (log) full-time and part-time wages generated by the model and equation (6.20) with the sample means of the observed wages. Under the null hypothesis that the data generating process is described by the parameters of the model, these sample means should be equal. The expected observed wages given in Table 6 are not used in this procedure, as they involve expected observed wages for those who did not actually obtain employment. Instead, the analogous statistics are computed as the means for the 696 sample members who eventually returned to employment. For the 508 individuals who exited to full-time jobs, this sample mean is 7.392, while the mean of actual observed wages is 7.271. Given that the standard deviations of these measures are 0.457 and 0.761, respectively, the standard error of the difference in these means is 0.039, so that the hypothesis that the observed wage data was generated by the model is rejected. For the 188 part-time jobs observed, the mean of expected log monthly wages is 6.710 (0.420), while the average

[28] See Devine and Kiefer (1991) for a thorough survey of the older literature.

observed wage is 6.618 (0.837). Again, the hypothesis that the model describes the wage generating process is rejected.

Table 7 reports actual and expected observed wages for across cell values of the observable variables, and generally confirms the above findings. For both part- and full-time wages, the model predictions track the pattern of actual wages, with males, whites, married individuals, those under age 56, and those with higher educational levels having relatively high predicted and observed wages. The only pattern in the data which is not replicated by the model is the advantage of those with some college versus college graduates in log part-time wages. As in Table 6, the predictions are generally higher than the data, with the exceptions being full-time wages for Hispanics and part-time wages for those with some college. The discrepancy between predicted and actual values varies across cells, but the model performs well in capturing the patterns of variation in observed wages across cells. However, these predictions almost uniformly overestimate observed wages regardless of the value of the covariates.

For both full-time and part-time jobs, the average predicted wage levels are too high, overestimating observed wages by 11 to 12 per cent. One culprit could be the likely underreporting of non-labor income and wealth,[29] which could bias the parameters of the offer distributions. If these estimates are biased, then estimates of all of the other parameters of the search model may be inaccurate as well. Since many components of non-labor income may be received whether the individual is working or not, the direction of the bias on the parameters of the distribution (and therefore reservation wages and the other parameters of the model) is ambiguous.[30]

Another possible explanation for the overprediction of observed wages becomes evident from a comparison of the mean of the wage offer distribution which is used in estimating the parameters of the distribution in Table 4, and the mean of the actual observed distribution. Since the latter mean comes from a distribution which is truncated from below, it should be larger than the former. This is not the case: for full-time jobs, the mean accepted offer is 7.271, but the mean of the distribution estimated in Table 4 is 7.380.

[29] Moon and Juster (1995) observe that the estimates of wealth and income found in most U.S. panel data sets are plagued by survey nonresponse and underreporting, but that the designers of the HRS appear to have reduced this bias through the use of bracketing and unfolding techniques.

[30] Underreporting of income which is available only when one is not employed would unambiguously bias estimates of the reservation wage and expected observed wages *downward*, so this cannot explain the overprediction of observed wages.

Since a misspecification of the offer distribution will bias all the parameters of the model, I examined the sensitivity of the estimates to a shift in the location of the wage offer distribution. Specifically, I reestimated the model assuming that the true mean of full-time wage offers was 0.1 less than the one used in Table 4. A leftward shift of 0.1 in a log wage distribution corresponds to a 10% decrease in the mean of wage offers themselves, so this is actually a sizable translation. The parameters describing job offer arrival rates are not sensitive to this change, and the full-time arrival rate in the reestimated model changes by less than 0.001. The offer acceptance probabilities do not change either, as the mean shift is offset by increases in estimated reservation wages and average preferences for leisure. However, the increase in the relative value of leisure is primarily absorbed in the constant term in the expression for $v(0)/v(1)$. The slope parameters do not change markedly, and those with higher education levels and married individuals still exhibit less disutility of working compared to the high school dropouts and singles. The fact that the parameter estimates do not change is comforting, and indicates that slight misspecifications of the offer distributions will not greatly affect the implications of the model. In contrast, the sample-wide estimate of the expected observed full-time log wage decreases to 7.338 from the 7.455 reported in Table 6, and the expected accepted log wage for those who actually returned to full-time work declines to 7.275 from 7.392. This estimate lies much closer to the mean observed log wage of 7.271, and the difference between these values is no longer significant at the 5% level. It appears that the *a priori* procedure for estimating offer distributions did not accurately capture the locations, but this slight misspecification will likely not lead to false inferences.

A final check of the model involves a comparison of the observed wages with the computed reservation wages. If a large proportion of observed wages are below the reservation wages, the model's predictions do not fit the data well. For the 588 spells that ended in full-time employment, 48 observed log wages lie below the reservation wage, and of the 188 observed part-time log wages, 19 are below the reservation wage. Only about 3% are more than 0.1 below the reservation values, so that many of these errors could be due to measurement error. Taken in conjunction with the previous tests of the model's implications, the fact that roughly 10% of observed wages are below computed reservation wages indicates that the fit of the model is imperfect. However, it is generally better than many search models which have been previously estimated, as evidenced by the discussion in Devine and Keifer (1991).

# 7 Simulations of the Model: Further Evidence on the Relative Importance of Preferences and Opportunities

The results presented in Table 6 tentatively imply that the observed phenomena of long unemployment spells and large earnings losses are due primarily to poor labor market opportunities for older workers, rather than preferences for leisure of the availability of non-labor income. However, the discussion at the end of Section 6.1 regarding the non-identifiability of offer distributions raises serious doubts about the interpretation of these estimates. In this section, I attempt to provide further evidence that age-related preferences for leisure cannot explain all of the variation in unemployment spell lengths.

Figure 2 presents Kaplan-Meier estimates of survivor functions for two age categories, those at least 56 years old at the start of their unemployment spell, and those younger than 56. As is apparent from the figure, the younger group has considerably higher reemployment rates, with lower than 50% remaining unemployed one year after displacement. Among the older group, approximately two-thirds of those displaced are still searching for unemployment after one year, and the median unemployment spell is roughly 21 months. 95% confidence intervals (not shown) of the survivor functions do not intersect after six months have elapsed, implying that over much of the observed durations, survivor functions for the under-56 group are significantly lower than for the 56-and-over group.

Given these reemployment patterns across age, it is natural to wonder what accounts for the discrepancy. To this end, I simulate the model under the restriction of no population heterogeneity (either observed or unobserved) in preferences for leisure. Removing this source of variation isolates the effect of market opportunities and provides a means by which the separate effects may be disentangled. First, I estimate the time path of reservation wages for every member of the sample, given non-labor income levels, wage distributions, and offer arrival rates, with the value of income in full-time work relative to nonemployment fixed for every member of the sample at the sample mean of 0.795, and the corresponding value for part-time work fixed at 0.948. Next, full-time and part-time offers arrive according to individual- and time-dependent rates, from the corresponding distributions. If an offer arrives that exceeds the relevant reservation wage, the spell is assumed to end in that period.

The simulated Kaplan-Meier survivor functions resulting from this procedure are displayed in Figure 3. Once again, the younger group exhibits higher rates of exit from unemployment, although the difference in the two functions is only statistically significant at the 5% level in months 7-15. Apparently the discrepancy in the survivor functions is lower than it was in the heterogeneous-preferences case, but some difference remains.

To investigate the magnitude of the differences between Figures 2 and 3, Table 8 presents reduced-form Cox duration models of exits from unemployment (as in the figures, exits to full- and part-time work are aggregated into a single measure). Column 1 gives the estimated parameters from another simulation of the model, in which heterogeneity in leisure preferences is determined by the parameters reported in Table 5[31]. Column 2 involves the estimation of the simulation described in the previous paragraph, in which leisure preferences are held constant across the sample. The estimated parameters have the same signs across the methods, and exhibit the same patterns with respect to schooling; however, there are a few differences. Most importantly, the difference between the two age coefficients, -0.682 and -0.310, is large and statistically significant (t-statistic = 2.56), implying that preferences for leisure are important in explaining the observed declining exits from employment with age. The coefficient on age in the second column is significantly different from zero, and its magnitude implies that a difference of ten years of age affects hazards similarly to the effect of a college education relative to dropping out of high school.

The estimates given in Table 8 indicate that preferences for leisure are important in explaining unemployment durations, but are not the whole story. Even if leisure valuations were homogenous, those 56 and older would have significantly lower exit rates than the younger group. I also estimated a model similar the one in column 2, except that the time to retirement was also fixed as a constant across the sample. The effect of this procedure is to hold the time until Social Security benefit receipt constant, thus capturing some age-related heterogeneity in the availability of non-labor income. Given that the results from this estimation are qualitatively similar to those given in column 2, these estimates are not reported.

[31] Given that these parameters were estimated from the data, simple Cox models of actual hazards look similar to those given in column 1 of Table 8 and are not reported.

# 8 Conclusions

I have analyzed the labor market transitions of displaced workers over 50 in the context of a dynamic structural job search model. Given the lack of efforts to model the labor market transitions of displaced older workers, it is important to document the determinants of these transitions. Exit rates from unemployment into full- and part-time work vary across several dimensions, with substantial heterogeneity across educational attainment, race, gender, age, and unobserved tastes for leisure. The estimates weakly support the hypothesis that part-time work is easier to find than full-time employment, although the existence of underemployment cannot be explained by the relatively small differences in full-time and part-time arrival rates. Full-time offers are estimated to arrive at the rate of 0.042 per month, while 97.7% of these offers are accepted. The average monthly probability of receiving a part-time offer is 0.079, with an acceptance rate of 45.3%.

The estimates imply that choice plays some part in the long unemployment durations of displaced older workers, but that full-time monthly reemployment rates would increase only marginally even if all full-time offers were accepted. The estimated mean duration until a full-time job offer arrives is roughly two years, and is significantly longer for minorities and the oldest displaced workers. These offer arrival rates suggest that the expected waiting time until a full-time offer is received is about 2 years, and that expected durations of unemployment would be relatively long even if every offer were accepted. The tentative implication of the model is that preferences for leisure and the availability of non-labor income cannot explain the observed long unemployment durations and earnings losses. However, these inferences are subject to serious objections, namely that the structural models are only identified with a parametric functional form of the distribution of wage offers.

The central findings of this paper arise from simulations which do not rely as heavily on functional form restrictions. In particular, I simulate the distribution of unemployment durations under the counterfactual assumption that preferences for leisure do not vary across individuals. I find that unemployment durations would be positively correlated with age even if preferences were homogenous, although the age effects are significantly reduced relative to the unrestricted model. Holding preferences constant, 10 additional years of age have an effect on reemployment rates similar to that of graduating from college relative to dropping out of high school. Both preferences and constraints explain the within-sample negative correlation between age and reemployment rates, and tentatively confirm that some of the differences between post-displacement outcomes of older and younger workers is due to market opportunities, rather than preferences for leisure or the availability of non-labor income. Additional tests indicate that the model fits the data reasonably well, at least relative to similar search models, and that slight misspecifications would likely not alter the central findings.

The results also provide directions for a great deal of future research. The analysis suggests that older workers have greater difficulties finding employment after a job loss than younger ones, and determining the reasons for these differences could provide guidance for policy interventions. In particular, the models estimated in this paper allow for the simulation of changes in a number of policy parameters, such as decreases in Social Security generosity or the upcoming increase in the Social Security full-benefit retirement age to 67. While several studies have investigated these possibilities within the context of life-cycle labor supply models, a useful measure of the welfare effects of these policy changes would account for those who have experienced a late-life job loss.

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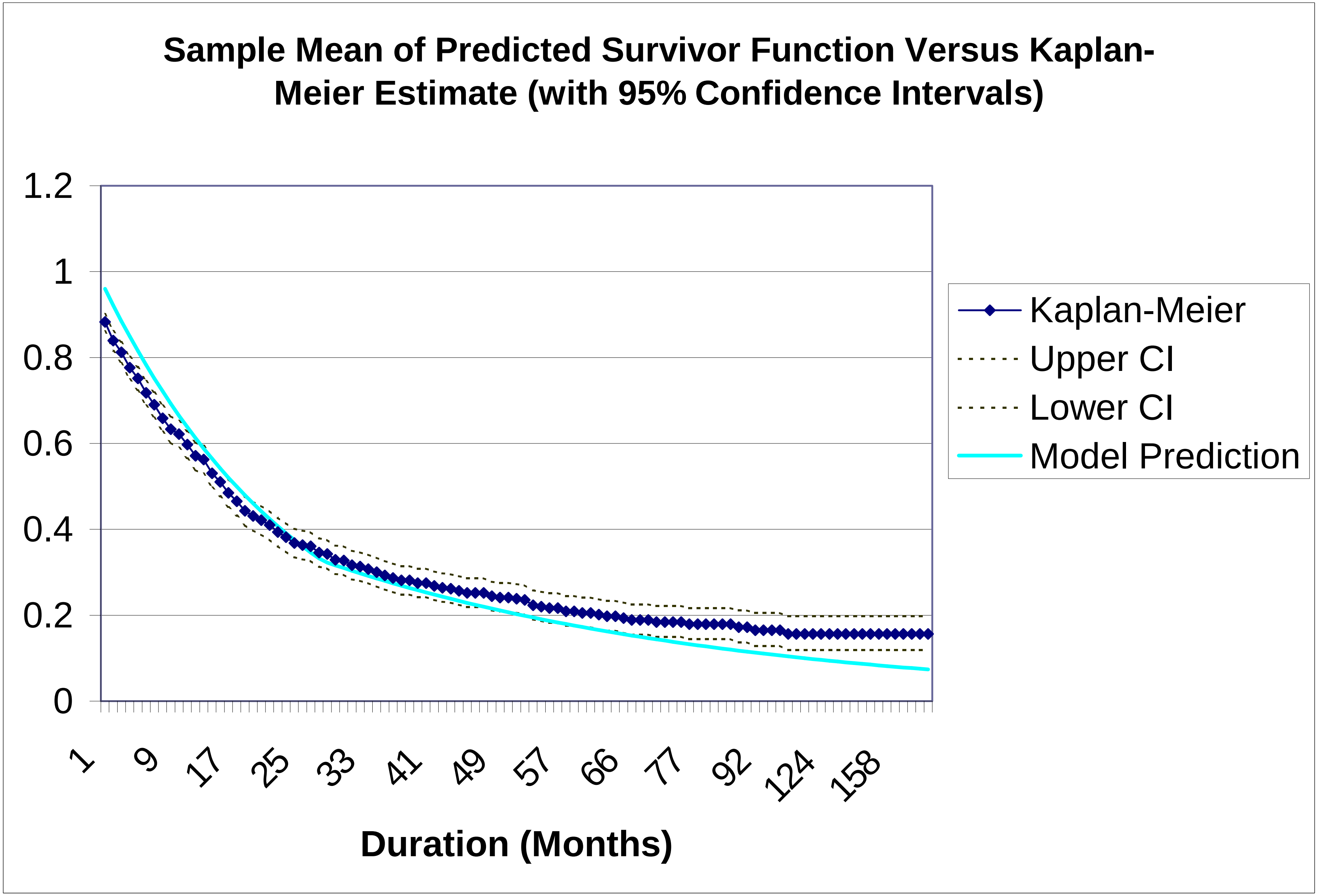
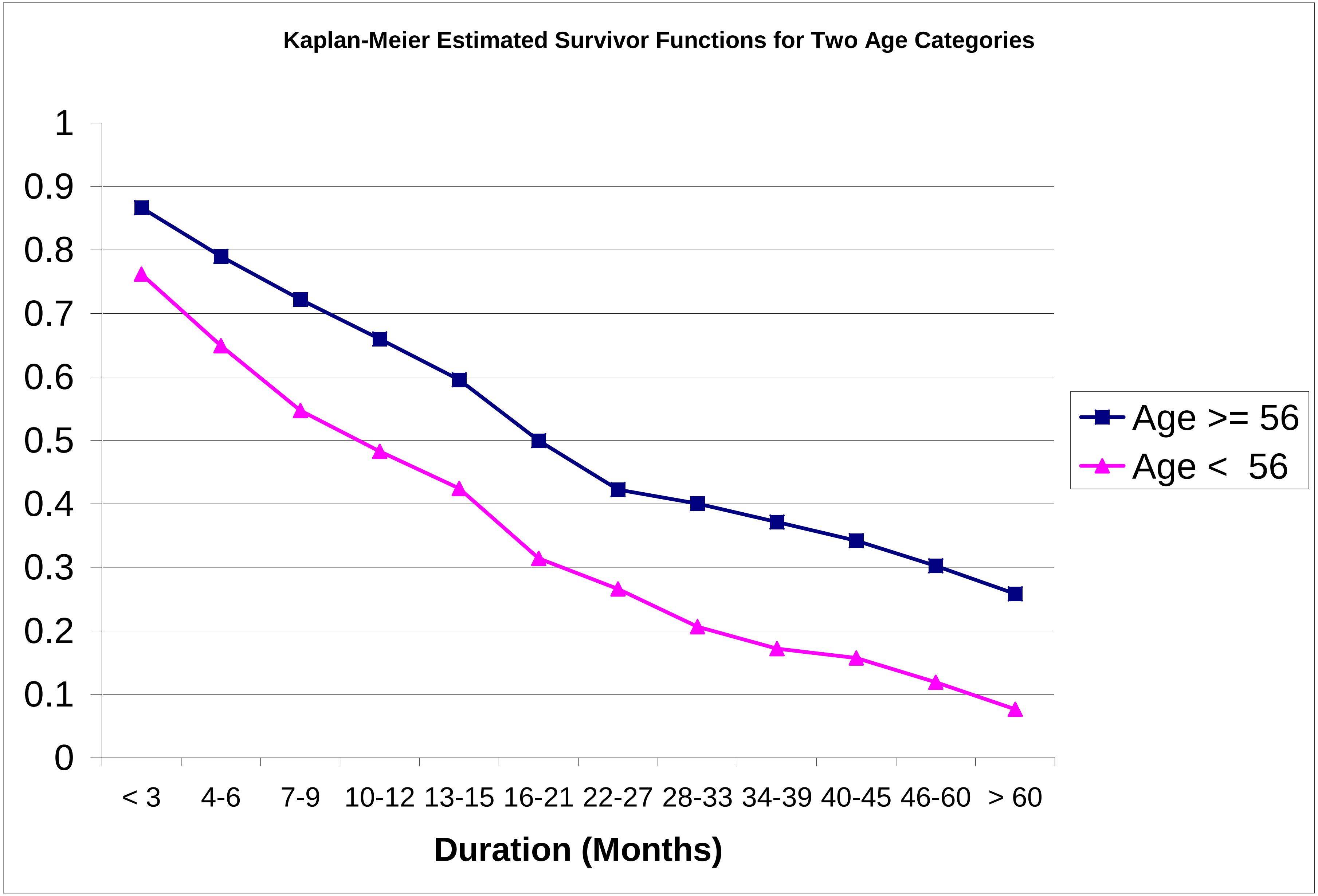
**Figure 1**



Sample Mean of Predicted Survivor Function Versus Kaplan-Meier Estimate (with 95% Confidence Intervals)
1.2
1
0.8
0.6
0.4
0.2
0
1
9
17
25
33
41
49
57
66
77
92
124
158
Duration (Months)
Kaplan-Meier
Upper CI
Lower CI
Model Prediction

**Figure 2**


Kaplan-Meier Estimated Survivor Functions for Two Age Categories
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
< 3
4-6
7-9
10-12
13-15
16-21
22-27
28-33
34-39
40-45
46-60
> 60
Duration (Months)
Age >= 56
Age <  56

## Figure 3

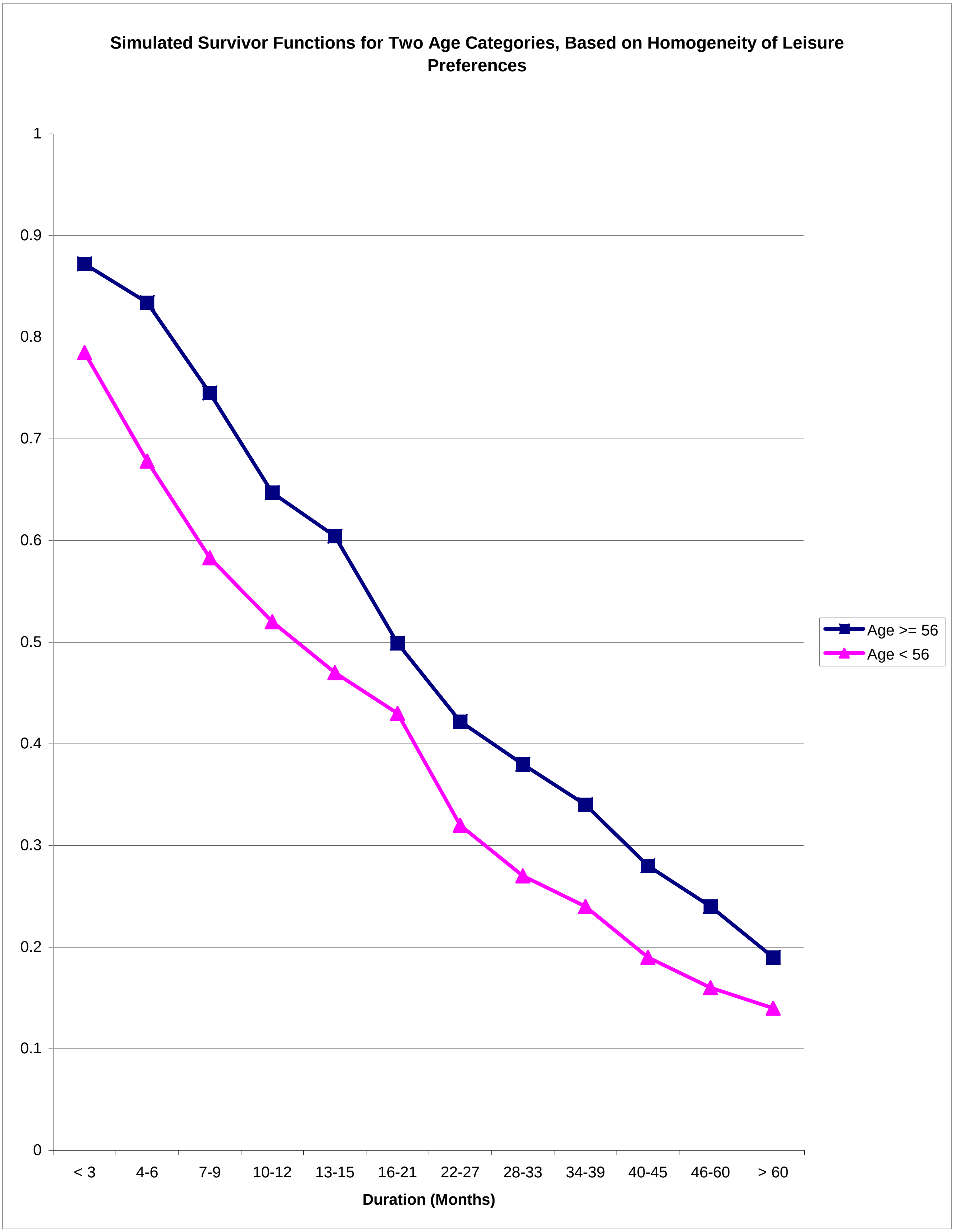

Simulated Survivor Functions for Two Age Categories, Based on Homogeneity of Leisure Preferences
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
< 3
4-6
7-9
10-12
13-15
16-21
22-27
28-33
34-39
40-45
46-60
> 60
Duration (Months)
Age >= 56
Age < 56

**Table 2**

**Duration to Employment for Displaced HRS Sample Members**

| Number of Months | Frequency–All Spells | Frequency–Complete Spells | % All Spells | Hazard Rate |
|---|---|---|---|---|
| 0-3 | 228 | 196 | 21.8 | 18.7 |
| 4-6 | 127 | 94 | 12.1 | 11.5 |
| 7-9 | 107 | 82 | 10.3 | 11.9 |
| 10-12 | 89 | 58 | 8.5 | 9.9 |
| 13-15 | 69 | 52 | 6.6 | 9.9 |
| 16-21 | 133 | 87 | 12.7 | 19.0 |
| 22-27 | 74 | 45 | 7.1 | 13.9 |
| 28-33 | 48 | 26 | 4.6 | 10.0 |
| 34-39 | 36 | 18 | 3.4 | 9.9 |
| 40-45 | 33 | 11 | 3.2 | 6.6 |
| 46-60 | 47 | 16 | 4.4 | 15.7 |
| <61 | 55 | 11 | 5.3 | 20.0 |
| | 1046 | 696 | | |

**Ending Reasons for Spells of Unemployment Following Displacement**

| | Number | Percent |
|---|---|---|
| Censored | 350 | 33.4 |
| Full-time job | 508 | 48.6 |
| Part-time job | 188 | 18.0 |

Notes: In Panel A, ”% All Spells”, refers to the percent of total spells that either ended or were censored in the given time period. ”Hazard Rate” refers to the fraction of spells that ended (not censored) in the given period, as a per cent of the total risk set, i.e. the number of spells which had not ended or been censored by the given time period.

**Table 3**

**Summary Statistics of the HRS sample of displaced workers**

| | Mean | Standard Deviation |
|---|---|---|
| High School Graduate | 0.315 | 0.465 |
| Some College | 0.187 | 0.390 |
| College Graduate | 0.175 | 0.380 |
| Black | 0.154 | 0.361 |
| Hispanic | 0.116 | 0.321 |
| Married | 0.712 | 0.453 |
| Age at Start of Spell | 55.095 | 3.704 |
| ln(Social Security Wealth) | 6.515 | 0.291 |

**Table 4**

**Parameters of Full-Time and Part-Time Wage Distributions**
**(Standard Errors in Parentheses)**

| Variable | Dependent Variable: ln(Part-Time Wage) | Dependent Variable: ln(Full-Time Wage) |
|---|---|---|
| Intercept | 6.479 | 7.561 |
| | (0.121) | (0.066) |
| Female | -0.204 | -0.409 |
| | (0.083) | (0.017) |
| Black | -0.041 | -0.092 |
| | (0.093) | (0.023) |
| Hispanic | -0.037 | -0.245 |
| | (0.133) | (0.032) |
| Age | -0.229 | -0.103 |
| | (0.067) | (0.021) |
| Age-Squared/10 | -0.070 | -0.076 |
| | (0.060) | (0.016) |
| Married | 0.065 | 0.039 |
| | (0.083) | (0.020) |
| HS Graduate | 0.188 | 0.231 |
| | (0.086) | (0.022) |
| Some College | 0.310 | 0.426 |
| | (0.102) | (0.026) |
| College Graduate | 0.518 | 0.717 |
| | (0.100) | (0.023) |
| Mills' ratio | ___ | 3.953 |
| | ___ | (2.624) |
| # of Observations | 935 | 4107 |
| R-Squared | 0.052 | 0.226 |

Notes:

(1) Dependent variables are ln(monthly) wages at the start of the current job, according to base-year HRS sample members' responses

(2) Variables which are included in the participation equation but excluded from the full-time wage equation include nonworking spouse . and the present value of Social Security wealth

**Table 5**

**Maximum Likelihood Estimates of Structural Search Model Parameters**
**(Standard Errors in Parentheses)**

| Variable | $\lambda_f$ (FT arrival rate) | $\lambda_p$ (PT arrival rate) | $v(0)/v(1)$ (Utility of FT work versus nonemployment) | $v(L)/v(0)$ (Value of PT work relative to FT work) | $\pi_2$ (Fraction of type 2) | $\pi_3$ (Fraction of Type 3) |
|---|---|---|---|---|---|---|
| Intercept | -3.201 | -2.556 | 0.009 | 1.209 | 0.142 | 0.467 |
| | (0.115) | (0.323) | (0.088) | (0.072) | (0.089) | (0.125) |
| HS Graduate | 0.331 | 0.284 | 0.098 | ___ | ___ | ___ |
| | (0.108) | (0.314) | (0.121) | | | |
| Some College | 0.531 | 0.167 | 0.301 | ___ | ___ | ___ |
| | (0.127) | (0.342) | (0.138) | | | |
| College Graduate | 0.642 | -0.067 | 0.398 | ___ | ___ | ___ |
| | (0.131) | (0.358) | (0.153) | | | |
| Age | 0.001 | 0.112 | 0.302 | ___ | ___ | ___ |
| | (0.113) | (0.276) | (0.124) | | | |
| Age-Squared/10 | -0.981 | -0.483 | -0.177 | ___ | ___ | ___ |
| | (0.202) | (0.510) | (0.215) | | | |
| Female | 0.112 | 0.461 | 1.574 | ___ | ___ | ___ |
| | (0.101) | (0.283) | (2.086) | | | |
| Black | -0.598 | -0.742 | 0.351 | ___ | ___ | ___ |
| | (0.124) | (0.375) | (0.280) | | | |
| Hispanic | -0.700 | -0.376 | -0.041 | ___ | ___ | ___ |
| | (0.153) | (0.420) | (0.347) | | | |
| Married | ___ | ___ | 0.345 | ___ | ___ | ___ |
| | | | (0.117) | | | |
| $\mu_j$ | 0.103 | 0.089 | ___ | ___ | ___ | ___ |
| | (0.036) | (0.105) | | | | |
| $\mu_2$ - Intercept | ___ | ___ | 0.098 | ___ | ___ | ___ |
| | | | (0.091) | | | |
| $\mu_3$ - Intercept | ___ | ___ | 0.201 | ___ | ___ | ___ |
| | | | (0.095) | | | |

Notes:
(1) Ln likelihood = - 2927.97
(2) Sample size = 1046
(3) Standard errors computed as the outer product of the numerical (finite-difference) gradient.

**Table 6**

**Sample Means of Search Model Parameters**

| | Mean |
|---|---|
| Part-time offer arrival rate ($\lambda_p$) | 0.079 |
| Part-time acceptance probability ($1 - F_p(\ln(rw_p))$) | 0.453 |
| Expected Observed Wage ($E(\ln(w_p) \mid \ln(w_p) > \ln(rw_p))$) | 6.742 |
| Full-time offer arrival rate ($\lambda_f$) | 0.042 |
| Full-time acceptance probability ($1 - F_f(\ln(rw_f))$) | 0.977 |
| Expected Observed Wage ($E(\ln(w_f) \mid \ln(w_f) > \ln(rw_f))$) | 7.455 |
| Utility of PT work relative to nonemployment | 0.948 |
| Utility of FT work relative to nonemployment | 0.795 |
| Type 1 | 0.391 |
| Type 2 | 0.142 |
| Type 3 | 0.467 |

**Table 7**

**Testing the Search Model: Comparing Actual Versus Expected Observed Wages for Different Values of Covariates (Standard Errors in Parentheses)**

| Variable | Actual PT Wage | $E(\ln(w_p) \mid w_p > rw_p)$ (Prediction from the Model) | Actual FT Wage | $E(\ln(w_f) \mid w_f > rw_f)$ (Prediction from the Model) |
|---|---|---|---|---|
| Female | 6.56 | 6.60 | 7.04 | 7.09 |
| | (0.83) | (0.44) | (0.71) | (0.28) |
| Male | 6.66 | 6.79 | 7.36 | 7.68 |
| | (0.85) | (0.43) | (0.78) | (0.39) |
| Hispanic | 6.52 | 6.67 | 7.15 | 7.15 |
| | (0.91) | (0.38) | (0.69) | (0.49) |
| Black | 6.50 | 6.58 | 7.12 | 7.13 |
| | (0.82) | (0.39) | (0.67) | (0.50) |
| White | 6.73 | 6.78 | 7.35 | 7.47 |
| | (0.85) | (0.46) | (0.71) | (0.51) |
| Age $<$ 56 | 6.66 | 6.74 | 7.38 | 7.47 |
| | (0.82) | (0.42) | (0.74) | (0.51) |
| Age $>=$ 56 | 6.58 | 6.67 | 7.18 | 7.26 |
| | (0.83) | (0.43) | (0.68) | (0.50) |
| Married | 6.62 | 6.73 | 7.28 | 7.41 |
| | (0.78) | (0.41) | (0.71) | (0.47) |
| Single | 6.61 | 6.67 | 7.25 | 7.35 |
| | (0.87) | (0.44) | (0.72) | (0.56) |
| HS Dropout | 6.48 | 6.59 | 7.01 | 7.16 |
| | (0.79) | (0.42) | (0.58) | (0.43) |
| HS Graduate | 6.60 | 6.67 | 7.15 | 7.33 |
| | (0.84) | (0.43) | (0.64) | (0.38) |
| Some College | 6.77 | 6.74 | 7.35 | 7.59 |
| | (0.83) | (0.42) | (0.69) | (0.43) |
| College Graduate | 6.66 | 6.80 | 7.89 | 7.95 |
| | (0.90) | (0.44) | (0.84) | (0.40) |

Notes:

(1) Sample sizes: N=508 for FT jobs, N=188 for PT jobs.

(2) Cell entries are the sample mean of the variable listed at the top of each column, conditioned on the variable in the corresponding row being equal to one. To illustrate, the mean of actual full-time log wages for females is 7.04, with a standard deviation of 0.71.

**Table 8**

**Simulations of the Search Model: The Effect of Observables on Durations of Post-Displacement Unemployment and the Importance of Preferences for Leisure (Standard Errors in Parentheses)**

| | **Cox Hazard Models** | |
|---|---|---|
| Variable | Heterogeneity in Preferences for Leisure, Given by Model Estimates | Homogeneity in Preferences for Leisure |
| Female | 0.052 | 0.034 |
| | (0.084) | (0.091) |
| Black | -0.399 | -0.405 |
| | (0.122) | (0.131) |
| Hispanic | -0.503 | -0.451 |
| | (0.150) | (0.155) |
| Age/10 | -0.682 | -0.310 |
| | (0.097) | (0.108) |
| Married | 0.146 | 0.078 |
| | (0.093) | (0.101) |
| HS Graduate | 0.276 | 0.291 |
| | (0.106) | (0.120) |
| Some College | 0.259 | 0.203 |
| | (0.122) | (0.131) |
| College Graduate | 0.481 | 0.330 |
| | (0.124) | (0.143) |

Notes:
(1) Using the estimated parameters of the structural search model, post-displacement outcomes are simulated as follows: job offers arrive from the individual- and time-specific wage offer distributions according to a Poisson process with individual-specific . parameters $\lambda_f$ and $\lambda_p$. In column 1, acceptance probabilities (and reservation wages) are dependent on individual-specific preferences for leisure, while in column 2, every member in the sample is assigned the sample means of the preferences for leisure, v(0)/v(1) and v(L)/v(1). See Table 5.
(2) All specifications estimated as reduced-form Cox models of hazards of exit from unemployment.

**Appendix Table 1**

**The Relationship Between Covariates and Search Model Parameters**
**(Standard Errors in Parentheses)**

| Variable | $v(0)/v(1)$ (Utility of FT work versus nonemployment) | $\lambda_f$ (FT arrival rate) | $rw_f$ (Reservation wage for FT work) | $1-F_f(rw_f)$ (Acceptance Probability) | $E(w_f \mid w_f > rw_f)$ (Expected Observed Wage) | $T$ (Expected Retirement Date) |
|---|---|---|---|---|---|---|
| Intercept | -4.212 | 0.047 | 9.957 | 0.588 | 9.874 | 47.261 |
| | (0.272) | (0.004) | (0.225) | (0.034) | (0.070) | (3.085) |
| Female | 5.869 | 0.004 | -2.704 | 0.102 | -0.756 | -0.598 |
| | (0.044) | (0.001) | (0.037) | (0.056) | (0.011) | (0.285) |
| Black | 0.013 | -0.021 | -0.607 | 0.006 | -0.062 | -0.619 |
| | (0.061) | (0.001) | (0.051) | (0.008) | (0.016) | (0.346) |
| Hispanic | -0.107 | -0.022 | -0.903 | 0.027 | -0.239 | 0.330 |
| | (0.069) | (0.001) | (0.057) | (0.008) | (0.018) | (0.415) |
| Age/10 | 0.081 | -0.002 | -0.062 | 0.004 | -0.040 | 0.301 |
| | (0.005) | (0.001) | (0.004) | (0.001) | (0.001) | (0.054) |
| Married | 1.274 | -0.004 | -0.652 | 0.102 | -0.182 | -1.023 |
| | (0.048) | (0.001) | (0.040) | (0.006) | (0.012) | (0.353) |
| HS Graduate | -0.020 | 0.011 | 0.452 | -0.001 | 0.237 | -0.618 |
| | (0.086) | (0.001) | (0.045) | (0.007) | (0.014) | (0.392) |
| Some College | -0.044 | 0.019 | 0.641 | 0.001 | 0.405 | 0.456 |
| | (0.062) | (0.001) | (0.052) | (0.008) | (0.016) | (0.528) |
| College Graduate | 0.044 | 0.026 | 0.901 | 0.003 | 0.740 | 1.167 |
| | (0.065) | (0.001) | (0.053) | (0.008) | (0.016) | (0.473) |
| R-Squared | 0.947 | 0.717 | 0.866 | 0.347 | 0.889 | 0.301 |

Notes:

(1) All models estimated by OLS, with the dependent variable being the search model parameter listed at the top of each column.