TO SEARCH OR NOT TO SEARCH: FEMALE LABOR SUPPLY FOLLOWING JOB DISPLACEMENT

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INTRODUCTION

Conventional survival time models have been widely used to model jobless spell lengths of workers following displacement.[1] These models assume that all workers engage in job search and will eventually return to work. This is a reasonable assumption for prime-age males, but not for women, many of whom withdraw from the labor force following displacement.

Whether displaced or not, the work histories of women include more spells of nonparticipation in the labor force than is the case for men [Mincer and Polachek, 1974]. In part, greater female intermittency reflects role differentiation in home and market work: women are more likely than men to assume responsibilities for parenting and other home activities that limit their participation in paid employment. The weaker attachment of some women to the work force implies that a reduction in potential earnings following displacement may lead them to drop out of the labor force.

We believe that labor force withdrawal plays an important role in explaining the wide variation in post-displacement jobless spells among women. Forty-four percent of displaced women in the 1988 Displaced Worker Survey reported relatively short jobless spells of 10 or fewer weeks, but 27 percent report being out of work for a year or more. The sample reemployment hazard thus declines sharply as time passes. Conventional survival time models explain this wide dispersion as reflecting either deteriorating job search prospects (true negative duration dependence) or strong individual heterogeneity in job search efficiencies [Podgursky and Swaim, 1987a]. In either case, a significant group of workers is searching without success and might be considered structurally unemployed.

Another possibility, however, is that many long jobless spells following displacement reflect labor force withdrawal rather than long-duration job search. This leads us to generalize conventional survival time models to encompass both the labor force participation decision and unemployment spell durations for workers choosing to search. Maximum likelihood estimates of the resulting *split-population* model confirm the importance of labor force withdrawal and indicate a much smaller probability of long-duration unemployment for women who search. In other words, search is productive for those who search.

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THEORETICAL MODEL

We require a model that explains both the labor force participation decision following displacement and jobless spell durations for women who search for a new job. The basic job search model analyzed by Mortensen [1986] and many others provides a useful theoretical framework. We now summarize that model and show that post-displacement labor supply can be characterized in terms of individual reservation wages.

Assume that risk-neutral workers adopt a job search strategy to maximize expected future income. Future income is discounted by the interest rate r, and workers and jobs are assumed to be infinitely-lived. Jobless workers receive nonmarket income b, but incur direct search costs of c if they choose to search. For workers engaged in search, the number of job offers received in any given period is assumed to be Poisson-distributed with parameter λ. Job offers are fully characterized by their wage rates (w), which are random draws from the cumulative distribution function G(w). Workers are assumed to know the probability distributions determining job offer arrivals and wage levels.

Conditional on searching, the optimal strategy is to accept only those job offers associated with wages that exceed the reservation wage (w^*) defined by:

$$(1) \qquad (\lambda/r)\int_{w^*}^{\infty}(w-w^*)\,dG(w) = c + w^* - b.$$

That is, the reservation wage is set so as to equalize the expected marginal benefit from continuing to search for a job paying more than w^* with the marginal cost of rejecting a job offered at wage w^*. The hazard into employment for a worker following the optimal search strategy is thus the product of the offer arrival rate (λ) and the probability that a randomly sampled job pays at least w^*:

$$(2) \qquad h = \lambda(1 - G(w^*))$$

One important implication of equation (2) is that the reemployment hazard remains constant as a unemployment spell progresses. The theoretical search model can, however, be generalized to incorporate nonstationarities that cause the hazard either to increase or decrease. For example, the progressive depletion of savings may result in a falling reservation wage and, hence, a rising hazard (positive duration dependence). Alternatively, searchers already unemployed for some time may be stigmatized with prospective employers. As a result, the offer arrival rate might fall as a search spell progresses causing negative duration dependence. Strongly decreasing hazards seem implausible, however, for workers searching according to equations (1) and (2).

The job search strategy indicated by equation (1) need not be preferable to labor force withdrawal. Since w^* can be interpreted as the shadow value of job search and b as the shadow value of nonmarket time, the condition for labor force participation is simply:

$$(3a) \qquad w^* > b$$

or, equivalently:

$$(3b) \qquad (\lambda/r)\int_{b}^{\infty}(w-b)\,dG(w) > c$$

Equation (3b) merely states that the expected net income gain from search must exceed the direct costs of search.

Displacement may result in a decision to drop out of the labor force. Prior to displacement, workers are employed because the wage on their job exceeds the value of nonmarket time (i.e., $w^0 > b$). Studies of post-displacement earnings have shown that permanent layoffs cause substantial losses of specific human capital and other job rents that result in a wage offer distribution centered well below prior earnings for many workers [Hamermesh, 1989; Podgursky and Swaim, 1987b]. The post-displacement wage offer distribution ($G(w)$) may thus be sufficiently disadvantageous that equations (3a) and (3b) are not satisfied and the worker drops out of the labor force.

We denote post-displacement labor force status by the dummy variable S, which takes the value of 1 if workers choose to search and 0 for dropouts. Equation (3b) suggests the following formulation:

$$(4a) \qquad S = \begin{cases} 1, \text{ if } S^* > 0 \\ 0, \text{ if } S^* \leq 0 \end{cases}$$

where S^* is the net value of search, hence an index of labor force attachment, defined by:

$$(4b) \qquad S^* = (\lambda/r)\int_{b}^{\infty}(w-b)\,dG(w) - c$$

It can be shown that: a) increases in λ, or the mean (μ) or variance (σ) of w, increase S^*, hence increase the probability of search; and b) increases in r, b, or c cause S^* to fall, hence reduce the probability of search [Mortensen, 1986].

EMPIRICAL MODEL

The data requirements for estimating the structural model described by equations 1-4 are considerable. Unfortunately, our data source, the Displaced Worker Survey (DWS), contains largely retrospective data, which is prone to measurement error, and lacks direct measures of important search costs and benefits. We thus adopt a reduced-form approach which allows us to estimate the net effect of covariates but does not allow us to identify structural parameters such as λ and μ.

The reduced form equation for engaging in search suggested by equations (4a) and (4b) is:

$$(5a) \qquad S_i = \begin{cases} 1 \text{ (i.e., search), if } S_i^* > 0 \\ 0 \text{ (i.e., drop out), if } S_i^* \leq 0 \end{cases}$$

where subscript i denotes individual i and S^* is an unobserved index of labor force attachment defined by:

(5b) $$S_i^* = Z_i\,\alpha + \epsilon_i$$

Z_i is a vector of observable personal characteristics and labor market conditions affecting the benefits and costs of searching, and ϵ_i is a mean zero, i.i.d. error term that reflects omitted determinants of labor supply.

The conditional reemployment hazard function for workers choosing to search is assumed to take the proportional hazards form:

(6) $$h_i(T_i{=}t \mid S_i{=}1) = e^{(Z_i\beta)} h_0(t)$$

where T_i is the random variable denoting search time for individual i and $h_0(t)$ is the baseline hazard function common to all individuals. As equations (1) and (2) indicate, all factors influencing the costs and benefits of search should be included in Z_i.

Many variables associated with shorter search spells also tend to increase the value of search, hence the probability of searching. For example, the mean of the distribution of wage offers (μ) is likely higher for more educated workers. Because the reservation wage increases less than one-for-one with μ (i.e., $0 < \partial w^*/\partial\mu < 1$), the conditional reemployment hazard in equation (2) increases with education and the β coefficient for education in the hazard estimating equation (6) should be positive.[2] Equation (3a) indicates that the increase in the reservation wage will also increase the probability of labor force participation. This implies a positive sign for the education α coefficient in the participation estimation equation (5b).

Search theory predicts different effects on the search probability and the reemployment hazard rate in two cases. First, some regressors may have opposite effects in the two equations. For example, variables positively correlated with the direct costs of search (c) will have a negative α coefficient, but a positive β coefficient.[3] The second source of qualitatively different effects is transitory factors, such as cyclical swings in labor demand or initial differences between workers in the perceived probability of recall to their former jobs. The reemployment hazard is likely responsive to transitory labor market conditions, but the participation decision for experienced workers should be much less sensitive. The fact that absences from employment of even a year or two lead to significant reductions in earnings capacity suggests that the participation decision largely reflects long-run earnings prospects [Mincer and Polachek, 1978].

Given data on Z_i and the (possibly right-censored) time until the first post-displacement job is found (t_i), the sample likelihood function can be constructed using equations (5) and (6). The likelihood contribution for an individual who found a new job after t periods of search is the joint probability of choosing to search and the search duration of t weeks:

(7a) $$l_i(\text{reemployed at } T_i = t) = \Pr(\epsilon_i > -Z_i\,\alpha) * \Pr(T_i = t \mid h_i)$$

The likelihood contribution for an individual not observed to return to work is the sum of two components: a) the probability that i chooses not to search; and b) the joint probability that i chooses to search but that T_i exceeds the observation period (t_i). Thus:

(7b) $$l_i(\text{not reemployed by } T_i = t_i) = \Pr(\epsilon_i < -Z_i\ \alpha) + \{\Pr(\epsilon_i > -Z_i\,\alpha) * \Pr(T_i > t_i \mid h_i)\}$$

TABLE 1
Reemployment Rates by Years Since Displaced: Women Displaced from Full-Time Wage and Salary Jobs, 1983-1987

Years Since Displacement (year displaced)	Proportion Who Held At Least One Post-Displacement Job (standard error)
0-1 (1987)	.646 (.023)
1-2 (1986)	.838 (.020)
2-3 (1985)	.882 (.018)
3-4 (1984)	.845 (.023)
4-5 (1983)	.846 (.025)

Equations (7a) and (7b) constitute a "split-population" survival time model of the type analyzed by Schmidt and Witte [1989]. In order to evaluate these likelihood contributions, distributional forms need to be specified for the probabilities contained in equations (7a) and (7b). We will assume a Weibull density for search times (T), and a logistic density for ϵ. These distributions are widely used to model spell durations and dichotomous dependent variables, respectively.

DATA AND ESTIMATES

Our data are from the 1988 Displaced Worker Survey (DWS) which was a special supplement to the January 1988 Current Population Survey (CPS). The DWS was designed to identify a large nationally representative sample of workers displaced from jobs due to plant shutdowns or other permanent layoffs [Flaim and Sehgal, 1985]. For this study, we focus on women who lost full-time wage and salary jobs due to plant shutdowns or partial reductions in force. Limiting the sample to full-time workers provides a stronger test of the hypothesis that displacement causes women with a substantial labor force attachment to drop out.[4]

The resulting sample includes 1,552 women displaced in the years 1983-1987. Table 1 presents reemployment rates by years since displacement. The share of women reporting one or more jobs since being laid-off increases during the first two years following displacement and then stabilizes at approximately 85 percent. This pattern suggests that the remaining 15 percent are not engaged in active job search and may be best viewed as labor force dropouts.

Equations (7a) and (7b) satisfy the usual regularity conditions for maximum likelihood (ML) estimation, but proved difficult to estimate.[5] We thus adopted a sequential estimation strategy. First, we calculate ML estimates of α using data for women displaced at least three years prior to the survey (i.e., in 1983 and 1984). When estimating the participation equation, we assume that $S_i = 1$ for women who reported employment at one or more jobs since being displaced, and that $S_i = 0$ otherwise. In other words, we assume that women engaging in job search following displacement all locate a job within three years.[6] Next, we use these estimates for α to calculate fitted values for the search probability for each worker displaced in 1985-1987. Finally, we use equations (7a)-(7b) and jobless duration data for workers displaced in 1985-1987 to calculate ML estimates for β and the Weibull shape parameter (ρ), conditional on the fitted values for search probabilities.

Although dictated by necessity, our "two-step" estimation strategy may minimize the effect of reporting errors in the data. Reporting errors on jobless duration are likely worse for the women displaced more than three years prior to the survey than for those displaced less than three years earlier. Our procedure simply requires the women in the former group to recall whether or not they have worked since displacement. It seems unlikely that many individuals will be in doubt concerning this question. Information on the number of weeks jobless is then only used for the most recently displaced workers, who are more likely to recall such data accurately.

Table 2 provides descriptive information on our sample and Table 3 presents ML coefficients for our model of post-displacement labor force participation and job search duration. The estimates in column 1 are from a logit model for the probability that the worker searched and, hence, held at least one job following displacement (i.e., $\Pr(S_i{=}1)$). Columns 2 and 3 then present two alternative estimates of the Weibull hazard models. Column 2 presents conventional single-population estimates, which assume that all women search, and column 3 presents our split-population estimates, which allow some women to drop out of the labor force.[7]

Older and high tenure women are significantly more likely to withdraw from the labor force following displacement. Both groups may be particularly vulnerable to large reductions in earnings potential that depress the value of job search. Older women and women who have not searched for a new job in many years may also experience greater than average difficulty in locating job offers (i.e., a low offer arrival rate), further discouraging search. Finally, some of these women may be eligible for pensions.

More educated women are substantially less likely to drop out of the labor force following displacement. The mean of the wage offer distribution relative to the shadow value of home time for more educated women is apparently higher than for less educated women, suggesting that education increases market productivity more than home productivity. The positive effect of education on participation is also consistent with earlier studies finding that more educated workers experience a smaller reduction in earnings capacity following displacement [Swaim and Podgursky, 1989] and experience more rapid depreciation of earnings power when out of the labor force [studies cited in Mincer and Polachek, 1978].

As expected, transitory labor demand factors do not have significant effects on labor force participation. Area unemployment has no significant effect on the probability of

TABLE 2
Descriptive Statistics[a]

Variable	Minimum	Maximum	Mean	Standard Deviation
Age	16.00	84.00	35.76	12.20
1 = Black	0.00	1.00	0.12	0.32
Years of schooling completed	0.00	18.00	12.55	2.30
1 = Married, spouse present	0.00	1.00	0.61	0.49
Number of children under 18	0.00	7.00	0.75	1.04
Tenure on lost job (years)	0.00	42.00	6.08	2.38
Log of weekly wage on lost job	3.73	7.65	5.59	0.49
1 = Total shutdown	0.00	1.00	0.56	0.50
Area unemployment rate in year of displacement (percent)	2.50	18.00	7.09	2.31
Unionization rate in prior industry (percent)	0.5	86.8	16.1	1.01
1 = Has not worked since displaced	0.00	1.00	0.21	0.40
Weeks until next job[b]	0.00	99.00	23.81	30.50

[a] Women displaced from full-time jobs by total shutdowns or partial layoffs in 1983-1987 (N = 1552).
[b] 23.6 percent of these values are right censored.

search. Women displaced due to plant closings or other total shutdowns are less likely to anticipate recall to their former job than workers displaced by partial layoffs. As the duration of the layoff increases, however, the subjective probabilities of recall for both groups should converge to zero and hence not affect the long-run participation decision [Katz, 1986]. Consistent with this prediction, the coefficient for the total shutdown dummy is very close to zero.

Conditional on search, the reemployment hazard is significantly affected by many of the independent variables. Transitory labor demand variables that were insignificant in the participation model have large and highly significant effects in the conditional hazard model. Area unemployment has a significant negative coefficient. High unem-

TABLE 3
ML Coefficients for the Labor Force Participation and Jobless Duration Models[a]
(asymptotic standard errors in parenthesis)

	(1) Labor Force Participation Logit[b] (α)	Reemployment Hazard[c] (2) Single Population (β)	Reemployment Hazard[c] (3) Split Population (β)
Constant	.802	-3.890***	3.027***
	(2.078)	(.661)	(.641)
Age	-.043***	-.024***	-.014***
	(.014)	(.005)	(.005)
Education	.155**	.074***	.061***
	(.072)	(.024)	(.023)
Black	-.492	-.027	.008
	(.434)	(.167)	(.161)
Tenure	-.066***	-.023**	-.011
	(.023)	(.011)	(.011)
Married (with spouse)	-.098	-.384***	-.397***
	(.301)	(.106)	(.103)
Number of Children	-.240	-.180***	-.145***
	(.151)	(.054)	(.054)
Area unemployment	-.072	-.114***	-.089***
	(.053)	(.026))	(.025)
Total shutdown	.020	.445***	.433***
	(.307)	(.103)	(.101)
Log of old wage	.359	.340***	.157
	(.339)	(.113)	(.111)
Industry unionization rate (percent)	-.005	-.003	-.005
	(.008)	(.003)	(.003)
Weibull shape parameter (r)	---	.703***	.769***
		(.020)	(.022)
Log of Likelihood	-167.2	-3272.7	-3316.7
Sample Size	455	1,097	1,097

***,**,* denote coefficient significantly different from zero at the 1%, 5%, and 10% level of significance (two-tailed test).
[a] Women displaced from full-time jobs by total shutdowns or partial layoffs in 1983-1987.
[b] Dependent variable takes the value 1 (0) if the worker held at least one (no) job since displacement. Estimated for women displaced in 1983-1984.
[c] Estimated for women displaced in 1985-1987.

ployment rates thus appear to slow job search, but do not induce labor force withdrawal among these experienced full-time workers. The plant shutdown dummy has a significant positive coefficient. This is consistent with the hypothesis that many workers idled by partial layoffs postpone search for a new job so long as recall to their prior job appears possible [Katz, 1986; Podgursky and Swaim, 1987a]. Although *waiting for recall* lowers the reemployment hazard, it does not increase the probability of labor force withdrawal.

Older women have lower conditional hazards, hence longer expected jobless spells while searching. This suggests that older workers receive fewer job offers or set higher reservation wages in response to pension income. The strong negative coefficient on the marriage dummy also suggests that the availability of other sources of family income allows women to hold out for better jobs.

More educated women move into new jobs more rapidly. Since the optimal reservation wage rises less than one-for-one with the mean offered wage, the increase in the hazard likely reflects the superior distribution of wage offers available to women with more schooling. It is also possible that shorter jobless spells reflect more efficient search (e.g., a higher offer arrival rate or smaller variance in wage offers) resulting from better search skills of more educated workers.

IMPLICATIONS FOR POST-DISPLACEMENT JOBLESSNESS

In Panel A of Table 4 we present estimates of the individual hazard functions averaged over the first 16 weeks of search and over the subsequent 84 weeks. We calculated the hazard values implied by the ML coefficient values reported in Table 3 for each observation (i.e., at each Z_i) and then averaged the hazards over the sample. For comparison, we also include in column (1) the step-wise hazard function for a life table method widely used in actuarial calculations (Cutler-Ederer).[8]

One notable pattern in Table 4 is the extent to which the very strong negative duration dependence indicated by the life table hazard is muted by the introduction of successively more flexible treatment of individual heterogeneity. The life table calculations indicate that the sample hazard between 17 and 100 weeks is just 29 percent of that in the first 16 weeks of search. Incorporating observed covariates and labor force withdrawal both increase the relative level of the hazard after 16 weeks and, hence, imply less negative duration dependence.

The split-population estimates in column 3 indicate that the hazard between 17 and 100 weeks averages 59 percent of the hazard in the first 16 weeks of search. There is good reason to believe that even this estimate overstates the extent to which search prospects deteriorate as a spell progresses. If reemployment hazards differ between workers in ways that are not fully captured by the covariates then unobserved heterogeneity is present and, hence, spurious negative duration dependence.[9] In related work, we estimate a semi-parametric version of our split-population model that treats both observable and unobservable heterogeneity more flexibly [Podgursky and Swaim, 1991]. We find that the evidence for negative duration dependence then completely vanishes.

Survivor function values reported in Panel B show that long duration search spells are much less common than the life table and the single-population survival time model suggest. For example, the estimated survival value at 53 weeks (i.e., the probability of a year or more of job search) is 15.1 percent for the life table model, but falls to 9.7 percent in the split-population model. The corresponding survival values for 100 weeks of search are 11.6 versus 3.0 percent. The lesson from Panel B is that it is important to distinguish

TABLE 4
Comparison of Fitted Hazard and Survival Functions and Expected Spell Durations for Alternative Specifications[a]

	(1) Life Table	(2) Single Population	(3) Split Population
		Weibull Hazard Models	
A. Average Hazards			
1. 0<t<16 weeks	.050	.060	.070
2. 17 t<100 weeks	.015	.030	.041
Ratio of (2)/(1)	.292	.500	.589
B. Survival Function			
Weeks Jobless			
0	1.000	1.000	1.000
11	.481	.508	.457
26	.310	.308	.236
49	.195	.177	.109
53	.151	.163	.097
100	.116	.073	.030
C. Expected Durations[b]			
E(T | S=1)	---	31.6	20.6
E(T)	---	31.6	16.4
E(J | J≤100)	---	24.5	30.4
E(T | T≤100)	---	24.5	15.2
T-Share of J (%)	---	100.0	56.8

[a] The column 1 life table calculations use the method of Cutler and Ederer (Cox and Oakes, 1984, pp. 54-6). Column 2-3 calculations are based on the ML coefficient estimates for the Weibull proportional hazards models reported in columns 2-3 of Table 3. Values in columns 2-3 were calculated for each worker in the estimation sample and then averaged across the sample.

[b] T and J denote job search and total jobless weeks, respectively.

TABLE 5
Simulated Effects of a Unit Increase in the Covariates[a]

	Weibull Single-Population Model	Weibull Split-Population Model			
	(1)	(2)	(3)	(4)	(5)
Covariates	ΔE(T)	100* ΔPr(S=1)	ΔE(T | S=1)	ΔE(T)	ΔE(J)
Age	0.4	-0.5	0.2	0.1	0.5
Education	-1.3	1.6	-1.0	-0.4	-2.1
Black	0.5	-5.9	-0.1	-1.4	4.5
Tenure	0.4	-0.7	0.2	-0.0	0.7
Married	6.6	-1.1	6.1	4.8	5.9
Number of kids	3.2	-2.8	2.4	1.3	4.1
Area unemployment	2.0	-0.8	1.5	1.0	1.8
Total shutdown	-7.8	0.2	-7.0	-5.7	-5.9
Log old wage	-5.5	3.5	-2.4	-1.2	-4.8
Industry unionization	0.1	-0.1	0.1	0.1	0.1

[a] S=1 denotes active search, T denotes weeks searching, and J denotes total weeks jobless.

labor force dropouts from searchers if one is to estimate accurately the distribution of search spells.

Panel C of Table 4 compares the expected spell durations implied by the two Weibull hazard models. The first row presents the expected search duration conditional on searching (i.e., E(T | S=1)), while the second presents the unconditional expected search duration (i.e., E(T) = Pr(S=1) * E(T | S=1)). Rows 3-5 present a decomposition of expected total weeks jobless in the first 100 weeks following displacement (i.e., E(J | J< 100)) into time searching (i.e., unemployed) and time out of the labor force. In performing this decomposition, we truncate spell durations after 100 weeks.[10]

The expected duration of job search is 16.4 weeks in the split-population model but 31.6 weeks in the single-population model. One major factor reducing expected search time in the split-population models is that 15.2 percent of the sample is estimated to dropout of the labor force, hence engage in no search. Perhaps more surprising, however, is that conditional on searching the expected spell length is 20.6 weeks, still considerably less than the 31.6 weeks indicated by the single-population model. Clearly, the single-population model exaggerates the amount of unemployment experienced by this group of displaced workers.

Further insight into these differences is gained by examining the decomposition of total jobless time in the first 100 weeks following displacement. Expected total weeks jobless is 30.4 for the Weibull split-population model. Just 56.8 percent of this jobless time reflects active job search, while the remainder reflects labor force withdrawal. The single-population model lacks this distinction and appears to *split the difference* in the sense that it implies expected durations intermediate between true search time and total jobless time. As a result, conventional single-population models do not accurately reflect either the reemployment process for displaced workers remaining in the work force nor the total time jobless for all displaced workers.

One clear lesson from Table 4 is that single-population methods yield biased estimates of the distribution of jobless spells following displacement. It is thus not surprising that estimates of the effects of covariates on search behavior and outcomes are biased as well. Table 5 decomposes the overall effect on expected jobless time of a unit change in an independent variable into the effects on the probability of searching (i.e., (Pr(S=1)) and on the expected search time for searchers (i.e., E(T | S=1)) for the single and split-population Weibull models.

It is instructive to contrast the effect of a covariate on expected search time (column 4) with its effect on total jobless time (column 5). For example, on average a one year increase in the level of education decreases total jobless time by 2.1 weeks, but total search time by just 0.4 weeks. This is because more schooling both increases the probability of search and reduces expected search time conditional on search. These effects are off-setting for E(T), but reinforcing for E(J). Another interesting pattern is that some covariates with large effects on expected jobless time only operate through one of these two channels. Race, for example, changes the probability of search, but not search time, while the reverse is true for plant shutdowns. At best, single-population models provide a composite measure of these two effects.

The estimates in column 1 of Table 5 show that conventional, single-population models, which do not distinguish dropouts from searchers, produce biased estimates of even the total effects of the covariates on time jobless. For example, the split-population model indicates that blacks experience 4.5 more weeks of total joblessness, but spend 1.4 fewer weeks searching. The simulated effect for the single-population model is 0.5 additional weeks of joblessness for blacks. Again, the single-population model is producing an unsatisfactory average of the true values for the effect on total jobless time and the effect on search time.

CONCLUSION

In this paper, we generalize conventional survival time models to encompass both the labor force participation decision and jobless spell durations for workers choosing to search following displacement. We then use 1988 DWS data to estimate this model for women displaced from full time jobs in the years 1983-87. Our results highlight the importance of labor force withdrawal for displaced women and show that single-population models — which do not explicitly model the withdrawal decision — result in large biases.

The split-population approach provides much greater insight into post-displacement labor force behavior of women. Post-displacement job search appears much more productive once allowance is made for labor force dropouts. In particular, the probability of very long search spells falls considerably. This suggests that displacement results in less structural unemployment than previous studies indicated. Our findings, however, also highlight the need for further research on the reasons for and welfare effects of labor force withdrawal following displacement.

NOTES

1. This paper draws from a longer technical working paper by the same authors [Podgursky and Swaim, 1991]. A complete list of studies is cited in that paper.
2. Note that we have parametarized equations 5b and 6 so that positive coefficients correspond to more rapid reemployment. A positive α value indicates an increased probability of searching for a new job and a positive β value an increase in the hazard rate for searchers (hence a reduction in expected time jobless).
3. Since $\sphericalangle w^*/\sphericalangle c < 0$, an increase in c decreases the probability of choosing to search, but increases the hazard rate if job search is pursued.
4. Because full-time workers, in general, make a larger contribution to household income than do part-time workers, displacement of such workers is probably also of the greatest policy interest. We also exclude from our sample women displaced due to the ending of a seasonal job, the failure of a self-employed business, or for "other" reasons; observations with missing information; and a small number of observations with inconsistent information. A full description of sample construction procedures is available from the authors.
5. The ML computations used the GAUSS-386 MAXLIK procedure. The DWS dataset as well as estimation programs used in this study are available on request from the authors.
6. This seems a conservative assumption, because the reemployment rates in Table 1 reach a plateau of approximately 85 percent within two years.
7. The standard errors reported for the split-population Weibull hazard model in column 3 are downward biased, because they have not been adjusted for our use of fitted, rather than actual, individual search probabilities when estimating these second-step coefficients. Our experience with a closely related model suggests that the standard error adjustment would be very small and not alter conclusions concerning the statistical significance of the coefficients [Podgursky and Swaim, 1991].
8. The life table method adjusts for the presence of many right censored (i.e., incomplete) jobless spells in the DWS data, but does not allow for individual differences in search efficiency.
9. As spells progress, high hazard workers sort themselves out of the sample faster than others. Workers who remain unemployed after 16 weeks or longer are, thus, primarily low hazard types and the group hazard rate will fall. Negative duration dependence might thus be inferred even if individual hazard functions are constant or modestly increasing. Our Weibull models correct for observable heterogeneity (i.e., hazard rate differences related to the covariates) but some unobservable heterogeneity undoubtedly remains.
10. Truncation is necessary because labor force withdrawal is assumed permanent. Truncation also appears desirable because the attribution of current labor force status to the loss of a specific job becomes increasingly tenuous as time since displacement increases.

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