

Preliminary Draft

**UNEMPLOYMENT INSURANCE AND THE RATE OF RE-EMPLOYMENT
OF DISPLACED WORKERS***

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UCLA Working Paper No. 550

September, 1988

Revised: March 1989

*Assistant Professor, University of California, Los Angeles. Financial support for this work was provided by the National Science Foundation under a Graduate Fellowship. I am grateful to Janice Madden, Paul Taubman, Michael Wachter, Janet Currie, Bill Gale, and Finis Welch, among others, for helpful comments.

Abstract

The rate of transition from unemployment to re-employment for a sample of displaced workers is estimated using a semiparametric specification which allows the effects of unemployment insurance benefits to vary over time. The effects of UI benefits are seen to decline and eventually disappear as the date of expiration approaches, a result which is consistent with the predictions of search theory. However, the expiration of UI benefits are seen to be an inadequate explanation of the spikes commonly observed in Kaplan-Meier and other nonparametric sample hazard rates for re-employment.

UI benefits affect only the rate at which a displaced worker becomes re-employed in an industry other than the one from which he or she was displaced. They do not significantly affect the rate of re-employment for the worker's previous industry. Thus UI benefits appear to retard the industrial mobility of displaced workers.

1. Introduction

The effect of unemployment insurance is no doubt the most common concern of empirical studies of unemployment duration and job search behavior. The consensus is that UI benefits tend to increase the duration of unemployment spells by increasing reservation wages and decreasing the amount of time or effort devoted to searching for a job.^{1 2} However, the empirical specifications used in these studies have not tended to be in accord with the theoretical predictions, or with the unruly appearance of the data. This paper uses a sample of displaced workers to estimate the effects of UI on transitions from unemployment to employment in a theoretically consistent and less restrictive manner.

According to theories of optimal job search, UI benefits should reduce the hazard rate for re-employment by increasing the opportunity cost of taking a job, both because UI benefits are lost when a job is taken, and due to the possible complementarity of the extra income provided by UI and leisure or search activity. In addition, the fact that UI benefits expire after a fixed interval is predicted to lead to duration dependence in the rate of escape from unemployment: the effect of UI on the hazard rate is

¹On the duration of unemployment spells see Ehrenberg and Oaxaca (1976), Lancaster (1979), Solon (1985), Katz (1985), Moffitt (1985), Blau and Robins (1986), Han and Hausman (1986), Steinberg and Monforte (1987), and Classen (1977) among others. On reservation wages and other dimensions of search behavior, see Barron and Mellow (1979), Warner, Poindexter and Fearn (1980), and Feldstein and Poterba (1984).

²Other empirical studies are concerned with the related issue of duration dependence. In addition to the expiration of UI benefits, duration dependence may stem from such sources as a finite horizon or finite working life, learning or revision of expectations, discouragement, reputation effects, systematic search, and the depletion of assets. For empirical studies see Kaspar (1967), Barnes (1975), Kiefer and Neumann (1979a), Lancaster (1979), Katz (1985), and Han and Hausman (1986). For theoretical work, see Gronau (1971), Whipple (1973), McCall (1970), Chalkley (1984), Katz (1985), Berkovitch (1985), and Salop (1973).

predicted to decline as the date of expiration approaches and to disappear, possibly discontinuously, when the benefits expire.³ Nevertheless, econometric studies of the duration of unemployment have generally constrained UI benefits to have the same effect on the hazard function at each point during a spell of unemployment.⁴

In contrast, a simple look at the data reveals marked spikes in the hazard rate around the time when UI benefits typically expire, at 26 and 39 weeks. Despite the exhortations of theory, this pattern has often been attributed to the expiration of benefits. Yet such attribution has rarely been incorporated into the empirical specification of hazard functions and has not been seriously tested.

This study allows the data to tell their own story of the effects of UI benefits on the hazard rate. A semiparametric estimator is employed in which the hazard rate contains a component representing the effect of UI benefits and a component which is independent of the receipt of benefits. Each of these components is permitted to vary from period to period in a reasonably unconstrained fashion. Thus the estimated effect of UI may be constant over time, may change monotonically, or may exhibit jumps over the course of an unemployment spell.

The results turn out to be consistent with the predictions of theory: The effects of UI benefits begin strong and die out by the 26th week. Furthermore, the expiration of UI benefits is not an adequate explanation of the spikes observed in the simple hazard rates. The spikes do come through, but they show up in that part of the hazard function which is independent of

³ See Mortensen (1977).

⁴ but see the discussion of Solon (1985) and Moffitt (1985) in Section 6.B below.

the receipt of benefits. A different phenomenon, such as rounding in the survey responses, is likely to be responsible.

Economists generally model a worker's search for a job as taking place in a single labor market, and this study will commence with such an analysis. However for displaced workers, which is the group studied in this paper, considerations such as industry-specific human capital, credentials, tastes, differing labor market opportunities, and familiarity with a particular industry point to a distinction between the industry from which a worker was displaced and other industries. I have recently demonstrated the usefulness of this distinction.⁵ Jacobson (1984), Kletzer (1986), Podgursky and Swaim (1986), and Madden (1988) have found that a displaced worker makes significantly higher wages when he becomes re-employed in the same industry from which he was displaced than when he changes industries. Furthermore, a displaced worker may have chosen to work in his old industry because he prefers the nonpecuniary attributes of jobs there, or may have invested in working in that industry in ways which make a new job in the old industry preferable to a job elsewhere. The present study estimates the rates of re-employment into two sets of industries rather than a single overall rate of re-employment. This analysis reinforces the results on the effects of unemployment insurance benefits, but finds that benefits have their effect only on the hazard rate for re-employment in industries other than the one from which the worker was displaced.

2. Framework for Analysis

Assume that the probability of receiving more than one offer during a

⁵ See Fallick (1988), Chapter 3.

single period is negligible. For an individual worker i , the hazard function for transitions from unemployment to employment in industry j during period t may be written as:⁶

$$(1) \quad h_{ij}(t) = g(t, j, Z_i)$$

where t is the number of periods of unemployment thus far and Z_i is a vector of characteristics of the worker and the labor market conditions in the worker's "old" and "new" industries. Which specific industries comprise the "old" and "new" industries depend upon the individual's history, as will be explained below. I have estimated a version of the reduced form hazard function (1) for the old industry and for the new industry, as well as a version which does not make this distinction.

3. Data

My sample is drawn from the BLS Displaced Worker Survey attached to the Current Population Survey of January 1984.⁷ Each individual is at least 20 years old and lost a job in the past five years (January 1979 to January 1984) due to a plant closing, layoff from which he was not recalled or a similar reason. I refer to that job as the worker's old job. I included in my sample only those workers who were employed full-time at their old jobs, were in the labor force at the time of the survey or reported that they wanted a job, and last worked at their old jobs in 1983 or January 1984.⁸

⁶That is, the probability of a worker who was unemployed at the beginning of period t making the transition from unemployment to employment in sector j during period t .

⁷A description of the survey and a summary of the data can be found in Flaim and Sehgal (1985).

⁸I also included only those workers who lost their old jobs for reasons other than the end of a seasonal job, were not missing relevant data, did not report impossible values for important variables, and were not in the

The characteristics of the members of the sample are summarized in Table 1.

In addition I constructed several variables meant to reflect the labor market conditions in each industry using Census major industry groups. These include the rate of employment growth, mean weekly earnings, and rate of growth of mean weekly earnings in each industry. They were constructed using the full CPS for January 1983 and 1984, each of which was comprised of approximately 60,000 households.⁹

4. Life-Table Sample Hazard Rates

The life-table estimates of the hazard rates out of unemployment into a new job are shown in Figures 1 and 2 for people who reported receiving and not receiving UI benefits. Only under the assumption of homogeneity are these reasonable estimates of the hazard rates. Still, they are a useful first look at the data, especially as they relate to UI, and establish a prima facia case for analyzing the duration dependence of both hazard rates and the effects of UI.

By and large the estimated hazard rates are lower for UI recipients than for nonrecipients. Also, the hazard rates for nonrecipients appear to exhibit negative duration dependence, which may simply reflect heterogeneity in the sample. For UI recipients, humps occur roughly around 26 and 39 weeks. For nonrecipients, humps or inflections occur in the vicinity of 13, 26 and 39 weeks.¹⁰ Peaks of this kind around 26 and 39 weeks are commonly

Armed Forces at their old jobs.

⁹For a further discussion of the sample, problems with the data, and a description of the control variables, see Fallick (1988).

¹⁰These hazard rates were generated using intervals of 3 weeks, so the humps in the figures always appear to be centered about even multiples of 3, plus or minus 1.5, weeks. Their exact placement should not be taken too

found among UI recipients, and have been attributed to the exhaustion of UI benefits at 26 weeks and of supplemental UI benefits at 39 weeks.¹¹ Katz (1985), who found peaks at approximately 26 and 39 weeks in a sample from the Panel Study of Income Dynamics, found that UI recipients who exited unemployment at 39 weeks matched well with those states which provided supplemental UI benefits. However, these data present problems for this explanation. The nonrecipients' hazard rates exhibit humps at points which correspond very nicely with the expiration of UI benefits. The expiration of benefits should not affect nonrecipients, so something else must be at work if these humps are significant at all. Also, although the complementarity of leisure and current income could produce humps at the expiration of UI benefits, theory suggests a decline in the effects as expiration approaches. We shall test this explanation and these objections with more careful econometric analysis.

5. Estimation Procedure

A. The Hazard Function

I assume that transitions are the outcomes of a continuous process. The hazard rate is easily reinterpreted to fit the assumption of continuous time. The hazard rate for transitions from unemployment to employment in industry j at duration t is the instantaneous probability of exit from unemployment into employment in industry j given that unemployment has

seriously. The size of the sample precluded estimating a hazard rate for each week.

¹¹For example, see Katz (1985). If leisure and income are substitutes, then the model of Mortensen (1977) could yield such peaks, but search models typically do not predict them. Katz also discusses alternative explanations for the peaks, such as that respondents have a tendency to report "round" numbers, like six months.

persisted until duration t . That is,

$$(2) \quad h_j(t) = \lim_{r \rightarrow 0} \frac{\Pr(t \leq \text{duration} \leq t+r, \text{ employed in industry } j; \text{ given duration} \geq t)}{r}$$

One attractive class of specifications for (2) is the proportional hazards model.¹² Here the hazard rate for transitions from unemployment to employment in industry j at duration t for individual i is

$$(3) \quad h_{i,j}(t) = h_{o,j}(t) \exp(Z_i' \beta_j)$$

where $h_{o,j}$ is a baseline hazard rate common to all individuals, Z_i is a vector of individual characteristics and conditions and β_j is a vector of coefficients on the Z_i . In this model the baseline hazard rate is the only component which can vary with the duration of the unemployment spell.

B. A Semi-Parametric Model

Fully parametric models of duration, such as the Weibull or exponential models used by several authors, suffer from two major faults. The first is that they involve assuming a smooth shape for the baseline hazard function, contrary to the shapes of the life-table hazard rates of Section 4. Hence, nonparametric or semiparametric estimation of the baseline hazard rates is recommended.¹³ Second, the weekly data on duration of unemployment available in the Displaced Worker Survey represent discrete observations of a continuous process. Prentice and Gloeckler (1978) have proposed an estimator which can meet both of these difficulties in a single-risk context.¹⁴ I will employ a version of this estimator for the analysis which does not

¹²For studies of the proportional hazards model see Cox and Oakes (1983) or Kalbfleisch and Prentice (1980).

¹³See, for example, Meyer (1986) or Han and Hausman (1986).

¹⁴See also Meyer (1986).

distinguish between changing industries and becoming re-employed in the same industry. I derive a comparable estimator for a competing risk model for use when making distinguishing between industries.

Let T_i be the duration of unemployment for individual i , in weekly units. Let C_i be the censoring time which is independent of T_i . C_i is the time between becoming displaced and the date of the survey (less any time spent in intervening jobs (see Fallick (1988))). Then $t_i = \min[T_i, C_i]$ is the observable duration. Assume that a person reports a week as without a job only if he or she is without a job for the entire week. Let $k_i = \text{int}(t_i)$ be the reported duration of unemployment.

The proportional hazard rate for transitions into employment in sector j at time t for individual i is given in equation (3), where j takes on the values "old" and "new". The hazard rate for exiting unemployment, regardless of destination is

$$\begin{aligned} h_i(t) &= \lim_{\epsilon \rightarrow 0^+} \{ \Pr(t+\epsilon > t_i \geq t \mid t_i \geq t) / \epsilon \} \\ &= h_{i,\text{old}}(t) + h_{i,\text{new}}(t) \\ &= h_{o,\text{old}}(t) \exp(Z_i' \beta_{\text{old}}) + h_{o,\text{new}}(t) \exp(Z_i' \beta_{\text{new}}) \end{aligned}$$

The probability of remaining unemployed until time t is

$$\begin{aligned} G_i(t) &= \exp\left[-\int_0^t h_i(s) ds\right] \\ &= \exp\left[-\int_0^t h_{i,\text{old}}(s) ds\right] \exp\left[-\int_0^t h_{i,\text{new}}(s) ds\right] \\ &= G_{i,\text{old}}(t) G_{i,\text{new}}(t) \end{aligned}$$

where $G_{i,j}(t)$ is the probability of surviving until time t that would obtain if transitions into sector j were the only transitions possible,

holding $h_{i,j}$ constant. Define $T_{i,j}$ as the latent duration until exit into sector j , that is the duration of unemployment that would obtain if transitions into sector j were the only transitions possible, holding $h_{i,j}$ constant. Then

$$G_{i,j}(t) = \Pr(t_{i,j} \geq t).$$

If t is an integer, the survivor function can be broken up into discrete parts which correspond to the units of measurement (in this case weeks) in the data. For an individual whose spell was censored after k_i weeks, the contribution to the likelihood function is simply the survivor function for time k_i :

$$G_i(k_i) = \Pr(T_i \geq k_i) = \prod_{t=1}^{k_i} \Pr(T_i \geq t | T_i \geq t-1)$$

Now,

$$\begin{aligned} \Pr(T_i \geq t | T_i \geq t-1) &= \exp\left(-\int_{t-1}^t h_i(u) du\right) \\ &= \exp\left[-\exp(Z'_i \beta_{old}) \int_{t-1}^t h_{o,old}(u) du \right. \\ &\quad \left. - \exp(Z'_i \beta_{new}) \int_{t-1}^t h_{o,new}(u) du\right] \\ &= \Phi_{old}(t)^{\exp(Z'_i \beta_{old})} \Phi_{new}(t)^{\exp(Z'_i \beta_{old})} \end{aligned}$$

where $\Phi_j(t) = \exp\left(-\int_{t-1}^t h_{o,j}(u) du\right)$ is the latent probability of not exiting from unemployment into a job in sector j during period $t-1$.

Therefore, for an individual whose spell was censored after k_i weeks the

contribution to the likelihood function is

$$(4) \quad L^i = G_i(k_i) = \prod_{t=1}^{k_i} \left[\Phi_{\text{old}}(t)^{\exp(Z_i' \beta_{\text{old}})} \times \Phi_{\text{new}}(t)^{\exp(Z_i' \beta_{\text{old}})} \right]$$

In the single-risk model, for uncensored spells we only have to multiply the analogous expression for the survival function by $\Pr(T_i < t+1 | T_i \geq t)$. In a competing risks model, for an uncensored spell ending in employment in sector j after k_i weeks, the contribution to the likelihood function is

$$\begin{aligned} L^i &= \Pr(T_i^j \in [k_i, k_i+1], \tilde{T}_i^j \geq T_i^j) \\ &= \int_{k_i}^{k_i+1} \Pr(\tilde{T}_i^j \geq r) dr, \end{aligned}$$

where $\sim j$ is the sector other than sector j .

Assumption #1: Assume that T_i^{old} and T_i^{new} are independently distributed.

Then,

$$\begin{aligned} L^i &= \int_{k_i}^{k_i+1} \Pr(T_i^j = r) \Pr(\tilde{T}_i^j \geq r) dr \\ &= \int_{k_i}^{k_i+1} h_{i,j}(r) \left[\exp - \int_0^{k_i} (h_{i,\text{old}}(u) + h_{i,\text{new}}(u)) du \right] \\ &\quad \left[\exp - \int_{k_i}^r (h_{i,\text{old}}(u) + h_{i,\text{new}}(u)) du \right] dr \end{aligned}$$

The middle factor can be taken out of the outer integral and is simply

$G_i(k_i)$, which has already been divided into discrete pieces in equation (4).

$$L_i = \prod_{t=1}^{k_i} \phi_{\text{old}}(t)^{\exp(Z'_i \beta_{\text{old}})} \phi_{\text{new}}(t)^{\exp(Z'_i \beta_{\text{old}})} \times$$

$$\int_{k_i}^{k_i+1} h_{i,j}(\tau) \left[\exp \int_{k_i}^{\tau} (h_{i,\text{old}}(u) + h_{i,\text{new}}(u)) du \right] d\tau$$

In order to simplify further, I make

Assumption #2: For all $\tau \in [t, t+1)$ and $j = \text{old, new}$, $h_{o,j}(t)$. That is, within any given week, the baseline hazard rates are constant. Thus, for $\tau \in [k_1, k_1+1)$,

$$\exp \int_{k_i}^{\tau} h_{i,j}(u) du = \exp \{ -(\tau - k_i) h_{i,j}(k_i) \}.$$

$$L_i = \prod_{t=1}^{k_i} \Phi_{\text{old}}(t)^{\exp(Z'_i \beta_{\text{old}})} \Phi_{\text{new}}(t)^{\exp(Z'_i \beta_{\text{old}})} \times$$

$$h_{i,j}(k_i) \frac{1 - \exp[-h_{i,\text{old}}(k_i) + h_{i,\text{new}}(k_i)]}{h_{i,\text{old}}(k_i) + h_{i,\text{new}}(k_i)}$$

Under Assumption #2, $\phi_j(t+1) = \exp(-h_{o,j}(t))$, so that $h_{i,j}(t) = h_{o,j}(t) \exp(Z'_i \beta_j) = (-\ln \phi_j(t+1)) \exp(Z'_i \beta_j)$ and the contribution to the likelihood function of an individual, L^i , can be written entirely in terms of Φ 's rather than h 's.

Since $\Phi_{\text{new}}(\cdot)^{\exp(Z'_i \beta_{\text{new}})}$ represents a probability, it is best to restrict it to always be between zero and one. Define $\Gamma_j(t)$ by $\Phi_j(t) = \exp(-\exp[\Gamma_j(t)])$. Then we have $\Phi_j(t)^{\exp(Z'_i \beta_j)} = \exp\{-\exp[\Gamma_j(t) + Z'_i \beta_j]\}$ and $h_{o,j}(t-1) = -\ln(\Phi_j(t)) = \exp[\Gamma_j(t)]$.

Define $M_{i,j}(t) = \exp[\Gamma_j(t) + Z'_i\beta_j]$. Now,

$$L^i = \prod_{t=1}^{k_i} \exp\{-\exp[M_{i,\text{old}}(t)]\} * \exp[M_{i,j}(k_i+1)] \\ * \{1 - \exp\{-\exp[M_{i,\text{old}}(k_i+1)] - \exp[M_{i,\text{new}}(k_i+1)]\}\} \\ / \{\exp[M_{i,\text{old}}(k_i+1)] + \exp[M_{i,\text{new}}(k_i+1)]\},$$

or, for a person whose spell of unemployment was censored, simply

$$L^i = \prod_{t=1}^{k_i} \exp\{-\exp[\Gamma_{\text{old}}(t) + Z'_i\beta_{\text{old}}] - \exp[\Gamma_{\text{new}}(t) + Z'_i\beta_{\text{new}}]\} \\ - \prod_{t=1}^{k_i} \exp\{-\exp[M_{i,\text{old}}(t)] - \exp[M_{i,\text{new}}(t)]\}.$$

Define S_c as the set of those members of the sample who were unemployed at the time of the survey (censored), and S_j , $j = \text{old, new}$, as those members of the sample who were employed in their old and new sectors, respectively, at the time of the survey. The log-likelihood for the entire sample is

$$\ln L = \sum_{i=1}^N \sum_{t=1}^{k_i} \{-\exp[M_{i,\text{old}}(t)] - \exp[M_{i,\text{new}}(t)]\} \\ + \sum \{\ln[1 - \exp\{-\exp[M_{i,\text{old}}(k_i+1)] - \exp[M_{i,\text{new}}(k_i+1)]\}]\} \\ - \ln\{\exp[M_{i,\text{old}}(k_i+1)] + \exp[M_{i,\text{new}}(k_i+1)]\} \\ + \sum_{i \in S_{\text{old}}} \{M_{i,\text{old}}(k_i+1)\} + \sum_{i \in S_{\text{new}}} \{M_{i,\text{new}}(k_i+1)\}.$$

The data measure unemployment duration in weeks, and spells can range up to 55 weeks. In order to estimate a different baseline hazard rates for each week, one would have to estimate 110 parameters. In order to estimate

the effects of UI benefits in a similar fashion one would have to estimate 220 parameters. To reduce the number of estimated parameters, assume that the baseline hazard rates are constant within each five-week interval.¹⁵

This reduces the number of baseline parameters to 44. Such a restriction is not so severe since there appears to be a considerable amount of rounding in the responses to the question on the number of weeks one was without a job following displacement, as indicated by the following table:

Weeks w/o a Job	19	20	21	...	25	26	27	...	29	30	31
# of Workers	14	40	5	...	14	55	6	...	6	36	3
Weeks w/o a Job	39	40	41	...	50	51	52	53	54		
# of Workers	10	19	1	...	9	3	26	2	1		

Therefore, define $B(t) = \text{int}[(t-0.1)/5] + 1$ and make

Assumption #3: For all t, s , if $B(t) = B(s)$ then $\Gamma_j(t) = \Gamma_j(s)$ for $j = \text{old, new}$. Define $\delta_j(B(t)) = \Gamma_j(t)$. Then

$$\begin{aligned}
 (5) \quad \ln L &= \sum_{i=1}^N \sum_{t=1}^{k_i} \{-\exp[\delta_{\text{old}}(B(t)) + Z'_i \beta_{\text{old}}] - \exp[\delta_{\text{new}}(B(t)) + Z'_i \beta_{\text{new}}]\} \\
 &+ \sum_{i \in S_2, S_3} \{\ln[1 - \exp[-\exp[\delta_{\text{old}}(B(k_i+1)) + Z'_i \beta_{\text{old}}] \\
 &\quad - \exp[\delta_{\text{new}}(B(k_i+1)) + Z'_i \beta_{\text{new}}]]] \\
 &- \ln[\exp[\delta_{\text{old}}(B(k_i+1)) + Z'_i \beta_{\text{old}}] \\
 &\quad + \exp[\delta_{\text{new}}(B(k_i+1)) + Z'_i \beta_{\text{new}}]]\} \\
 &+ \sum_{i \in S_{\text{old}}} (\delta_{\text{old}}(B(k_i+1)) + Z'_i \beta_{\text{old}}) + \sum_{i \in S_{\text{new}}} (\delta_{\text{new}}(B(k_i+1)) + Z'_i \beta_{\text{new}}).
 \end{aligned}$$

¹⁵ Shorter intervals were tried without altering the character of the results. Similarly, the results are not sensitive to the placement of the breaks between the intervals in a material way.

As described above, a major purpose of this paper is to estimate the effects of UI on re-employment rates in a way which is consistent with the predictions of search theory. In order to allow these effects to vary during the spell of unemployment, I define

$$(6) \quad \delta_j(i,t) = a_{B(t)} + u_{B(t)} UI_i,$$

where $UI_i = 1$ if the individual received UI benefits and $= 0$ if not.

Thus,

$$h_{i,j}(t) = \exp[a_{B(t)}] \exp[u_{B(t)} UI_i] \exp[Z_i' \beta_j]$$

and the log-likelihood function to be estimated is (5) with $\delta_j(i,t)$ defined by (6).

6. Results

The likelihood functions described in Section 5.B were maximized using the conjugate gradient method POWELL in the package GQOPT to an accuracy level of less than .0001. For the competing risks model, the old industry is defined as the Census Major Industry group for the worker's old job. (See Table 1). The new industry is defined as the set of all other Census Major Industry groups.¹⁶ The vector Z_i includes controls for race, household position, education, family income, job tenure, gender, advance notice, the reason for the job loss, six occupational categories, and the state unemployment rate. It also includes the rate of employment growth, mean weekly earnings, and rate of growth of mean weekly earnings in both the worker's old industry and in his/her new industry as described above.

¹⁶For a discussion of results other than duration dependence and the effects of UI, see Fallick (1988).

A. Baseline Hazard Rates and Duration Dependence

The first question to address is how the function $h_0(t)$ varies with t apart from the influence of unemployment insurance.¹⁷ The results on duration dependence for workers who do not receive unemployment insurance benefits are summarized in Table 2. The estimates for the hazard rates for the first base period, weeks 1 to 5, are much higher than for any other but the last period. This reflects the fact that out of the 698 members of the sample who were re-employed at the time of the survey, 318 of them reported less than 5 weeks of unemployment (147 reported zero weeks). Much of this activity probably reflects search or preparation conducted before the job actually ended, rather than search-theoretic considerations. Otherwise, the estimates of the baseline hazard rates do not indicate any pattern of duration dependence.

In contrast, a Weibull specification similar to that used by Katz (1985) indicated significantly negative duration dependence in the hazard rates. The semi-parametric model indicates that this is misleading, since the duration dependence occurs only in the first few weeks.¹⁸

B. Unemployment Insurance

The shapes of the simple hazard rates make it clear that UI benefits should not be expected to affect hazard rates out of unemployment in the

¹⁷Several authors have studied this question. Lancaster (1979), for example, found slight indications of negative duration dependence. Katz (1985) found positive duration dependence for the hazard rate for transitions out of unemployment into new jobs using a fully parametric Weibull specification. Moffitt (1985) suspected negative duration dependence in a semi-parametric model. Han and Hausman (1986), using a semi-parametric model on Katz' data and allowing UI benefits to interact with the baseline hazard function at 26 and 29 weeks, found no indication of systematic duration dependence.

¹⁸Han and Hausman (1986) similarly found the Weibull specification to be misleading.

same way at all points of a spell of unemployment.¹⁹ Search theory indicates that the effect of UI benefits should become progressively weaker as the date of their expiration approaches.²⁰ Nevertheless, past studies of UI and the duration of unemployment have by and large not allowed the effect of UI on hazard rates to vary over time.

Solon (1985) and Moffitt (1985) are exceptions.²¹ In a generalized Weibull model, Solon found that the effect of UI benefits decreases as the expiration date approaches. Using a spline function in a semiparametric proportional hazards model of a different type than used here, Moffitt comes to the same conclusion, although his specification does not allow one to distinguish duration dependence in the effects of UI from ordinary duration dependence. In the semi-parametric model used here UI is included in the baseline hazard (see Section 5.C) so that the time pattern of its effects can be estimated in a less restrictive manner. Both Solon and Moffitt use data from the Continuous Wage and Benefit History. This data set includes only recipients of UI benefits and all observations are censored when benefits expire (if the individual reaches that point). Accordingly, the authors are unable to estimate the effect, or lack thereof, of UI benefits after they have expired and are limited in their ability to test that it is the expiration of UI benefits, as opposed to something else associated with the same duration of unemployment, which is important. The data used here

¹⁹ See Moffitt, p. 96.

²⁰ See, for example, Mortensen (1977).

²¹ Also, Han and Hausman (1986) interact UI benefits with the baseline hazards at 26 and 39 weeks of unemployment, when benefits commonly expire. However, search theory predicts that UI should have little or no effect on the hazard function (as opposed to the probability density function) at these points, unless the complementarity in the utility function between leisure and current income is strong (see Mortenson (1977)).

suffer from neither of these weaknesses.

UI3 is a dummy variable equal to 1 if the individual reported that he received UI benefits and 0 if he reported that he did not receive UI benefits.²² The effects of this variable on the point estimates of the baseline hazard rate for the single-risk model can be seen in Figure 3, which plots the difference between the estimated baseline hazard rate for recipients and for non-recipients. The estimates can be found in Table 3.

For weeks 1-5, the coefficients on UI3 for the single-risk hazard rate is significantly negative (at the 0.05% level), and the point estimate is that UI3 reduces h_0 by 92%. While UI benefits may have a negative effect on hazard rates and employment outcomes during this period, the causality probably goes the other way. That is, people who experience little unemployment do not receive UI benefits because they were not unemployed long enough to be eligible or to take the trouble to apply. Such people are selected into the UI3 = 0 group on the basis of the length of their unemployment, which biases the coefficient on UI3 downward.

The estimated effects of UI3 on h_0 during subsequent weeks tell a story consistent with theory. During weeks 6 to 20, UI benefits significantly reduce the baseline hazard rate between 46 and 50%. Shortly before and after the benefits commonly expire, at 21-30 weeks, the coefficient loses significance while the point estimate still indicates a substantial reduction in h due to UI. Thereafter, they have no significant effect and the point estimates indicate a reduction only in the last base period. While the exact placement of the break is due to my choice of how to group weeks, job-seekers reduce their search intensity or increase their reserva-

²²UI3 is also set equal to 1 if respondent did not know whether or not s/he received benefits. The results are not sensitive to this choice.

tion wages while they are receiving benefits, but after the benefits stop they behave no differently from non-recipients.

No significant change is indicated around 39 weeks. The survey did not provide information on the length of benefits or the number of people receiving extended UI benefits, so we have no way of knowing how seriously to take this lack of significance. However, I found no relationship among UI recipients between unemployment of approximately 26 or 39 weeks and whether or not the state of residence offered supplemental benefits.

The pattern of estimated effects of UI on the hazard rates becomes clearer and more interesting when some account is taken of the industry in which the worker becomes employed. The effects of UI3 on the point estimates of the baseline hazard rate for recipients and non-recipients can be seen in Figures 4 and 5 for the competing risks model. The estimates can be found in Table 4.

For weeks 1-5, the coefficients on UI3 for both hazard rates are once again significantly negative, and the point estimates are that UI3 reduces $h_{0,old}$ by 91% and $h_{0,new}$ by 93%. In subsequent weeks, however, the effects of unemployment insurance on the two hazard rates diverge.

The estimated effects of UI3 on $h_{0,new}$ tell a story consistent more in accordance with theory than the single-risk results. During weeks 6 to 20, UI benefits significantly reduce the baseline hazard rate between 50 and 69%.²³ Shortly before the benefits commonly expire, at 21-25 weeks, the coefficient loses significance while the point estimate still indicates a

²³ On average, for weeks 6 through 25, receiving UI benefits is associated with a reduction of between 40 and 70 percent in the latent probability of becoming reemployed in the new industry during this week, given that the individual had been unemployed up until then. This latent probability is equal to $1 - \exp(-h_{new}(k))$, where k is the week in question.

substantial reduction in h_{new} due to UI. Thereafter, they have no significant effect and the point estimates indicate a reduction of only 3%, in only one base period. Again, no significant change is indicated around 39 weeks.

In contrast, excepting the first baseline period, only one of the estimated coefficients on UI3 for $h_{0,old}$ was significantly different than zero at the 10% level. That one was negative and represented weeks 11-15. It may be that because most workers have human capital or contacts which are specific to their old industries, the jobs for which they would apply in their old industries may be characterized by: a) wage offers which are mostly above the reservation wages of recipients as well as those of non-recipients so that the differences between these reservation wages do not matter much, and b) these higher-paying jobs are rationed by queuing, so that the intensity of search in the old industry does not matter much.

On the other hand, the point estimates for $h_{0,old}$ for non-recipients, shown in Figure 6, exhibit jumps at 26-30 and 36-40 weeks of unemployment despite the controls for UI.

C. Duration Dependence in the Competing Risks Model

Given the usefulness of the two-industry model for analyzing UI benefits, one suspects that the results for duration dependence in the two-industry model may be interesting. For example, displaced workers may know more about their old industries than new ones, and so concentrate their early search in the former while they learn about the latter. Such a pattern could lead to negative duration dependence in h_{old} and positive duration dependence in h_{new} . The results from the two-industry model, however, do not yield any new information on this score. No pattern of duration dependence is evident in either the old industry or the new

industry baseline hazard functions.

7. Conclusion

By estimating the effects of unemployment insurance benefits at each point during an unemployment spell, I have demonstrated that benefits reduce the rate at which a worker finds and takes a job in the new industry while and only while they are received. Thus, the analysis indicated that unemployment insurance should be permitted to influence the hazard functions in a way consistent with theory: that its effects should be permitted to vary over the course of an unemployment spell. In this way, the receipt and expiration of unemployment benefits were also seen to be an inadequate explanation of the spikes commonly observed in the simple non-parametric sample hazard rates for re-employment.

Unlike the hazard rate for re-employment in a new industry, UI benefits do not appear to affect the rate of re-employment for jobs in the old industry. Thus UI benefits appear to retard the mobility of displaced workers between industries, which may be beneficial or detrimental to the economy as a whole.

There is no indication of duration dependence of any theoretical interest in the hazard rates for re-employment in either the single risk or competing risk models, aside from the effects of unemployment insurance, while the pattern of the estimates adds evidence to the argument that semi-parametric specifications of duration dependence are called for when studying unemployment duration.

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TABLE 1

Summary Characteristics of the Sample

Sample size = 1290

<u>Variable</u>	<u>mean</u>	<u>s.d.</u>	<u>Variable</u>	<u>mean</u>	<u>s.d.</u>
Weekly earnings (old job)	342	193	Age	36.9	11.6
Wks. unemp.	14.1	13.3	Tenure (old job)	5.7	6.2
			Education	12.3	2.5

<u>Variable</u>	<u>frequency</u>	<u>Variable</u>	<u>frequency</u>
Current Industry:		Unemployment Insurance:	
unemp	45.9%	recipients	62.3%
old	22.9	nonrecipients	36.7
new	31.2	don't know	0.9
Sex:		Notified of impending job loss:	
male	69.5%	yes	50.8%
female	30.5	no	49.2
Race:		Hh position:	
white	88.1%	head	68.2%
nonwhite	11.9	other	31.8

Why left?		
(1)	Plant or co. closed or moved	32%
(2)	Slack work	40
(3)	Position or shift abolished	12
(4)	Self-operated business failed	4
(5)	Other reason	12

Major Occupation At Old Job

<u>Occupation</u>	<u>#Workers</u>	<u>Percent</u>
(1) Executive, administrative, managerial	140	10.9%
(2) Professional Specialty	74	5.7
(3) Technicians and related support	36	2.8
(4) Sales	124	9.6

Table 1 (Cont.)

<u>Occupation</u>	<u>#Workers</u>	<u>Percent</u>
(5) Administrative support	125	9.7
(6) Private household services	0	0.0
(7) Protective services	14	1.1
(8) Other services	74	5.7
(9) Precision production, craft, repair	273	21.2
(10) Machine operation, assembly, inspection	214	16.6
(11) Transportation, material moving	92	7.1
(12) Handlers, equipment cleaners, etc.	100	7.8
(13) Farming, forestry, fishing	24	1.9

Major Industry At Old Job

<u>Industry</u>	<u>#Workers</u>	<u>Percent</u>
(1) Agriculture	33	2.6
(2) Mining	65	5.0
(3) Construction	151	11.7
(4) Durable Manufacturing	324	25.1
(5) Nondurable Manufacturing	171	13.3
(6) Transportation	75	5.8
(7) Communications	12	0.9
(8) Utilities & Sanitary Services	7	0.5
(9) Wholesale Trade	71	5.5
(10) Retail Trade	137	10.6
(11) Finance, Insurance, Real Estate	26	2.0
(12) Private Household Services	0	0.0
(13) Business & Repair Services	84	6.5
(14) Personal Services	22	1.7
(15) Entertainment & Recreation	17	1.3
(16) Hospitals	4	0.3
(17) Medical	19	1.5
(18) Education	6	0.5
(19) Social Services	15	1.2
(20) Other Professional Services	27	2.1
(21) Forestry & Fishing	2	0.2
(22) Public Administration	22	1.7

Geography:

New England	6.7%
Middle Atlantic	11.7
East North Central	14.1
West North Central	11.0
South Atlantic	13.3
East South Central	5.8
West South Central	11.3
Mountain	10.2
Pacific	15.8

Education Level:

< 4 grades high school	21.0%
4 grades high school	46.9
1-3 grades college	19.0
4 grades college	8.8
> 4 grades college	4.3

TABLE 2

Single-Risk Semiparametric Model: Baseline Hazard Rates

<u>Estimated Relationship</u> <u>(weeks)</u>	<u>t-statistic for the Null Hypothesis</u> <u>That the Baseline Hazard Rates Are Equal</u>
$\frac{h}{o}$	
1- 5 > 6-10	56.71*
6-10 < 11-15	-9.88*
11-15 > 16-20	0.26
16-20 > 21-25	0.09
21-25 < 26-30	-0.10
26-30 > 31-35	0.30
31-35 < 36-40	-7.16*
36-40 > 41-45	64.54*
41-45 < 46-50	-0.66
46-50 < 51-55	-46.51*
6-10 < 21-25	
21-25 > 36-40	

Legend: * reject H_0 at the 5% level (one tailed test)

TABLE 3
 Results from the Single-Risk Semiparametric Model:
 The Proportional Effect of Unemployment Insurance

<u>Weeks</u>	<u>Proportional effect on the Single-Risk Hazard Rate</u>
1-5	0.082 ^{***} (-16.61)
5-10	0.54 ^{***} (-2.83)
11-15	0.53 ^{***} (-2.63)
16-20	0.50 ^{**} (1.96)
21-25	0.85 (-0.38)
26-30	0.88 (-0.29)
31-35	1.78 (0.56)
36-40	1.16 (0.20)
41-45	4631 (0.13)
46-50	1898 (0.12)
51-55	0.85 (-0.24)

Legend: The figures are exp(coefficient).
 t-statistics for the coefficients appear in parentheses.

* significantly different from 1 at the 10% level

** significantly different from 1 at the 5% level

*** significantly different from 1 at the 1% level

TABLE 4

Two-Industry Semiparametric Model:
The Proportional Effect of Unemployment Insurance

<u>Weeks</u>	<u>h_{old}</u>	<u>h_{new}</u>
1-5	0.088 ^{***} (-11.57)	0.074 ^{***} (-11.96)
5-10	0.78 (-0.68)	0.41 ^{***} (-3.21)
11-15	0.57 [*] (-1.28)	0.51 ^{***} (-2.30)
16-20	2.29 (0.81)	0.32 ^{***} (-2.88)
21-25	24.94 (0.85)	0.61 (-1.16)
26-30	0.53 (-0.99)	1.24 (0.36)
31-35	16.94 (0.59)	0.99 (-0.00)
36-40	0.35 (-0.91)	2.07 (0.73)
41-45	20.42 (0.47)	26.13 (0.54)
46-50	0.17 (-0.00)	32.68 (0.44)
51-55	0.59 (-0.61)	1.26 (0.22)

Legend: The figures are exp(coefficient).
t-statistics for the coefficients appear in parentheses.

* significantly different from 1 at the 10% level

** significantly different from 1 at the 5% level

*** significantly different from 1 at the 1% level

Figure 1: Life-Table Estimates of h_0 for Recipients of UI

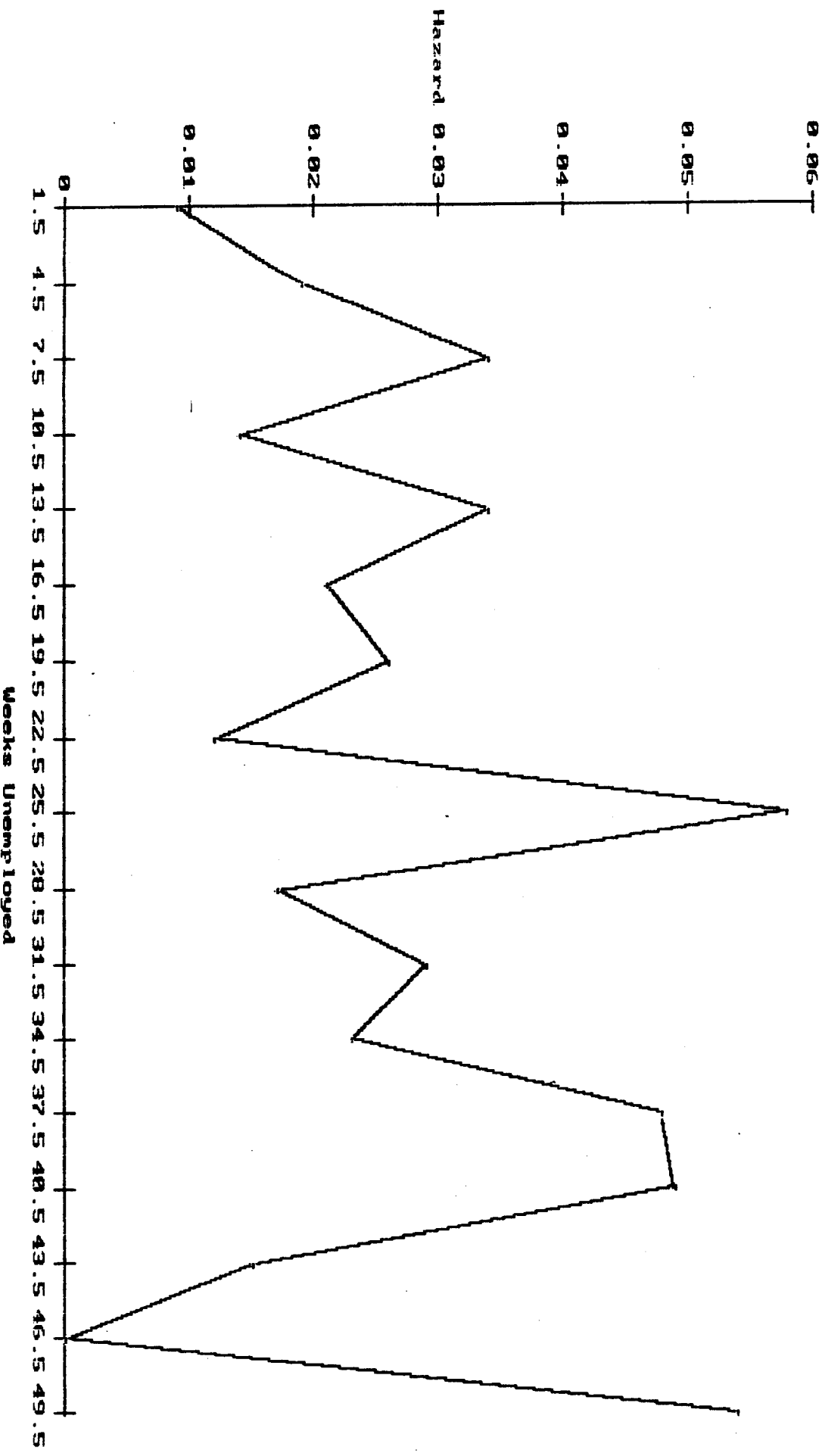


Figure 2: Life-table Estimates of h_0 for Nonrecipients of UI

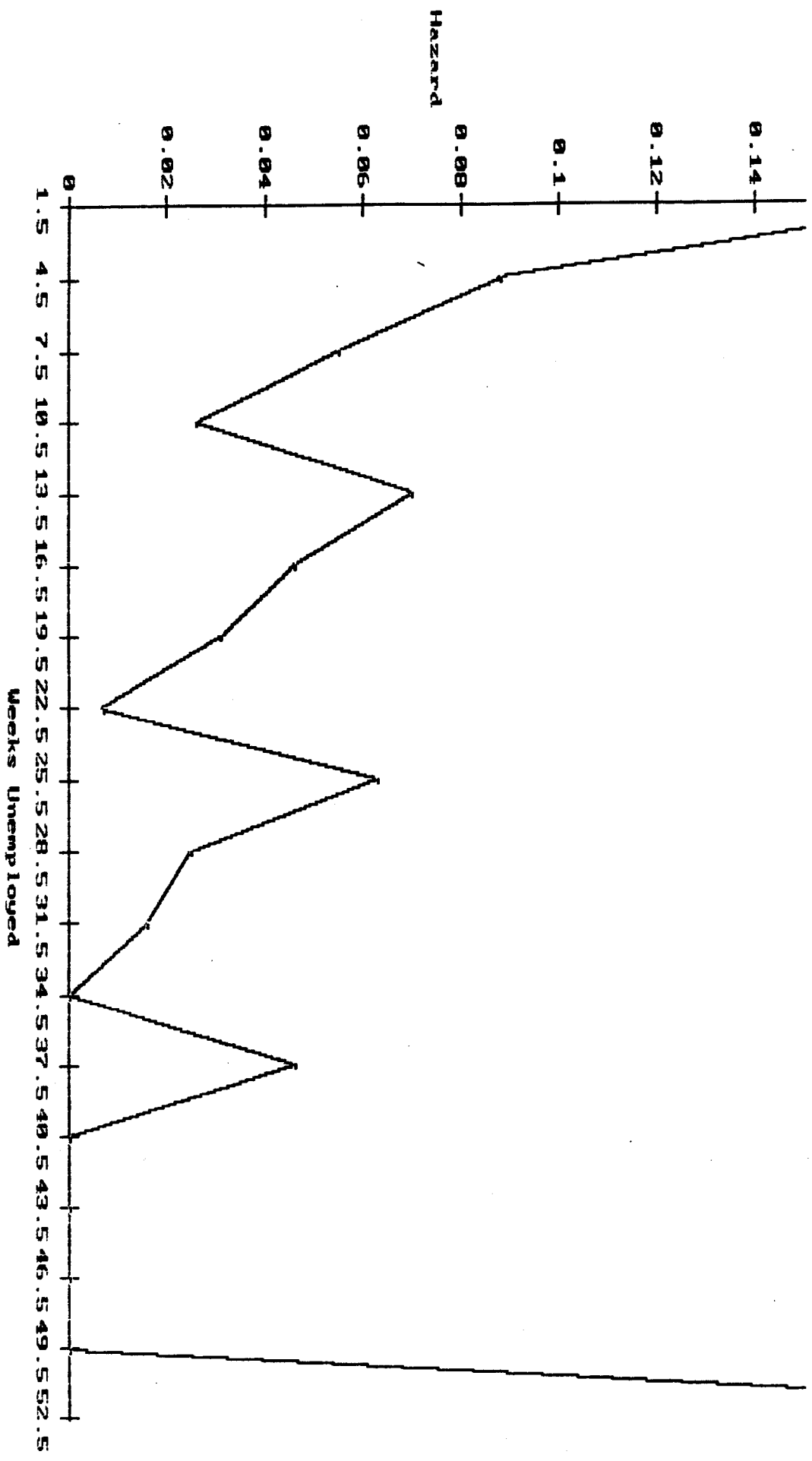


Figure 3: Difference between the Baseline Hazard Rates for Recipients and for Nonrecipients of UI, Single-Risk

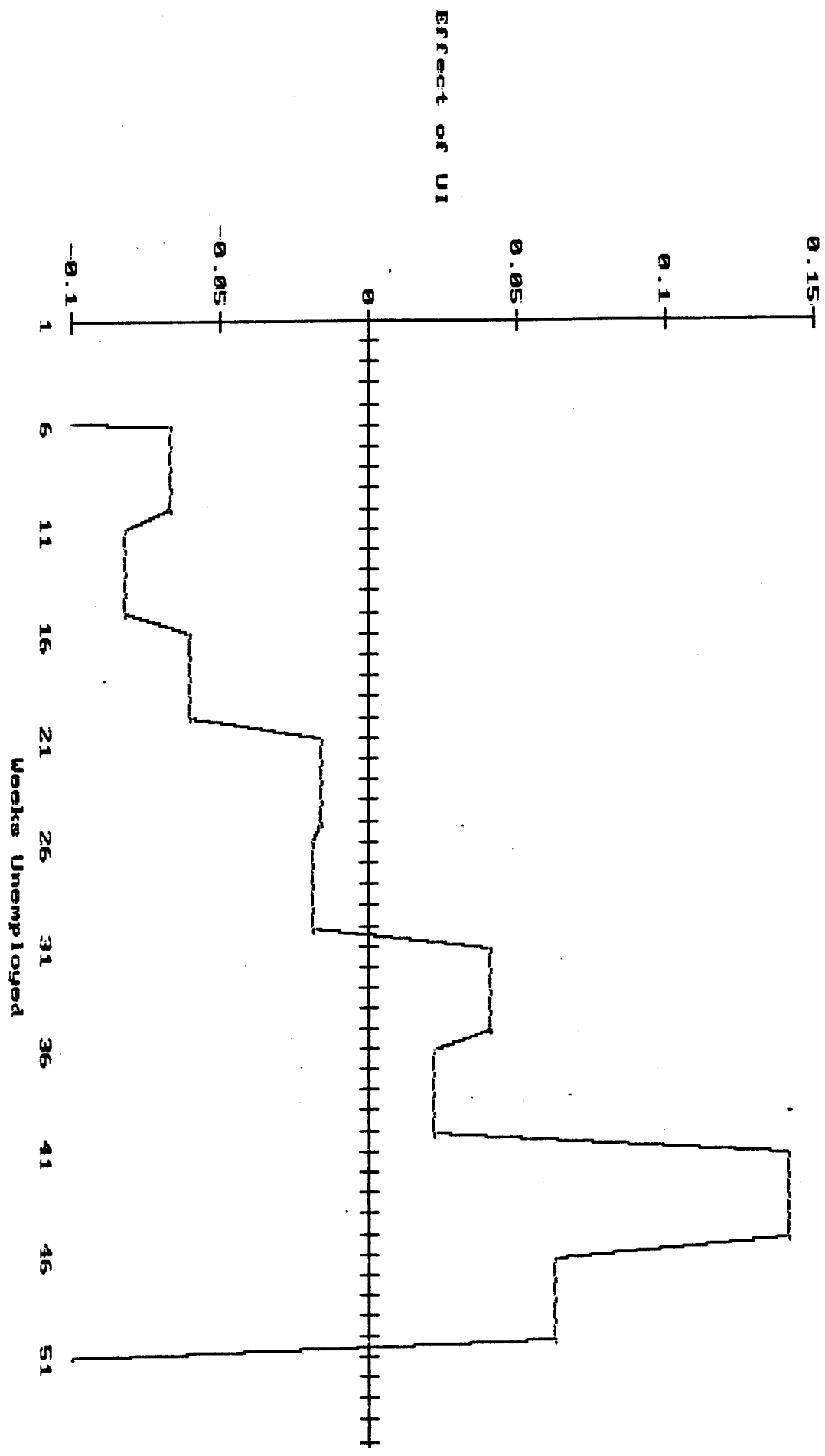


Figure 4: Difference Between Baseline Hazard Rates of Recipients and Nonrecipients of UI, Old Industry

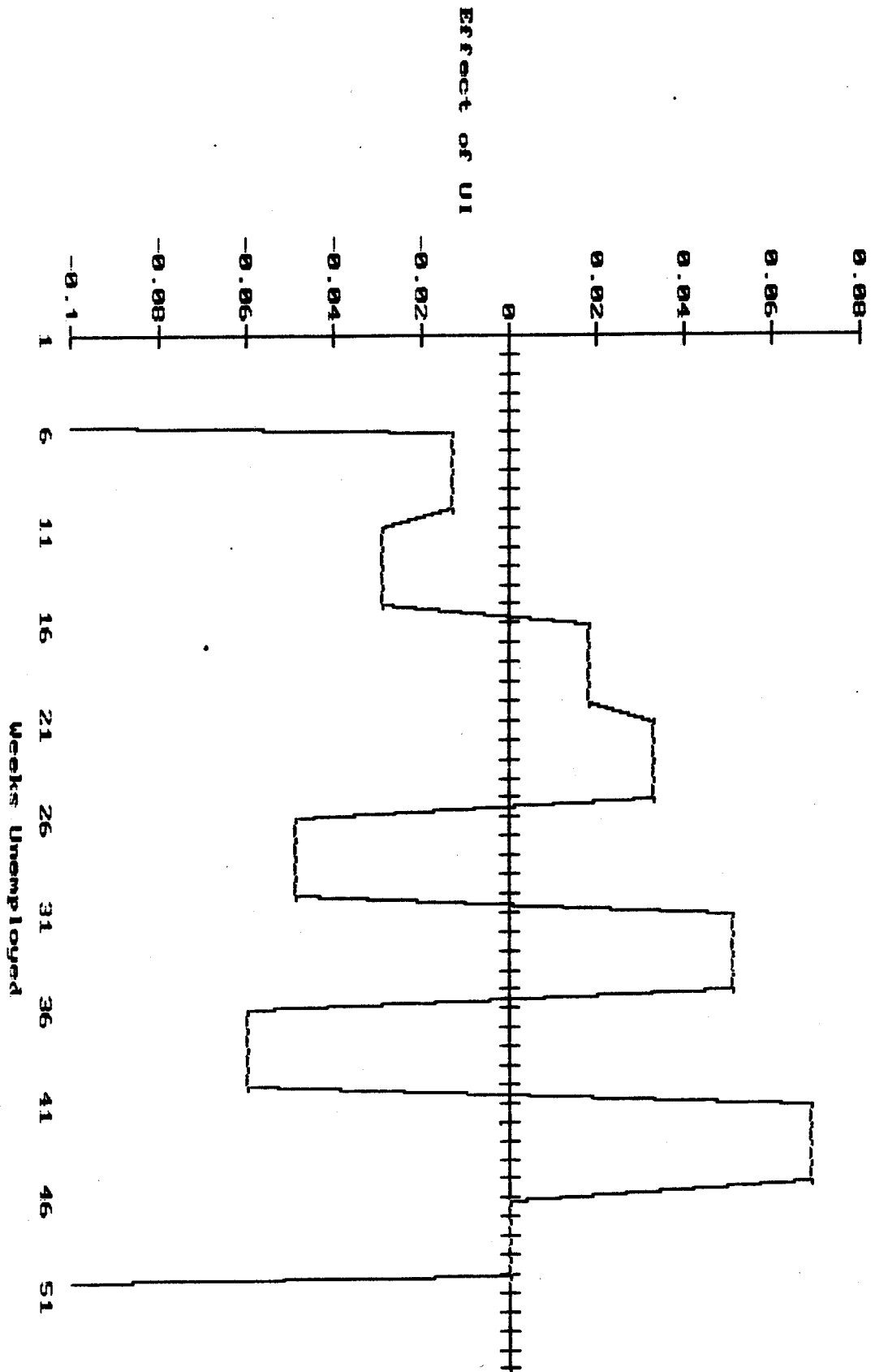


Figure 5: Difference between the Baseline Hazard Rates for Recipients and for Nonrecipients of UI. New Industry

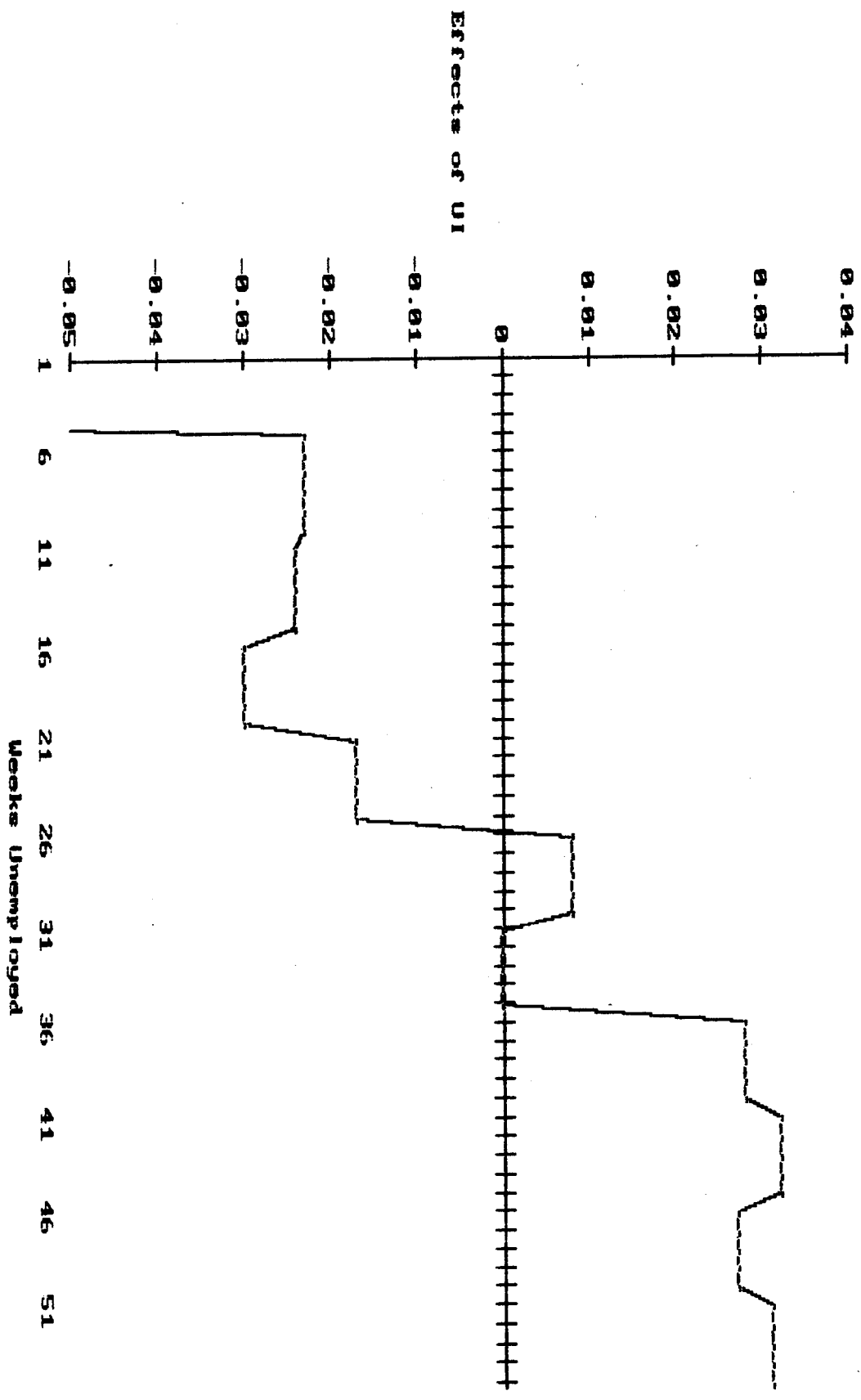


Figure 6: Baseline Hazard Rates for Nonrecipients of UI, Old Industry

