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Abstract
This paper examines the determinants of unemployment duration in the framework of a competing risks model, where the destination states are employment and inactivity. The major innovation is the use of a split-population approach to accommodate the presence of defective risks in the context of the competing risks model. Certain of the regressors that affect the conditional hazards are allowed to influence defective risks. Unobserved individual heterogeneity among the susceptible populations is also controlled for. Access to unemployment benefits and age are accorded special emphasis because of their influence on defective risks and escape rates.

I. Introduction

This paper uses a competing risks model of unemployment duration in which exit from unemployment can result from finding a job or becoming inactive, which destinations are properly viewed as behaviorally distinct states (Flinn and Heckman, 1983). Use of a competing risks specification while familiar is not commonplace in empirical unemployment duration analysis (but see Han and Hausman, 1990; Meyer, 1990; Fallick, 1991; and Narendranathan and Stewart, 1993).[1] Altogether less familiar, is the notion that risks may be defective. This possibility is especially relevant in European labor markets, and our focus will be on Portuguese unemployment data. In Europe the arrival rate of job offers is low, leading to long unemployment duration (10.5 percent in the EU in 1998) and a high share of long-term unemployed in the jobless count (50.1 percent) (OECD, 1999: 19, 242).

Whereas in single-risk models one aggregates over a number of exit modes, for competing risks one has to confront the possibility that some exit routes are simply not viable. Furthermore, if indeed there exists a subpopulation with a zero hazard rate, we should observe a declining aggregate hazard function. This phenomenon is no more than a special case of unobserved individual heterogeneity.

Once one allows for defective risks, there is scope for determining the factors that influence the possibility of being "immune" to a specific type of transition. The approach is not very different from conventional selection models or, more pertinently, zero inflated Poisson regression models. Although identification remains an issue, information that individuals with given characteristics tend to exhibit a flat (specific) survival function after some point should assist in the identification of defective marginal distributions.

The empirical model used here reflects the sample information and the sample plan (observation over a fixed interval). We use a grouped duration model in which remaining duration is conditioned on elapsed duration. A flexible semiparametric baseline hazard function is specified, namely, a piecewise-constant hazard function with 13-segments. Modes of failure are treated as independent competing risks. This competing risks framework is next extended to encompass defective risks, which are then allowed to depend on the characteristics of the individual while allowing for gamma heterogeneity of the "susceptible" subpopulation.

To anticipate some of our more important findings, we report that access to benefits increases the proportion of those who will never get an acceptable job offer (the long-term jobless, or "employment-immunes"); decreases the escape rate into employment among those who will get such offers ("employment-susceptibles"); and decreases the hazard rate into inactivity of those who actively consider that destination state ("inactivity-susceptibles"). For its part, age increases the proportion of employment-immunes; decreases the proportion of the long-term active ("inactive-immunes"); and increases the hazards into inactivity of inactive-susceptibles. These effects, and the implications of the split-population model for conventional duration analysis, are carefully discussed in the paper.

II. Data

Our data are taken from the nationally representative Portuguese quarterly employment surveys (*Inquérito ao Emprego*), conducted by the National Institute of Statistics (INE) (*Instituto Nacional de Estatistica*). The sample period is 1992(2)-1997(4), the starting date being dictated by changes in survey design after the first quarter of 1992.

The quarterly employment survey has a quasi-longitudinal capacity. One sixth of the sample rotates out each quarter, allowing us to track transitions out of unemployment for up to five quarters, and hence pursue the conditional approach. Transition rates are obtained simply by identifying those unemployed individuals in the survey, and their elapsed duration in a given quarter, who move out of unemployment over the subsequent quarter. The destination states of previously unemployed workers can also be identified. For present purposes, we distinguish between the two destination states of employment and inactivity.

More technically the stock sampling basis of the employment survey provides backward recurrence times for the relevant labor market state. Information on forward recurrence times has thus to be inferred. Specifically, remaining duration of unemployment, conditional on elapsed duration, distributed as the entrant conditional density function (Lancaster, 1990).

Each survey contains information on the length of the current unemployment spell (in months) and the unemployment benefit status of the worker. It is also possible to track time to exhaustion of benefits because maximum duration is a function of age. We eschew using this benefit measure here, but the seven-element structure of the age regressor is designed to exactly mimic the stepped increases in benefit duration entitlement with age. We note parenthetically that the replacement rate is to all intents and purposes fixed in Portugal (at 65 percent). Accordingly, it is not deployed as an independent variable. (Neither duration of benefits nor the replacement rate changed over the sample period.)[2]

The employment survey contains additional information on variables that may be expected to shift the baseline hazard up or down, namely, the individual's age, level of schooling, marital status, tenure on the last job, whether he or she was a new entrant, and the reason for job loss. The local unemployment rate, derived from separate sources, was also allowed to influence the baseline hazard function.

Since we also wish to account for defective risks, some of the selfsame arguments are used to estimate the split-population regression equations. All the variables that are specific to the individual are used here (namely, being married, schooling, tenure, and age). The general point is that we are interested in considering variables that affect the probability of being a long-term survivor. Age is expected to be critical in this regard, and is now expressed in continuous form. Unemployment benefits and the unemployment rate are also used as arguments: the former because it the key policy variable; the latter because it is expected to inform on discouragement. Descriptive statistics are provided in the Appendix table.

The sole restrictions placed on the data were that the individual be unemployed at the time of the quarterly survey, male, aged between 16 and 64 years, and resident in mainland Portugal.

Given the possibility of sample attrition, we also ensured that individuals appearing in contiguous surveys with the same identifier were in fact the same individual. The sample size is 9,451 individuals.

III. Methodology

The basic empirical model used here exploits the particular nature of our data set. It will be recalled that we can follow the individual (transitions) over a period of up to 6 (5) quarters. Given this sampling plan, unemployment transitions are observed over a fixed period of 3 months.

The instantaneous escape rate function to destination *j* , *j*=1, 2 (in our case, *j* denotes the two destination states of employment and inactivity) has been called the *cause-specific hazard function*. It gives, for a set of covariates *x*, the instantaneous probability of exiting unemployment at t, into destination j, given that the individual stayed unemployed until t

$$\theta_j(t;x) = \lim_{\Delta t \to 0} \frac{P(t \le T < t + \Delta t, J = j \mid T \ge t, x)}{\Delta t}, \qquad (1)$$

which yields the aggregate hazard function

$$\theta(t;x) = \sum_{j=1}^{2} \theta_j(t;x). \qquad (2)$$

The relevant information is given by the observed elapsed duration of unemployment, the mode of exit out of unemployment and, for continued unemployment, the indication of an incomplete duration (i.e. the censoring indicator). Our estimation is thus based on data provided by the triplet (*T, J, C*), where *C* is the indicator of a censored duration.

The model has a conventional competing risks interpretation. In this framework, a latent duration (T_j) unemployment attaches to each exit mode. We only observe the minimum of each latent variable. If risks are assumed to be independent, with continuous duration, this model simplifies to separate single-cause hazard models (but see below).[3]

Assuming proportionality of covariates, the cause-specific hazard function in equation (2) can be rewritten for the arbitrary baseline hazard θ_0j(t)

$$\theta_j(t; X) = \theta_{0j}(t)\exp\lfloor x'\beta_j \rfloor . \tag{3}$$

Recall, however, that our information on elapsed duration of unemployment is grouped into monthly intervals (while transitions can solely be identified over a fixed interval of 3 months). Consider a time axis that is divided into K intervals by points c_1, c_2, … , and c_{K-1}, and let $M=m$ denote the occurrence of an exit in the interval $[c_{t-1}, c_t)$, where t is the realization of a discrete random unemployment duration variable $M\in(1,..., K)$. In practice, we use 13 intervals and employ a piecewise-constant baseline hazard function (where the hazard function is assumed to be constant within each interval).[4,5] The probability that an event occurs in the m^{th} interval, and that such an exit is to destination r, will be given by

$$\frac{S^r_{m-1} - S^r_m}{S^r_{m-1}} S_{m-1} = h^r_m S_{m-1} = f^r_m \quad , \tag{5}$$

where $S^r_{m-1} = e^{-\Lambda^r_{m-1}}$, $\Lambda^r_{m-1} = \int_0^{c_{m-1}} \phi_r(u)du$, and $S_{m-1} = \prod_{j=1}^{2} S^j_{m-1}$.

The functions f^r_m and $1 - S^r_m$ provide a convenient characterization of the pdf and cdf associated with the marginal distribution for each latent duration, T_j, in terms of the specific hazard function. A censored observation occurs with probability $S_m = \prod_{j=1}^{2} S^j_m$, which is simply the product of the two specific "survivor" functions.

Recall, however that the individuals in our sample are observed over a fixed interval of 3 months (Lancaster, 1990, p. 183); that is, at the time of the first survey the elapsed duration of unemployment is recorded. Three months later, the labor status of the same individual is observed, providing us with information on whether he or she had left unemployment and, if so, the destination state (employment or inactivity). With this sample plan, we need to condition on elapsed duration in order to recoup the entrant density function. The likelihood contribution from a single individual is given by

$$L_i = \left\{ \prod_{m=1}^{K-1} \prod_{j=1}^{2} \left[\frac{S_{m-1}^{j} - S_{m}^{j}}{S_{m-1}^{j}} \right]^{\delta_{imj}} \right\} \left\{ \prod_{m=2}^{K} \left[\frac{S_m}{S_{m-1}} \right] \right\}^{1-\delta_{mi}}, \quad (6)$$

where δ_{imj} assumes the value 1 if the individual *i* exits to destination *j* during the m^{th} interval, and 0 otherwise. The indicator $\delta i_{im} = \sum_{j=1}^{2} \delta_{imj}$ identifies completed durations, so that, $1-\delta_{im}$ equals one for a censored observation.

Up to this point we have assumed non-defective risks; that is, all destination states are considered (viable) ex-ante. We now have to account for the possibility that certain or all choices may be ruled out. Technically speaking, latent duration may not be finite (i.e. marginal specific survival functions do not converge to zero, and thus marginal cumulative density functions do not integrate to one), leading to a defective distribution. This approach has been used in the econometric literature in the context a "split-population" framework for a single risk (Schmidt and Witte, 1989).[6]

In the context of a grouped duration model, a straightforward way to incorporate the possibility of defective risks is to redefine the specific "survival" function as $S_m^j = 1 - P_j + P_j S_m^j$, where ($1$-$P_j$) is the probability of a defective risk associated with destination *j*. Taking P_j as additional unknown parameters to be estimated, the new paramaterization of the specific "survivor" function can be employed in a likelihood function identical to (6). In order to guarantee that P_j lies between 0 and 1, we employ the logit reparameterization for $P_j = \exp(\mu_j)/1+\exp(\mu_j)$. A natural extension of this model is to allow P_j to depend on a set of regressors *z*, leading to a logit link function $P_j = \exp(\mu_j + z'\gamma_j)/1+\exp(\mu_j + z'\gamma_j)$ (see Yamaguchi, 1992). That is, we specify the following likelihood function for individual *i*

$$L_i = \left\{ \prod_{m=1}^{K-1} \prod_{j=1}^{2} \left[\frac{P_j \left(S_{m-1}^{j} - S_{m}^{j} \right)}{1 - P_j + P_j S_{m-1}^{j}} \right]^{\delta_{imj}} \right\} \left\{ \prod_{m=2}^{K} \left[\frac{1 - P_j + P_j S_m}{1 - P_j + P_j S_{m-1}} \right] \right\}^{1-\delta_{mi}}, \tag{7}$$

Finally, we attempt to accommodate the presence of unobserved individual heterogeneity by assuming a multiplicative error term associated with each specific hazard function. We further assume that the errors are gamma distributed with mean 1 and variance σ_j^2 and are uncorrelated (mantaining the risk independence assumption).[7] We proceed by redefining the specific "survivor" function using the well-known result for gamma mixtures with grouped data $S_m^j = (1+\sigma_j^2 \Lambda_m^j)^{-1/\sigma_j^2}$. In order to account for both defective risks and gamma heterogeneity, we employ the transformation $\tilde{S}_m^j = 1 - P_j + P_j S_m^j$. In short, we define the following likelihood function

$$L_i = \left\{ \prod_{m=1}^{K-1} \prod_{j=1}^{2} \left[\frac{P_j \left((1+\sigma_j^2 \Lambda_m^j)^{-1/\sigma_j^2} - (1+\sigma_j^2 \Lambda_{m-1}^j)^{-1/\sigma_j^2} \right)}{\left(1 - P_j + P_j (1+\sigma_j^2 \Lambda_{m-1}^j)^{-1/\sigma_j^2} \right)} \right]^{\delta_{imj}} \right\} \times$$

$$\left\{ \prod_{m=2}^{K} \left[\frac{\left(1 - P_j + P_j (1+\sigma_j^2 \Lambda_m^j)^{-1/\sigma_j^2} \right)}{\left(1 - P_j + P_j (1+\sigma_j^2 \Lambda_{m-1}^j)^{-1/\sigma_j^2} \right)} \right] \right\}^{1-\delta_{mi}}. \tag{8}$$

The ML routine from the econometric package TSP (Time Series Processor) was employed to obtain the maximum likelihood estimates. In each case, starting values from a simple single risk specification were used.

IV. Findings

Results of fitting our multiple destination model are provided in Table 1. The first two columns of the table give results for the basic competing risks specification. The next two columns give results for the same specification now supplemented with a control for gamma heterogeneity for the susceptible population. Estimates for the most parsimonious version of the defective risks model are provided in the fifth and sixth columns. Results for a specification in which defective risks are affected by certain of the regressors used in the conditional model are contained in the seventh and eighth columns. Finally, our preferred specification in which in addition to defective risks we also allow for gamma heterogeneity of the susceptible population are given in the last two columns of the table.

(Table 1 near here)

Results for the basic competing risks model indicate that the disincentive effects of access to unemployment benefits are similar for the two destination states. Recipients are 42.3 (40.0) percent less likely to enter into employment (inactivity) than their non-recipient counterparts. The effects of the other regressors do, however, differ more markedly across destination state. Thus, the strongest depressing effects of age on transitions into employment are found among the two oldest age groups, whereas for inactivity statistically negative effects are confined to the two youngest age groups.

Familiarly, transitions into reemployment are higher among married workers, those who have completed a fixed-term contract, and those losing a job by reason of mass (rather than individual) layoffs, and are lower for higher tenure workers. In each case, opposite results are obtained in respect of transitions into inactivity. Interestingly, however, schooling does not seem to affect transition rates into either destination state, while higher unemployment rates lead to reduced transitions into both employment and inactivity (the coefficient estimate is statistically significant for inactivity).

A number of these results change when we allow for unobserved individual heterogeneity via a gamma-distributed error term. Most obvious are the sharply elevated disincentive effects of unemployment benefits. Access to benefits now reduces transitions into each destination state by 64 percent (but see below). Most of the other coefficient estimates also increase in absolute magnitude.

Note, however, that at this stage we are assuming that each individual is likely to exit unemployment either by obtaining a job or becoming inactive. If there are defective risks, the parametric specification for unobserved individual heterogeneity might not adequately capture this type of heterogeneity. Here we are referring to split-population heterogeneity, that is, a mixture of two subpopulations one of which has a zero probability of an event - say, exit into a given destination.

The basic defective risks model (columns five and six) indicates that a small number of the unemployed do not receive acceptable offers of employment. Consider the μ parameters for each destination state. In the case of reemployment, it can be inferred that employment-susceptibles constitute 94.4 percent of the unemployed population (i.e. exp 2.821/(1 + exp 2.821). Alternatively put, some 4.6 percent of this sample are in fact permanently jobless or "employment immunes"; they will either drift into long-term (actually permanent) unemployment or become inactive. As far as inactivity is concerned, the inference is that 45.7 percent of unemployed workers will never consider this destination state. These may be called the permanently active or "inactive immunes." For the 54.3 percent of unemployed workers who consider inactivity (the inactivity-susceptibles), the outcome can of course be either inactivity or reemployment. Conditional on facing employment or inactivity, it can be seen that transitions are reduced by access to benefits. The disincentive effects are lower than in the two preceding columns but of the same order of magnitude as reported for the most parsimonious competing risks specification. The qualitative effects of the other regressors are qualitatively unchanged as between the three specifications.

For each destination state, the surviving fraction is next allowed to be influenced by the six regressors shown in the lower panel of columns seven and eight of the table. We estimate that, among individuals with average characteristics for continuous variables and zero values for the dummy variables (namely, non-recipients and unmarried individuals), the probability of receiving an acceptable job offer is now 89.5 percent, while the corresponding percentage of those who will never enter inactivity falls to 42.7 percent. Variables increasing the probability the probability of being permanently jobless are unemployment benefits, age, and tenure. On the other hand, being married decreases the probability of observing a zero hazard rate. The signs of these variables match the effect of the corresponding regressors affecting the conditional baseline hazard (i.e. for employment-susceptibles). (The age variable will be considered in more detail below). Thus, unemployment benefits, age, and tenure increase the proportion of employment-immunes, while being married reduces that proportion.

As far as inactivity is concerned, the variables of the split-population equation are generally poorly determined. The proportion of inactive-immunes is increasing in schooling, tenure, and unemployment, and decreasing in unemployment benefit receipt, age, and being married. Alone among these covariates, the (reduced) probability of being an inactive-immune is statistically significant for schooling. The association is sensible. When we consider the conditional hazard into inactivity, it can be seen that unemployment benefit receipt reduces hazard rates and age increases them. Both results again seem sensible. The negative effect of schooling on the hazard rates of inactive-susceptibles is also reassuring as indeed are the similar effects of being married and laid off. That said, it remains something of a puzzle that transitions into inactivity are decreasing in unemployment.

Our preferred specification is given in the final two columns of the table, where we accommodate unobserved individual heterogeneity of the susceptible subpopulations. An initial observation is that the disincentive effects of unemployment benefits on escape rates into employment and inactivity effects are modestly higher when we take account of unobserved heterogeneity (though nowhere near as large as in the heterogeneity-augmented competing risks model assuming non-defective risks). Specifically, benefits lower escape rates by approximately 50 percent for both destination-specific hazard functions.

Now 90.6 percent of unemployed workers will ultimately receive acceptable job offers and 28.7 percent will never consider inactivity, so that one effect of the heterogeneity correction is to reduce defective risks for inactivity. Variables increasing the probability that an individual is permanently jobless (i.e. destined to become long-term unemployed or inactive) are again unemployment benefits, age, tenure, and (rising) unemployment. Also as before, being married sharply reduces the probability of a defective risk for employment. In all cases, the coefficient estimates are increased in absolute magnitude, although the effects of schooling and the unemployment rate are imprecisely estimated.

With respect to those transitions into inactivity, the main result is again that schooling decreases the fraction of those who will never enter inactivity. Expressed differently, the fraction of individuals with a flat hazard at zero decreases.

Finally, the principal effects of the regressors on the specific hazards are qualitatively unchanged. The escape rates of employment-susceptibles are now more strongly influenced (in the expected direction) by labor market entry and tenure on the last job. For inactivity-susceptibles, the coefficient estimates are generally increased in absolute magnitude (especially age) although, with the notable exception of the marital status variable, they are not noticeably more precisely estimated.

(Figures 1 through 4 near here)

The crucial role of unemployment benefits in retarding transitions out of unemployment is now addressed in more detail. Hazard functions by destination state are charted in Figures 1 and 2. The estimates are again based on the defective risks model contained in the fifth specification of Table 1.[8] (A fourth-order polynomial was used to fit the curves.) For the employment cause-specific hazard function there is a tendency for escape rates to fall with jobless duration for both recipients and nonrecipients alike. The decline for non-recipients is fairly sharp over the first 12 to 18 months of the jobless spell, after which point the decline is modest - with a slight uptick after the twenty-fifth month. For recipients, the decline is both more muted and shorter lived. (Figure 4 makes a purely technical point that, if there were no employment immunes, the employment cause-specific hazard function for non-recipients would indicate a rise in escape rates a little after twelve months into the jobless spell.)[9]

Transitions into inactivity display a quite different pattern. For both non-recipients and recipients the hazard rises and then falls, peaking at around 12 months for the former and 18 months for the latter. As before, escape rates into inactivity are uniformly higher for non-recipients than recipients. While we have no cogent explanation for the shape of the hazard function, there is no suggestion that transitions into inactivity are an end-state realized after fruitless search for employment. This conclusion is underscored by Figure 3, which identifies the share of all monthly transitions that are into inactivity. In this case, the differences between recipients and non-recipients are muted, both functions peaking at a little under 30 percent after 18 months.

(Figures 5 and 6 near here)

Survival functions in aggregate (i.e. proper survival functions) and specific survival functions for the two destination states are given in Figures 5 and 6, respectively.[10] From Figure 5 it can be seen that median joblessness is around 6 months for non-recipients and over 16 months for recipients. Figure 6 makes it transparent that the survival rates for inactivity do not go to zero - although of course the same holds true for employment. In short, defective risks characterize both destination states. Consistent with the information provided earlier on the cause-specific hazard functions, survival rates for activity are much higher than for employment and in each case higher for recipients than non-recipients.

(Figures 7 and 8 near here)

Our analysis has also indicated that age is an important determinant of escape rates out of unemployment. Figures 7 and 8 reconsider the association between age and destination state (see also Table 2, below). Figure 7 indicates that the proportion employment-immunes - which we interpret as being those who will never receive acceptable job offers - rises with age and in the same manner for recipients and non-recipients alike. On the other hand, Figure 8 shows that proportion of inactivity-immunes is decreasing in age. Both effects are reinforcing in the unemployment duration of older workers. This result reinforces the disincentive effects.

(Table 2 near here)

Table 2 concludes with some simulation results on the effects of unemployment benefits and age on unemployment, again based on the final specification in Table 1. First consider survival rates in joblessness aggregated over both destination states. As can be seen from the table, survival rates decline over the jobless spell and are increasing in age and benefit receipt. The decline in survival rates with duration is more pronounced for non-recipients than recipients but age is more important than recipiency in arresting the decline in survival rates. Similarly, although the pattern of survival rates at 3, 12, and 36 months points to greater persistence among recipients and older individuals, the increase in survival rates with age always exceeds the corresponding increase in survival rates with benefits. Nevertheless, the effect of benefit receipt is profound; for example, at 36 months the survival rates of recipients are more than double those of non-recipients for each of the three age groups.

The entries for defective risks show that the proportion of those who never get a job offer rises steadily with age and with benefit receipt by age. Roughly 3 (8) percent of 20-year old non-recipients (recipients) will not receive an acceptable job offer, rising to 37 (63) percent in the case of their 50 year-old counterparts. The proportions of those who will never transition into inactivity declines with age and benefit receipt in roughly equal proportion (see also Table 8).

Finally, the estimated median jobless duration values - shown at the foot of the table - while again confirming the important role of age and benefits in retarding transitions out of unemployment, make the point that destination state matters. We present two sets of estimates of median duration. In one case, we admit that an individual can move into either employment or inactivity, consistent with a standard measure of (median) unemployment duration. In the other, we simulate a situation where the possibility of entering inactivity is precluded, and compute the length of time it will now take to find employment. It can be seen that with the latter exclusion, duration would increase from 5 to 7 weeks for a 20-year-old non-recipient and from 11 to 14 weeks for his recipient counterpart. By the same token, duration would rise from 11 to 24 weeks for a 50-year-old non-recipient.[11] Simulation of median duration for a single risk is straightforward in the framework of a competing risks model where all the other risks are taken to be absent.

V. Conclusions

The main lesson of this paper is that a substantial proportion of (Portuguese) long-term unemployment can be explained either by the failure of individuals to receive acceptable job offers or by their non-consideration of the inactivity option. We showed that some factors preempt options at the same time as they independently shape transition rates out of unemployment (i.e. for viable options). Defective risks are clearly manifested in cause-specific survival functions.

All of this is consistent with the conventional view of ossified European labor markets. The argument is that high firing costs not only decrease flows into unemployment but also strengthen the bargaining power of insiders. The result is a lower arrival rate of job offers, and higher unemployment duration to reestablish equilibrium (Blanchard and Portugal, 1999). In this setting, it is indeed likely that an important subset of the unemployed population (especially older individuals) will see their already slim chances of receiving acceptable job offers being reduced to zero.

We singled out for special attention the role of age and unemployment benefits. Each has statistically significant effects on hazard rates and defective risks. Age increases the proportion of those who will never receive acceptable job offers and symmetrically decreases the proportion of those active in the labor market. It also independently increases hazards into inactivity. Unemployment benefit effects are a little more tricky to the extent that even in Portugal one cannot be a recipient for ever. Subject to this caveat - although benefits can be received in one form or other for up to 5 years - benefits are associated with increases in the proportion of those who will never find work. Benefits also decrease the hazard rates into employment and inactivity among those for whom these options are not preempted.

In search of a more adequate specification of unemployment duration, modern duration analysis should not simply recognize alternative destination states (and here it would also seem profitable to consider a variety of employment options) but also explicitly incorporate defective risks. The relevance of the latter is most obvious in terms of understanding long-term unemployment and interpreting negative duration dependence. In general, if there are defective risks to begin with, and these are ignored in modeling unemployment duration, there is a bias toward a declining hazard function that results from the mixture of the two subpopulations. (In our case, there are in essence two hazard functions: one that declines before trending up, and another for which the hazard rate is zero. In conjunction, they produce a declining hazard.)

Endnotes

1. The approach is rooted in the biostatistics literature, where the context of competing risks is the presence of different diseases. In this setting, one can simulate the effect on the expected life of an individual resulting from the elimination of a single risk/disease (see Cox and Oakes, 1985; Kalbfleisch and Prentice, 1980).
2. Strictly speaking, the unemployment benefit variable includes two types of unemployment benefits: unemployment insurance (UI) proper, and unemployment assistance. The latter, lower-order benefits are payable to those previously employed individuals who do not meet the service eligibility criterion for UI (18 months insured employment within the last two years) and to UI-exhaustees on a means-tested basis. The survey does not distinguish between the two. However, it is possible crudely to identify the two types of benefit recipient on the basis of tenure on the last job. (Crude, insofar as some of those thereby classified as unemployment assistance recipients may actually have been eligible for UI benefits proper if they had accumulated 18-months' insured employment on more than one job.) Suffice it to say here that purging low-tenure workers from the sample of unemployment benefit recipients did not qualitatively alter any of the findings reported below.
3. That is, all events other than the one under consideration are taken as censored.
4. As noted earlier, we use month as the time calendar unit. In specifying the baseline hazard function, we used 3 initial intervals of 1 month length, 7 subsequent intervals of 3 months' duration, then 2 intervals of 6 months, and a final, open-ended interval.
5. See Prentice and Gloeckler (1978) for the derivation of the piecewise-constant hazard as a grouped version of the proportional hazards model, and Han and Hausman (1990) for an ordered-response model with competing risks.
6. See also Pudney and Thomas (1995) for an extension of the split-population model to multiple destinations, and Maller and Zhou (1996) for an exploitation of duration models with long-term survivors.

7. Cockx (1997) presents a similar treatment of unobserved individual heterogeneity in the context of competing risks.
8. The hazard functions in question are unconditional, that is, they reflect the presence of immunes on the transitions out of unemployment. Average values for the covariates were used in their construction.
9. The same holds for the recipient employment cause-specific hazard function.
10. Specific "survival" functions are not proper because, with competing risks, they fail to integrate to one. We use the expression "specific survival" for convenience, following Kalbfleisch and Prentice (1980). Furthermore, with defective risks, even marginal survival functions will be degenerate.
11. Note that the bottom-right cell entry is undefined for 50-year-old recipients for the simple reason that 63.2 percent of this group never receive acceptable job offers.

References

Blanchard, Olivier, and Pedro Portugal. 1999. "What Hides Behind an Unemployment Rate: Comparing Portuguese and U.S. Unemployment." NBER Working Paper No. 6636.

Cockx, Bart L. W. 1997. "Analysis of Transition Data by Minimum-Chi Square Method: An Application to Welfare Spells in Belgium." Review of Economics and Statistics 79 (August): 392-405.

Cox, D.R., and D. Oakes. 1985. Analysis of Survival Data. London: Chapman and Hall.

Fallick, Bruce Chelimsky. 1991. "Unemployment Insurance and the Reemployment Rate of Displaced Workers." Review of Economics and Statistics 73 (May): 228-235.

Flinn, Christopher J., and James J. Heckman. 1983. "Are Unemployment and Out of the Labor Force Behaviorally Distinct Labor Market States?" Journal of Labor Economics 1 (January): 28-42.

Han, A., and J. Hausman. 1990. "Flexible Parametric Estimation of Duration and Competing Risks Models." Journal of Applied Econometrics 5 (January-March): 1-28.

Kalbfleisch, J.D., and R.L. Prentice. 1980. The Statistical Analysis of Failure Time Data. New York: Wiley.

Lancaster, Tony. 1990. The Econometric Analysis of Transition Data. Cambridge: Cambridge University Press.

Maller, Ross, and Xian Zhou. 1996. Survival Analysis with Long-Term Survivors. Chichester and New York: John Wiley and Sons.

Meyer, Bruce D. 1990. "Unemployment Insurance and Unemployment Spells." Econometrica 58 (July): 757-782.

Narendranathan, Wiji, and Mark B. Stewart. 1993. "Modelling the Probability of Leaving Unemployment: Competing Risks Models with Flexible Base-Line Hazards." Applied Statistics 42 : 63-83.

OECD. 1999. Employment Outlook. Paris: Organisation for Economic Co-operation and Development.

Prentice, Ross, and L.M. Gloeckler. 1978. "Regression Analysis of Grouped Survival Data with Application to Breast Cancer Data." Biometrics 34 (March): 57-67.

Pudney, Stephen, and Jonathan Thomas. 1995. "Specification Tests for the Competing Risks Duration Model: An Application to Unemployment Duration and Sectoral Movement." Oxford Bulletin of Economics and Statistics 57 (August): 323-347.

Schmidt, P., and A.D. Witte. 1989. "Predicting Criminal Recidivism Using 'Split-Population' Survival Time Models." Journal of Econometrics, Annals I: 141-159.

Yamaguchi, Kasuo. 1992. "Accelerated Failure-Time Regression Models with a Regression Model of Surviving Fraction: An Application to the Analysis of 'Permanent Employment' in Japan." Journal of the American Statistical Association 87 (June): 284-292.

Table 1: Two-Destination Piecewise-Constant Hazards Regression Models (n=9,451)

	Transition to:		Transition to:		Transition to:		Transition to:		Transition to:	
Variable	Employment	Inactivity	Employment	Inactivity	Employment	Inactivity	Employment	Inactivity	Employment	Inactivity
UB	-0.555	-0.511	-1.012	-1.011	-0.595	-0.558	-0.439	-0.485	-0.691	-0.685
	(0.067)	(0.165)	(0.350)	(0.350)	(0.073)	(0.197)	(0.098)	(0.346)	(0.158)	(0.365)
AGE GROUP										
25-29	-0.008	-0.434	0.166	-0.477	0.139	-0.282	0.112	-0.461	0.235	-0.617
	-(0.080)	(0.217)	(0.166)	(0.425)	(0.084)	(0.265)	(0.079)	(0.273)	(0.149)	(0.387)
30-34	-0.141	-0.820	-0.119	-1.038	0.050	-0.781	0.025	-0.991	0.116	-1.404
	(0.022)	(0.306)	(0.194)	(0.470)	(0.103)	(0.357)	(0.096)	(0.395)	(0.175)	(0.567)
35-39	-0.238	0.550	-0.331	-0.611	-0.049	-0.665	-0.004	-0.833	0.046	-1.045
	(0.119)	(0.351)	(0.240)	(0.634)	(0.103)	(0.415)	(0.111)	(0.456)	(0.206)	(0.580)
40-44	-0.098	0.034	0.135	0.164	0.224	0.236	0.169	-0.105	0.409	-0.155
	(0.118)	(0.311)	(0.246)	(0.686)	(0.128)	(0.349)	(0.125)	(0.426)	(0.228)	(0.597)
45-49	-0.246	-0.098	-0.254	-0.084	-0.023	-0.101	-0.019	-0.404	0.059	-0.434
	(0.133)	(0.339)	(0.259)	(0.700)	(0.138)	(0.412)	(0.135)	(0.480)	(0.234)	(0.617)
50-54	-0.416	0.280	-0.628	0.289	-0.235	0.339	-0.038	0.021	0.075	-0.180
	(0.152)	(0.314)	(0.275)	(0.746)	(0.164)	(0.391)	(0.152)	(0.509)	(0.262)	(0.668)
55+	-0.972	0.244	-1.445	-0.018	-0.931	0.299	-0.322	0.001	-0.363	-0.384
	(0.159)	(0.310)	(0.283)	(0.691)	(0.167)	(0.382)	(0.166)	(0.521)	(0.258)	(0.633)
SCHOOLING	0.008	0.021	0.003	0.023	-0.002	0.191	0.010	-0.064	0.016	-0.079
	0.008	(0.020)	(0.015)	(0.045)	(0.009)	(0.025)	(0.008)	(0.031)	(0.015)	(0.045)
TENURE	-0.023	0.008	-0.043	0.033	-0.028	0.007	-0.016	0.002	-0.029	0.025
	(0.005)	(0.009)	(0.009)	(0.021)	(0.005)	(0.011)	(0.006)	(0.013)	(0.009)	(0.017)
MARRIED	0.308	-0.194	0.379	-0.902	0.103	-0.498	0.068	-0.857	0.046	-1.299
	(0.078)	(0.214)	(0.163)	(0.504)	(0.080)	(0.258)	(0.063)	(0.374)	(0.206)	(0.488)
FIRSTJOB	-0.415	0.360	-0.765	0.869	-0.416	0.523	-0.388	0.441	-0.654	0.735
	(0.093)	(0.182)	(0.196)	(0.580)	(0.103)	(0.223)	(0.095)	(0.232)	(0.181)	(0.428)
LAYOFF	0.022	-0.642	-0.128	-1.381	-0.145	-0.611	-0.121	-0.741	-0.163	-0.865
	(0.090)	(0.241)	(0.164)	(0.574)	(0.092)	(0.285)	(0.084)	(0.262)	(0.152)	(0.373)
END FIXED	0.185	-0.124	0.343	-0.366	0.050	-0.347	0.068	-0.211	0.155	-0.252
	(0.062)	(0.172)	(0.136)	(0.334)	(0.066)	(0.203)	(0.063)	(0.206)	(0.115)	(0.294)
UNEMPLOYMENT RATE	-0.021	-0.137	-0.082	-0.356	-0.006	-0.196	0.004	-0.267	-0.058	-0.427
	(0.027)	(0.061)	(0.054)	(0.160)	(0.027)	(0.070)	(0.025)	(0.094)	(0.047)	(0.152)
Sigma			0.979	2.800					0.823	1.724
			(0.112)	(0.357)					(0.155)	(0.451)
Split Population Equation										
Miu					2.821	0.171	2.138	0.296	2.270	0.910
					(0.150)	(0.141)	(0.172)	(0.331)	(0.189)	(0.690)
UB							-0.870	-0.085	-1.069	-0.378
							(0.306)	(0.797)	(0.284)	(0.758)
AGE							-0.078	0.019	-0.085	0.032
							(0.012)	(0.025)	(0.013)	(0.034)
SCHOOLING							-0.037	0.199	-0.044	0.264
							(0.027)	(0.067)	(0.029)	(0.108)
TENURE							-0.038	0.012	-0.038	-0.017
							(0.012)	(0.030)	(0.012)	(0.042)
MARRIED							1.374	1.113	1.415	2.011
							(0.264)	(0.799)	(0.278)	(1.340)
UNEMPLOYMENT RATE							-0.118	0.123	-0.118	0.209
							(0.120)	(0.184)	(0.121)	(0.218)
Log-likelihood	-5118.72		-5102.62		-5096.86		-5068.52		-5058.17	

Asymptotic standard errors in parentheses

Figure 1: Cause-Specific Hazard Function - Employment

Figure 2: Cause-Specific Hazard Function - Inactivity

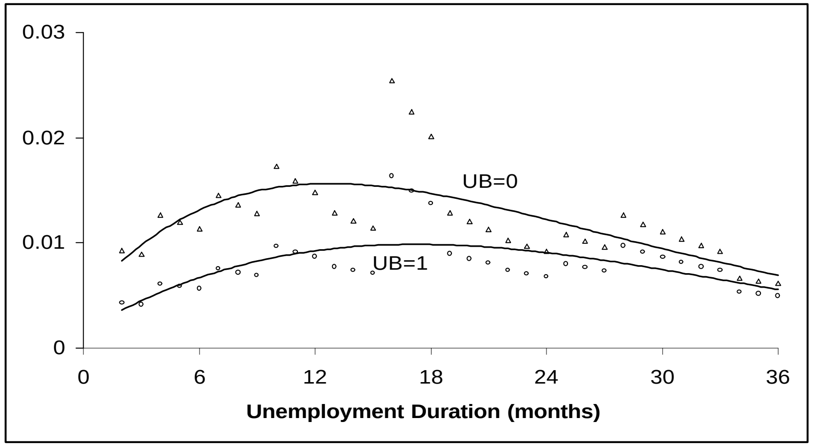

Figure 3: Those Moving into Inactivity as a Proportion of all Transitions

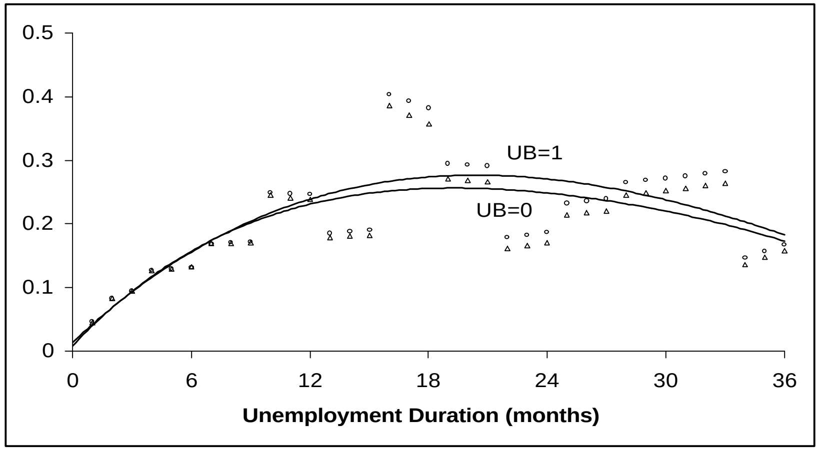

Figure 4: Non-recipient Employment Hazard Function with and without Defective Risks

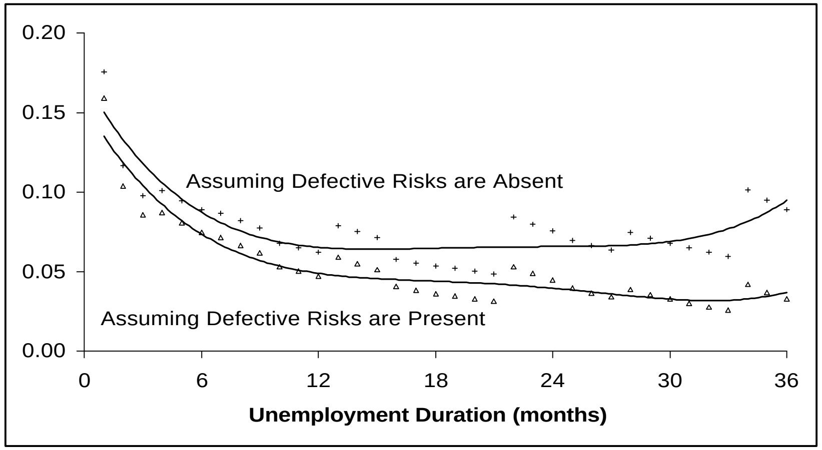

Figure 5: Aggregate Survival Functions

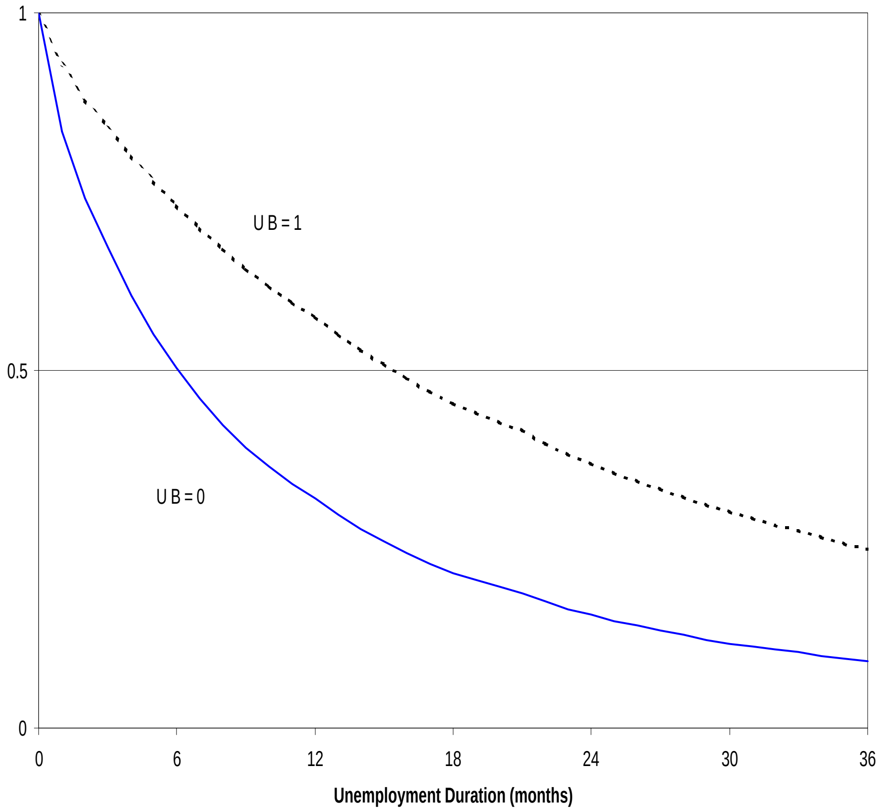

Figure 6: Specific "Survival" Functions

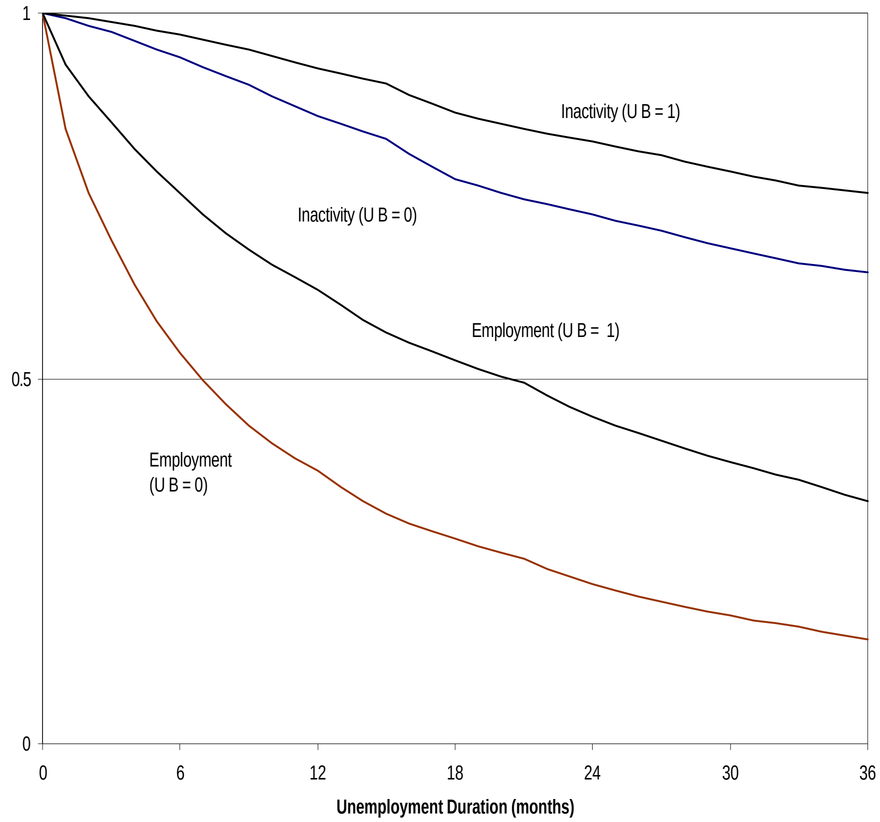

Figure 7: Defective Risk into Employment by Age

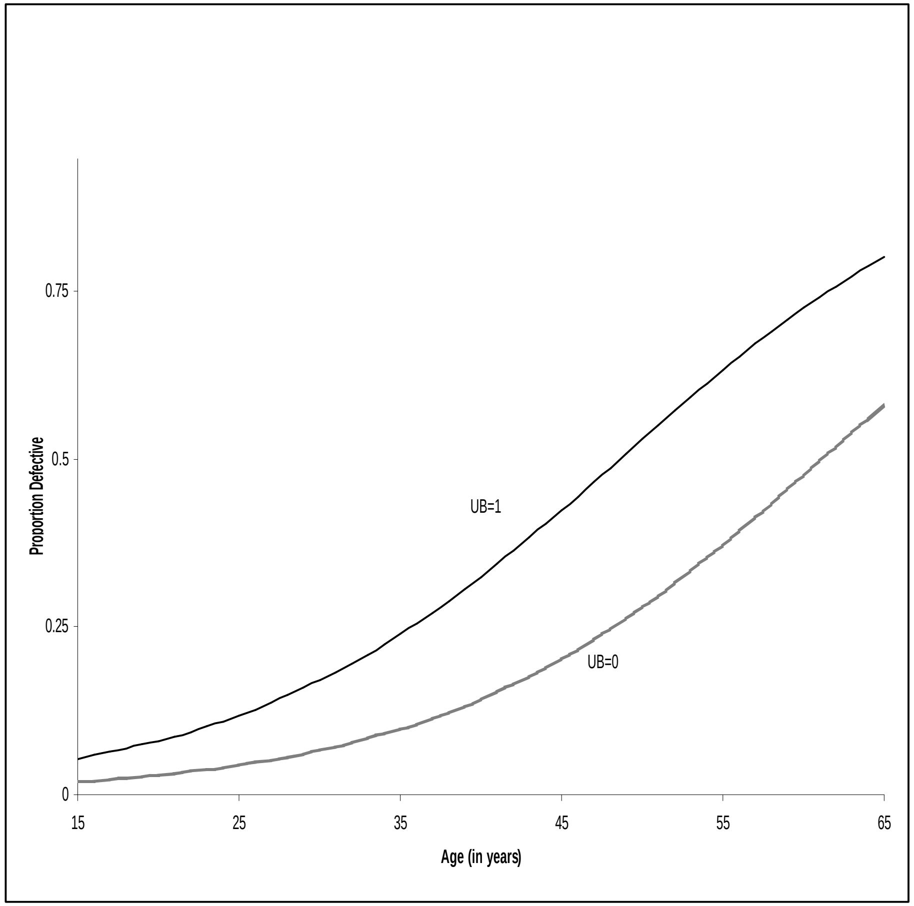

Figure 8: Defective Risk into Inactivity by Age

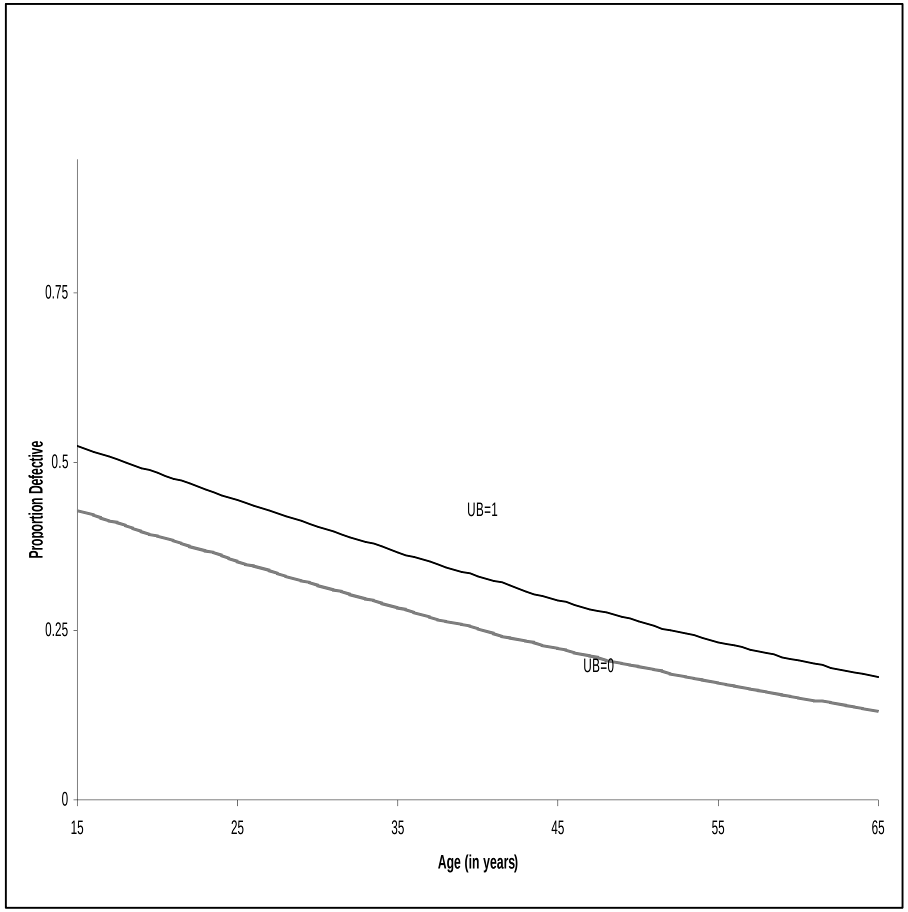

Table 2: Simulations from the Split-Population Model*

	Age=20 Years		Age=35 Years		Age=50 Years	
	UI=0	UI=1	UI=0	UI=1	UI=0	UI=1
Survival Rate after						
3 months	0.629	0.792	0.672	0.841	0.790	0.920
12 months	0.257	0.466	0.321	0.574	0.474	0.723
36 months	0.050	0.140	0.092	0.250	0.218	0.435
Defective Risk						
Employment	0.029	0.081	0.094	0.231	0.371	0.632
Inactivity	0.390	0.483	0.287	0.370	0.173	0.234
Median Duration (in months)						
two destinations	5	11	7	16	11	28
until employment	7	14	7	21	24	na

* The simulations are derived using the fifth specification in Table 1

Appendix Table: Definition of Variables and Sample Means by Unemployment Benefit Recipiency and Destination

	Recipient			Nonrecipient		
Variable	Unemployed	Employed	Inactive	Unemployed	Employed	Inactive
DURATION elapsed unemployment in months	12.082	9.027	15.250	16.138	9.919	13.548
AGE age in years	42.456	36.048	43.875	31.184	29.457	30.158
SCHOOLING years of schooling completed	5.765	5.912	5.312	7.089	7.104	7.743
TENURE years of tenure on previous job	10.221	5.739	11.775	4.159	2.749	4.215
JOBS number of previous jobs	3.431	3.958	3.250	2.419	3.011	1.892
MARRIED =1 if married, 0 otherwise	0.754	0.636	0.734	0.338	0.369	0.278
FIRSTJOB =1 if looking for first job, 0 otherwise				0.234	0.174	0.361
LAYOFF =1 if job lost by reason of mass layoff, 0 otherwise	0.316	0.227	0.203	0.093	0.082	0.046
END FIXED =1 if job lost through termination of a fixed-term contract, 0 otherwise	0.243	0.382	0.266	0.244	0.332	0.174
UNEMPLOYMENT RATE quarterly unemployment rate	6.648	6.570	6.684	6.557	6.498	6.388
n	2770	330	64	4882	1164	241