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# RE-EMPLOYMENT PROBABILITIES OVER THE BUSINESS CYCLE

Guido Imbens
Lisa M. Lynch

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## ABSTRACT

Using a Cox proportional hazard model that allows for a flexible time dependence that can incorporate both seasonal and business cycle effects, we analyze the determinants of re-employment probabilities of young workers from 1978-1989. We find considerable changes in the chances of young workers finding jobs over the business cycle, however, the characteristics of those starting jobless spells do not vary much over time. Therefore, government programs that target specific demographic groups may change individuals' positions within the queue of job seekers but will probably have a more limited impact on the overall re-employment probability. Living in an area with high local unemployment reduces re-employment chances as does being in a long spell of non-employment. However, when we allow for an interaction between the length of time of a jobless spell and the local unemployment rate we find the interaction term is positive. In other words, while workers appear to be scarred by a long spell of unemployment, the damage seems to be reduced if they are unemployed in an area with high overall unemployment.

Guido Imbens
Department of Economics
Harvard University
Cambridge, MA 02138
and NBER

Lisa M. Lynch
Fletcher School of Law and Diplomacy
Tufts University
Medford, MA 02155
and NBER

## 1. Introduction.

The business cycle can have a variety of effects on the unemployment experience of workers. Fluctuations can alter the rate at which workers move from employment to non-employment, and fluctuations can also influence the rate at which workers exit from non-employment into employment. Much of the debate on the distribution of unemployment spells or re–employment probabilities over the business cycle can be summarized by two distinct empirical research strategies. Macro–economists are typically interested in changes in unemployment durations as one of the explanations of changes in the aggregate unemployment rate. The issue is whether changes in the aggregate unemployment rate are driven by changes in the rate at which jobs end in separations, quits or layoffs, or by changes in the re–employment probabilities, which, in equilibrium, are equal to the inverse of the average duration of unemployment spells. These studies of incidence versus duration are often based on aggregate flows of groups of individuals over long periods of time, with limited controls for individual characteristics.

Micro economists, on the other hand, have focused on estimating the determinants of individual re–employment probabilities, utilizing detailed individual data from longitudinal surveys. Using individual characteristics, researchers model the instantaneous probability of finding job, the hazard rate, given a person's characteristics and employment history. These empirical studies typically cover a relatively short period of time, and usually ignore any aggregate changes in the economy.

Neither of these research strategies can provide a complete answer on how re–employment probabilities vary over the business cycle. Specifically, it is possible that at the individual level the re–employment probabilities are constant over time, while changes in the composition of those who become unemployed over the business cycle lead to changes in the average re–employment probabilities of those out of work. On the other hand, effects of individual characteristics on re–employment probabilities found using micro data may be confounded if the analysis has not controlled for changes in aggregate conditions. Specifically, it may appear that a particular characteristic has a negative effect on re–employment probabilities merely because individuals with that characteristic are more likely to become out of work during periods of low re–employment probabilities.

This distinction between effects of individual characteristics and macro conditions has policy implications. If individual differences are the main component of variation in re–employment probabilities, policies should be targeted at those with characteristics that are associated with low re–employment probabilities. If instead changes in macro conditions are the main source of variation, such policies are unlikely to be useful. In this study we attempt to combine these two research approaches to study one component of unemployment – variation in re–employment probabilities over the business cycle and across individuals. We analyze the determinants of re–employment probabilities taking into account the impact of aggregate changes due to business and seasonal cycles that are traditionally the concern of macroeconomic studies, while utilizing disaggregated data from a detailed longitudinal survey of individuals. One advantage of this research strategy is that we are able to examine what happens to the distributions of exit rates/durations of nonemployment when the overall exit rate is low. Understanding the role of the business cycle in determining the duration of unemployment is especially important if there is evidence of 'scarring' in unemployment. Scarring occurs when workers who are in a spell of unemployment find it more difficult to find employment as their spell of unemployment increases, ceterus paribus. This implies that even a one time demand shock can have long term employment consequences.

In this paper we estimate the determinants of the duration of nonemployment spells of young workers using data from the National Longitudinal Survey of Youth. To analyze the determinants of the duration of non–employment spells for youths we use a Cox regression, or proportional hazard model (Cox, 1974) that allows for a flexible time dependence that can incorporate both seasonal and business cycle effects. We construct a sample of approximately 5000 men and women who have just entered the labor market, and observe them through two complete business cycles from 1978 to 1989. We focus on youths for a variety of reasons. First, the share of total unemployment that is represented by youths aged 16-24 is quite large in the United States. For example, Blank and Card (1989) show that in 1977, youths represented 46 percent of all those unemployed, while registered unemployed represented only 31 percent of all those unemployed. By 1987 the share of youth unemployment had fallen to only 36 percent of all those unemployed. However, the share of registered unemployed had also fallen to 27 percent. So youths still represent an important demographic group in the composition of the unemployed.

There are several other reasons to focus on the determinants of the duration of unemployment for youths. For example, an early spell of unemployment (especially a long spell) for a worker who has relatively limited work experience may have a large negative impact on their longer term attitudes towards work. In a related argument, the early years of employment represent an important period for human capital development. Since most post school training in the U.S. is acquired informally on the job, especially for non-college graduates, early spells of non-work also mean reduced human capital accumulation.

We find considerable changes in the chances of young workers finding jobs over time both over the business cycle, as well as seasonal effects within the year. Even after controlling for a large set of individual characteristics these results do not change substantially. More specifically, we find that the characteristics of those starting spells of non–employment do not vary much over time. However, because the average duration alters as a result of the changes in the re–employment probabilities, the characteristics of the average non–employed person do change over time. We also find evidence of strong negative duration dependence. This means that the longer an individual is not working the more difficult it becomes for them to get a job. Individuals living in areas with high unemployment or who find themselves unemployed during a period of nationally high unemployment are also less likely to get re–employed. However, when we allow for an interaction between the unemployment rate and duration dependence the sign on the interaction term is positive. In other words, workers are not as scarred by a long spell of unemployment if they are unemployed in an area, or during a period, with high unemployment as those with a long spell out of work in an area, or during a period, with low unemployment.

## 2 Background Discussion.

In the steady state, the unemployment rate is a function of the inflow rate and the outflow rate (or the inverse of the average duration of unemployment). Surveys such as the Current Population Survey (CPS) give us information on the unemployment rate and the inflow into unemployment at a point in time. From this we can then back out the average duration of unemployment. We must use the steady state assumption to get an estimate of average duration of unemployment because respondents in the CPS are rotated in and out of the sample so that it is not possible to observe their completed duration of unemployment. In the U.S. in the 1960s and 1970s it has been argued, using this empirical estimation strategy, that the major determinant of fluctuations in the unemployment rate has been changes in the incidence of unemployment rather than changes in the average duration of unemployment.

Recent work by Blanchard and Diamond (1990) using the gross flows data from the CPS finds that the absolute size of the flow from unemployment to employment rises in a recession, while the hazard rate, or the relative size of the flow, actually falls. Clearly, the absolute flow of unemployed into employment might rise in a recession just because there is a bigger pool of unemployed. They conclude that for the U.S. it is job destruction rather than job creation which influences fluctuations in the unemployment rate. In other words, variation in incidence is relatively more important than variation in duration in the U.S..

On the other hand, work by Hal Sider (1985), again using the CPS, suggests that calculations on the relative importance of incidence and duration that are based on the steady–state framework will systematically underestimate durations during recessions, and overestimate durations in booms. He compares estimates of the relative importance of incidence and duration using steady state and non steady state assumptions. He finds that not imposing the steady state assumption results in the finding that over the 1968-82 period, 84 percent of the changes in the unemployment rate were due to changes in duration. The rest were due to cyclical fluctuations in incidence. If instead one assumes steady state, 55 percent of the changes in the unemployment rate are due to changes in incidence.

In all of this work on the relative importance or the incidence of unemployment versus the duration of unemployment, relatively little is done (due to data restrictions) to control for changing characteristics of the unemployed over the business cycle. One exception is recent work by Baker (1992) in which he examines the relationship between expected duration of unemployment and the unemployment rate using CPS data and a synthetic-cohort estimation framework. He reports separate elasticities for a range of demographic groups but he does not control for demographic characteristics simultaneously. Therefore, empirical work which can combine more detailed information on the characteristics of the unemployed with precise information on changes in their duration of unemployment over the business cycle would be useful. This would allow one to distinguish between changes in the characteristics of the unemployed versus business cycle effects on the duration of unemployment.

Another factor complicating comparisons between macro–economic and micro–economic studies of unemployment durations is the issue of seasonality. Most aggregate data on unemployment is reported seasonally adjusted but not 'business cycle adjusted'. This reflects a notion that seasonal fluctuations in employment patterns are due to very different factors than business cycle fluctuations. In addition, by definition, seasonal patterns are something that we can predict since they are an empirical regularity, whereas this is not the case for business cycle changes. Presumably the welfare losses due to an unexpected shock are larger than those associated with predicted fluctuations. Recent work has reexamined these assumptions (e.g. Barsky and Miron (1989)) and has argued that the underlying model of business cycles and seasonal cycles are more similar than dissimilar. As result, they and others argue that we should examine the seasonal pattern of various macroeconomic variables as well as the behavior of these variables over the business cycle. Seasonality and pure business cycle affects can not be treated by simply including dummy variables for the month in which a spell of non-employment began. Since it is presumably the conditions when searching for a job, not when one lost a job that affect re–employment probabilities at any point during a spell the researcher should allow for these time varying calendar effects.

In addition to the macroeconomic evidence on the link between business and seasonal cycles and unemployment duration, there are several microeconomic models which could be useful for analyzing the determinants of unemployment duration or re–employment probabilities. Examples of empirical studies which follow this second strategy, using much more detailed information on the characteristics of the unemployed by utilizing more detailed micro longitudinal data sets such as the PSID and NLS and estimate re–employment probabilities are Dynarski and Sheffrin (1990), Flinn and Heckman (1982), Lancaster (1979), Narendranathan, Nickell and Stern (1985), Katz (1986), Lynch (1989), Meyer (1989), Solon (1985). The advantage of this strategy is that we can observe the actual completed duration of unemployment and we have very detailed information on the characteristics of the respondents. A disadvantage, up to now, is that most of this work has estimated these re–employment probabilities over a relatively short period of time. This means it is difficult to examine the impact of the business cycle, or more generally the impact of calendar time on the expected duration of unemployment.

One of the most commonly used theoretical models when micro data is available is job search theory. In job search theory when a worker becomes unemployed, the expected completed duration of their unemployment (or inversely, the re–employment probability) will depend on two probabilities – the probability of receiving a job offer and the probability of then accepting this job offer. The probability of receiving a job offer will be determined by factors such as education, post-school training, and local demand conditions. The probability that an individual will then accept this job offer will be determined by their reservation wage. Factors which will influence this wage include the expected distribution of wages, the costs of search, any unemployment income, family characteristics, and the probability of receiving a job offer.

Search theory, however, gives an ambiguous prediction on the relationship between the business cycle and the duration of unemployment. In the simplest models, increases in unemployment will decrease the reservation wage but they will also decrease the probability of receiving a job offer. Therefore, the net effect of a recession in the theoretical model is ambiguous. In empirical work by Katz (1986) and Lynch (1989) using local unemployment rates, and Dynarski and Sheffrin (1990) using the national unemployment rate, it is found that higher unemployment results in lower re–employment probabilities. However, other work by Meyer (1990) and Solon (1985) using data on unemployment insurance claimants suggests that the average duration of unemployment falls in a recession. So there is some ambiguity in the empirical findings of the relationship between the business cycle and the duration of unemployment. One important difference that may account for the some of the differences across these papers is who is examined – those receiving unemployment compensation are just a subsample of the unemployed (27 percent) and may exhibit very different behavior from other workers.

Many micro-based studies have examined the impact of the current length of an unemployment or non-employment spell on the probability of becoming re–employed. Negative duration dependence occurs when there is a negative relationship between the current spell length and the re–employment probability. This negative duration dependence may reflect employers using the spell length as a proxy for some unobserved characteristics and not hiring workers with long spells. It might also represent workers becoming more discouraged over time and decreasing their search intensity, or other unobserved factors. Although it is difficult to distinguish between these various effects, we can use the interaction of the local unemployment rate with duration of non-employment spell to distinguish between ranking and signaling stories. In ranking models such as Blanchard and Diamond (1990), high ability individuals always do well in finding employment no matter what the local labor market conditions are. As unemployment rises an increasing proportion of the unemployed are those with the least skills. Employers use the length of a current spell of unemployment as a way to rank applicants for positions. Therefore, as local labor market conditions worsen those with longer spells of unemployment would have more difficulty in finding employment. If instead, as local unemployment rates rise all workers have difficulty in finding employment regardless of qualifications, then the signal attached to the spell length should weaken. This would be inconsistent with a pure ranking model.

## 3 The Data.

This study uses data from the National Longitudinal Survey, Youth Cohort, NLSY. This is a sample of originally 12686 males and females who were 14 to 21 years of age at the end of 1978. These youth were first interviewed in 1979 and have been interviewed every year since then about their education, jobs, military service, family characteristics, training, health, and attitudes. These interviews have been in person except in 1987 when there was a telephone survey. We have restricted our sample to those people whom we observe finishing school and then not returning to school for five years. This allows us to observe the entire labor market experience for young people who have 'permanently' left school. In principle this creates an endogeneity problem, because our definition of 'permanent' depends on future events. However, if one views returns to school as perfectly predictable at the individual level, one can reduce this to conditioning on knowledge at the beginning of the spell. We use data from the NLSY covering the period from January 1, 1978 until the 1989 interview date (i.e. more than 11 years worth of data over 2 business cycles).

We construct a sample made up of seven waves of 'school leavers'. Our sample includes those who finished school in 1979 and their labor market experience through the 1983 interview date; those who finished school in 1980 and their labor market experience through the 1984 date; etc... up to school leavers in 1985 and their labor market experience through 1989.[2] While the decision to leave school is clearly endogenous this selection rule gives us a sample of youths that are more permanently attached to the labor market. It is possible given our sample design to test for our pooling restrictions. If the pooling of these waves of school leavers is rejected this may be evidence of schooling selection. Table 1 presents some basic characteristics of our base sample at the entry date into the labor market. Given the age structure of the NLSY we have more college graduates entering the labor market in later years than in the earlier years. In addition, the number of school leavers in 1985 is much

[2] We have not included more than five years of labor market data for any of the observations in our sample. It would have been possible for those who finished school in the early years of the cohort (e.g. 1979, 1980) to have more years of data but then we would have ended up requiring the earlier school leavers not to have returned to school for a longer period than for later school leavers.

smaller than in any of the earlier years, again reflecting the age structure of the original NLSY cohort.

Besides detailed longitudinal information on individual characteristics, the NLSY has detailed information on the starting and ending dates of employment and non–employment spells. This allows us to construct a weekly employment history for all of the individuals in our sample. Unfortunately, in the NLSY, spells of nonemployment are not easily separable into spells of unemployment and spells of being out of the labor force. Therefore, the following analysis of re–employment probabilities focuses on the transition from nonemployment to employment rather than unemployment to employment. However, especially for young male workers, the distinction between these two states may be small.

## 4. Cyclical Effects in Nonemployment Durations.

Before looking at any models for nonemployment durations we first examine the distribution of spells over time. The simplest way to do this is by counting the number of people in each week who find a job. Clearly this is dependent on the number of people who are not working in that week, and therefore a more appropriate measure is the proportion of nonemployed in a given week who find a job in that week. This is an estimate of the hazard rate from nonemployment to employment in that week. Because we have weekly data from January 1978 to 1989, the number of weeks is large relative to the number of observations, and therefore we smooth this hazard rate estimate by assuming it is constant per quarter.

Figures 1 and 2 give these estimates of the weekly hazard rate. The continuous line is the estimate, the two dotted lines give the 95% (point wise) confidence interval. The solid vertical lines indicate the peaks and troughs of the business cycle according to the NBER dating committee. It is immediately clear that there is considerable variation in the hazard rates. For example, the probability of finding a job within a given week varies from a low of about 2% to a high of about 8% for the men in our sample. One can clearly recognize the effects of the recession in the early eighties, with the hazard dropping to about 3% at the end of 1982. Within years the variation is smaller (with the exception of 87–89 where we have far fewer observations, and the quality of the data in 1987 may be affected by the telephone interview) but very regular. For example in 1979, the hazard rate is relatively low in the first quarter, rises by about one percentage point in the second quarter and then returns to the first quarter level by the end of the year.

These hazard rates, rather than the durations themselves, are the focus of our analysis since changes over time are easier studied in terms of hazard functions. Nevertheless there is another way of looking at these calendar effects that brings out even stronger the importance of the variation found in Figures 1 and 2. We separate the spells by the year in which they started. Then taking all the spells started in a given year, say 1985, we estimate the quartiles of the distribution of spells using the Kaplan–Meier estimate of the distribution function. Looking at quantiles allows for censored spells, and leads to more robust inference than looking at means or other moments which are very sensitive to tail behavior. In Figures 3 and 4 we plot the quartiles of the distribution of the spells by year from 1978 to 1989. The differences by year are much more pronounced than they are for the hazard rates. Ignoring 1989 for which we do not have many spells, the median of nonemployment spells for males reaches a low of about seven weeks in 1987, and a high of eighteen in the recession year of 1982. The comparable numbers for young females are 12 and 22 weeks. Not only does the median length of nonemployment change over time but also the skewness varies over the cycle.

We also ordered the spells of nonemployment by the month in which the spell was started. In Appendix Figures A1 and A2 the quartiles are plotted against months the spells were started. Again the variation which was roughly of the order of 25% in the hazard rates, is much more pronounced in the quartiles. The median duration for men varies from eight weeks in June to seventeen weeks in February. Similarly for women, the median reaches a low in the early summer (thirteen in May) and a high early in the year (twenty six in March). The other quartiles tell a similar story.

So where the hazard rates suggest modest but regular changes in the average probability of finding a job, the quartiles of the spell distributions suggest that there is considerable variation in the durations of nonemployment as a result of these modest changes. One explanation of this large effect on durations coupled with modest changes in the hazard rate is the presence of strong duration dependence. If the hazard rate drops by a small amount, and picks up again the next quarter, it might be too late for people who did not find a job as a result of this drop if their chances of finding a job are decreased by the length of their unemployment spell. Another explanation is heterogeneity across individuals which will appear as duration dependence. We therefore pay close attention to evidence of duration dependence in the spell distributions. We also see in Figures 3 and 4 that the duration of nonemployment for men during the 1982 recession first increases (remains constant for women) and then falls for both men and women during the latter part of the recession. This suggests that in a long recession duration dependence may be less negative than in periods of expansion.

Figures 5 and 6 give estimates of the hazard rate as a function of the number of weeks not working. This is a simple ratio of the number of people who find a job in the $i^{th}$ week of their nonemployment spell to the number of people who have spells of at least $i$ weeks. There are a number of interesting features in these plots. First, it is clear that the hazard has a sharp peak at two weeks. In the second week the chances of finding a job are almost 9 percent for men, and more than 6 percent for women. After this peak the hazard rate for men very quickly drops to a level of about 4 percent at 8–10 weeks. After obtaining that level the hazard rate continues to decline slowly but steadily until it touches about 2 percent after a year of unemployment. While there is a lot of noise in the estimates, plotting confidence intervals around the estimates suggests that a hazard steadily declining after the first two weeks is consistent with the data. If we calculate the survivor function (the proportion of spells with length exceeding or equal to $t$, or one minus the distribution function at $t$) we find that about 43% of nonemployed men find a job within ten weeks. On the other hand, 20%

are still not working after forty weeks. For women the shape is very similar but the scale is different and lower. The hazard drops after the initial peak at two weeks to a level of about 0.03 at ten weeks, and then slowly drops to 0.015 after one year. The plots indicate that there is considerable negative duration dependence: once someone has been nonemployed for more than ten weeks, the chances of finding a job have substantially diminished. This reinforces the variation in the hazard over time. Relatively small changes in the hazard rate within years or over the business cycle can and do, as shown in Figures 3–4 and A1-A2, lead to large changes in the median duration of nonemployment spells.

Another interesting feature of Figures 6 and 7 is that we do not find the spikes around 25–29 weeks and 35–39 weeks that were found by Moffit (1985), and Meyer (1990). In their work these spikes were attributed to the exhaustion of unemployment benefits. The main reason why we do not find these spikes is because our sample is drawn from the NLSY and therefore consists of young people who are less likely to be eligible for benefits. In addition, we are examining all those not working, not just those who are categorized as continuously unemployed.

In spite of creating a relatively homogeneous sample of youths we find considerable variation in the duration of nonemployment over calendar time. There are a number of factors that could explain the cyclical behavior of the hazard rate found in Figures 1 and 2. There might be cycles in the inflow into nonemployment. For example, it may be that in the second or third quarter most of those who are not working are people with relatively high education levels. If a high level of education is associated with good chances of finding a job, i.e. a high hazard rate, one would expect to see high hazard rates in the second or third quarter. We will therefore in Section 5 try to control for the characteristics of the nonemployed to see how much of the variation in the hazard rate seen in Figures 1 and 2 can be explained by personal characteristics.

## 5. Empirical Framework - The Proportional Hazard Model.

We now proceed to estimates of the hazard rates taking into account variation due to observable covariates. This serves three purposes. First, it will tell us whether the qualitative results in the previous section are spurious in the sense that they do not reflect changes in the hazard rate at the individual level, but instead reflect changes in the composition of the pool of unemployed. Second, it allows us to determine whether taking account of calendar time alters conclusions reached in the literature concerning dependence of the hazard rate on duration and individual characteristics. We accomplish this by comparing parameter estimates with those found in studies that did not allow for flexible calendar time dependence. Third, we determine whether duration dependence varies according to the tightness of the labor market, as predicted by ranking and signaling models, and in which direction.

Consider an individual at time $t$ who has been unemployed since $t^0$, with characteristics, at time $t$, $x(t)$. These characteristics may contain variables reflecting local labor market conditions, as well as personal characteristics such as education, age, marital status, number of children, etcetera. Let $t^1$ denote the date of re–employment. The hazard rate gives the probability of finding a job conditional on the individuals' characteristics, and their history, $\{x(s)_{s\leq t}\}$, and given the time $t$ that he or she is unemployed. Formally, the hazard rate $\lambda$, for $t > t^0$, is

$$\lambda(t, t^0, x(s)_{s<t}) = \lim_{h \downarrow 0} Pr(t < t^1 < t + h | t^1 > t, t^0, x(s)_{s\leq t})/h$$

We assume that the only way in which the hazard depends on the history of the time-varying regressors is via the contemporaneous value $x(t)$. Thus, $\lambda = \lambda(t, t^0, x(t))$. In the standard Cox proportional hazards model the hazard depends only on duration, $(t - t^0)$, and characteristics $x$. In other words:

$$\lambda(t, t^0, x(t)) = \lambda_0(t - t^0) \cdot \omega(x(t); \beta)$$

The functional form of the baseline hazard $\lambda_0(t)$ does not need to be known for consistent estimation of the parameters of the systematic part of the hazard, $\omega(x(t); \beta)$. We use a different form of the Cox proportional hazard model where the unknown baseline hazard depends on calendar time, with the duration dependence parametrically specified. Formally,

$$\lambda(t, t^0, x(t)) = \lambda_0(t) \cdot \omega(t - t^0, x(t); \beta)$$

We use three main specifications. In the first we have no individual characteristics. The hazard depends on the duration of the spell, the duration squared, and the interaction of the duration and the national (monthly) unemployment rate:

$$\lambda_1(t, t^0, x(t)) = \lambda_0(t) \cdot \exp\Big[\beta_0 \cdot \ln(t - t^0 + 1)$$

$$+ \beta_1 \cdot \ln^2(t - t^0 + 1) + \beta_2 \cdot \ln(t - t^0 + 1) \cdot nu(t)\Big]$$

In the second specification we allow for individual characteristics.

$$\lambda_2(t, t^0, x(t)) = \lambda_0(t) \cdot \exp\Big[\beta_3' x_0(t) + \beta_4' d(t)$$

$$+ \beta_0 \cdot \ln(t - t^0 + 1) + \beta_1 \cdot \ln^2(t - t^0 + 1) + \beta_2 \cdot \ln(t - t^0 + 1) \cdot nu(t)\Big]$$

In this specification $x_0(t)$ is a vector of time–varying personal characteristics such as years of education, marital status, and number of children. $d(t)$ is a vector of dummy variables indicating the census region (North East, North Central, South and West) the individual is living in. $nu(t)$ is the monthly national unemployment rate. We still allow the dependence of the hazard rate on calendar time to be very flexible, only making the assumption that it is proportional to the remainder of the hazard rate. We also allow for a fairly flexible duration dependence, which is quadratic in the logarithm of duration plus one. Finally, we let the duration dependence interact with the local unemployment rate. Note that because we let the baseline hazard $\lambda_0(t)$ be an unrestricted function of time, this absorbs the effects of common, individual invariant (i.e. constant over individuals), but time–varying regressors such as business and seasonal cycle effects. The advantage of this approach is that it is difficult to completely model the impact of calendar time events, whereas, as discussed in section 2, there is a well developed economic theory to explain the pattern of duration dependence. Therefore, it may be relatively easier to model duration dependence with a low order polynomial than calendar time dependence. As shown in Figures 1–2 and 5–6 we would need a much higher order polynomial to even begin to come close to capturing calendar time effects while the duration dependence follows a simple pattern of initially rising and subsequently declining hazard rates.

In the third specification we let the systematic part of the hazard function depend on personal characteristics, duration and the local unemployment rate.

$$\lambda_1(t, t^0, x(t)) = \lambda_0(t) \cdot \exp\Big[\beta_0' x_0(t) + \beta_1 \cdot lu(t)$$

$$+ \beta_2 \cdot \ln(t - t^0 + 1) + \beta_3 \cdot \ln^2(t - t^0 + 1) + \beta_4 \cdot \ln(t - t^0 + 1) \cdot lu(t)\Big]$$

Instead of trying to capture regional differences by including dummy variables $d(t)$ for the census regions the local unemployment rate is used to capture these differences in local labor markets. In this specification we interact the duration term with the local unemployement rate ($lu(t)$) rather than the national unemployment rate. While the local unemployment rate may be better at capturing regional differences, it may not be as good at capturing dynamic aspects of the labor market as the monthly national unemployment rate since it only changes yearly in our data set. We assume that different spells for the same individual are independent, conditional on the time path of the time–varying regressors. Let $N$ be the total number of spells experienced by the $M$ individuals over the period of observation. The $n$th spell starts at $t_n^0$ and ends at $t_n^1$. If the period of observation ends before the spell, the censoring indicator $c_n$ is equal to zero. If the spell ends with a job, the censoring indicator is equal to one. The full likelihood function for a set of $N$ spells can then be written as

$$\mathcal{L}(\beta) = \prod_{n=1}^{N} \left[\lambda_0(t_n) \cdot \omega(t - t_n^0, x_n(t); \beta)\right]^{c_n}$$

$$\cdot \exp\left[- \int_{t_n^0}^{t_n^1} \lambda_0(s) \cdot \omega(s - t_n^0, x_n(s); \beta) ds\right].$$

We estimate the parameters of this model using the Cox partial likelihood estimator (Cox, 1972, Andersen and Gill, 1982, and Lancaster (1990)). The application of the partial likelihood estimator to the case where the proportional part of the hazard depends on calendar time rather than duration is discussed in detail in Imbens (1993). The estimator is based on comparing different individuals who are unemployed at the same calendar time. Assume, for expositional purposes, that individuals only have one spell of non–employment. Consider the risk set of spells in progress at $t$, denoted by $R(t)$ and formally defined as:

$$R(t) = \{n = 1, 2, \ldots, N | t_n^0 < t < t_n^1\}$$

$R(t)$ can also be thought of as the set of individuals not employed at $t$. (In our case we have multiple spells so in reality the notation is slightly more complicated than what is presented here.) Given that one spell from this set ends at $t$, the probability that it is spell $j \in R(t)$, given all information up to $t$, is the ratio of the hazard rate for that spell to the sum of the hazard rates for all the other spells in the risk set. Unfortunately, our risk set does not diminish over time as in the standard Cox case and this increases the computational time substantially.

Formally, let $\iota(t)$ be the index of the spell which ends at $t$. The probability that $\iota(t)$ is equal to $n$, given all the life histories up to $t$, is zero if $n$ is not in the risk set $R(t)$. Then the probability that $\iota(t)$ is equal to $n$, given all labor market histories up to $t$, is equal to:

$$Pr(\iota(t)=n)=\frac{\lambda(t,t_n^0,x_n(t))}{\sum_{m\in R(t)}\lambda(t,t_m^0,x_m(t))}.$$

The assumption we made concerning the functional form of the hazard function, and specifically the proportionality assumption, reduces this probability to

$$\begin{aligned}Pr(\iota(t)=n)&=\frac{\lambda_0(t)\cdot\omega(t-t_n^0,x_n(t);\beta)}{\sum_{m\in R(t)}\lambda_0(t)\cdot\omega(t-t_m^0,x_m(t);\beta)}\\&=\frac{\omega(t-t_n^0,x_n(t);\beta)}{\sum_{m\in R(t)}\omega(t-t_m^0,x_m(t);\beta)}.\end{aligned}$$

In this fashion we construct the partial likelihood function as the product of all individual contributions. At each exit time $t$ we condition on the fact that one spell ended, and look at the conditional probability that it is spell $n$ out of the set of spells $R(t)$ which potentially could have ended at that point in time. This technique removes the dependence of the likelihood function on the baseline hazard rate $\lambda_0(t)$. Since this baseline hazard is the same for all individuals, it does not affect the relative chances of any individual finding a job once we condition on someone finding a job at that point in calendar time.[3]

## 6. Empirical Results.

Tables 2 and 3 give the estimates based on this model for men and women. In these tables positive coefficients imply that an increase in the regressor is associated with an increase in

[3]The computational costs of these procedures are quite high. Every evaluation of the partial likelihood function is an operation of order $N^2$ where $N$ is the number of spells. This leads in our case with about 6000 spells to optimization routines that require a couple of hours of computer time on a IBM RS6000 workstation per iteration. As suggested by Bruce Meyer, this may be reduced by sampling from the risk set, rather than averaging over it.

the hazard rate, and therefore with a decrease in the duration of nonemployment. The first column of results only includes the duration dependence terms and an interaction of the duration and the national unemployment rate. This gives us a baseline measure of duration dependence that by definition will become smaller as we include other significant factors. In the second column we see how sensitive our results are to a different specification and include a set of individual characteristics. The third column of results allows the systematic part of the hazard function to depend on a range of time invariant and time varying personal characteristics, duration dependence and the local SMSA unemployment rate.

Most of the personal characteristics included in the estimation are self explanatory. Black men and women have lower re–employment probabilities, even after controlling for a wide range of characteristics. Higher levels of schooling reduce the duration of a spell of nonemployment. The number of children living at home has a strong negative effect on the chances of finding a job for women, but little affect on the re–employment probabilities for men. Living in the parental home has a significant but fairly small negative effect on the re–employment probabilities for women, and an insignificant, negative effect for men. Being married increases the chances of finding a job for men, and decreases them for women. Receiving unemployment compensation has a strong positive effect on the chances of leaving unemployment for both men and women. This presumably reflects the attachment to the labor market rather than incentive effects of unemployment benefits. Eligibility for these benefits requires that the person has significant labor market experience, and this is picked up by this coefficient. The dummy variable for disability has the expected coefficient. Government training increases re–employment probabilities for women but not for men. In addition, private sector training does lead to a modest, but significantly positive change in the chances of finding employment for both males and females. It should be noted that there is a potential problem with endogeneity of these variables, since private training includes on the job training. Therefore, for all time–varying regressors, we took the value of the regressor in the year preceding the year in which the current spell takes place. For example, if we are looking at a spell starting after the interview date in March 1982, we take the values of the time–varying regressors for the year between the interview dates in 1981 and 1982. If the variable on the job training (which is part of the private training variable) is one during a particular spell, it means that this individual received on the job training in the previous year. This strategy of using predetermined values of the explanatory variables also takes care of the endogeneity problem that could occur with the family status variables. In general, most of the coefficients on personal characteristics are comparable to estimates obtained using a Weibull distribution, not taking into account calendar time dependence, presented in Lynch (1989).

A decrease in the local unemployment rate of 10 percentage points leads to a increase in the log of the hazard of 0.71, or a 60% increase in the hazard rate. In addition, the duration dependence is found to be non–monotonic. The linear term in the log hazard is barely significant but the quadratic term is strongly significant. After 10 weeks of nonemployment the hazard rate is lower by 8%. After 20 weeks the hazard drops to about 79% of its original level. Interestingly, the interaction term of the duration of nonemployment and the local unemployment rate has a positive sign. This suggests that while a high unemployment rate and a long spell of nonemployment will each lower the re–employment probability on their own, when individuals are in long spells in an area with high unemployment they are not as 'scarred' or as discouraged by the nonemployment experience as individuals who have long unemployment spells in low unemployment areas. This is illustrated in Appendix Figures A3 and A4 where we plot the relative hazard rate as a function of duration for two different levels of the local unemployment rate (five and fifteen percent). This finding seems to be evidence against pure ranking models of unemployment. This also varies from Dynarski and Sheffrin (1990) where they find some evidence that being in a spell of more than three months at a time when the national unemployment rate was high increased the duration of unemployment. However, this is only true for those receiving unemployment insurance and they are not able to control for as detailed personal characteristics and calendar time effects as we are.

To capture heterogeneity and lagged duration dependence not accounted for by personal characteristics we included a number of regressors that depend on previous nonemployment experience. First we included a dummy variable indicating whether the current spell is the first nonemployment spell experienced by this individual. This regressor has a strongly significant, negative coefficient. Our interpretation is that people who have not experienced any unemployment before are recent entrants into the labor market who have more difficulty finding a job than more experienced individuals. The first spell indicator proxies for attachment to and experience in the labor market. The second aspect we considered is lagged duration dependence. The variable included was the logarithm of the previous spell length plus one. This was set equal to zero for first spells. We find that longer previous spells have a negative effect. In addition to the duration of the previous or last spell, we included the average of the logarithms of all preceding spells, including the previous one. This also has a negative effect. The fact that the previous nonemployment spell has an impact even after we include the average of all previous spells implies that experience with nonemployment hurts more, in the sense of lowering the hazard, the more recent this experience is. The last variable in this category that we included is the number of previous spells. This has an insignificant effect for men but a positive effect on the hazard rate for women. This may reflect the higher percentage of women who are employed in temporary help agencies where job changes are not viewed as a 'negative' characteristic.

In results available from the authors we also redo the estimations year by year. (Some spells start in one year and end in the next year. In this case we treat this as a right censored spell in the first year, and a left censored spell in the second year.) We then test the null hypothesis that the coefficient on a particular regressor is constant over the eleven years. We find that most of the coefficients seem relatively stable over time. One important exception to this pattern, however, is the coefficient on the education variable. This coefficient changes considerably over the period of observations. This may reflect the fact that the distribution of this variable in our sample changes considerably over the period as shown in Table 1. During the first few years (1978-1981) there are few college graduates in the sample, and most of the individuals are high school graduates. Slowly the sample changes to include more people with relatively high education (1984-1989). When we plot the coefficient on education against time we find the value of the coefficient drops during the 1982 recession.

In Figures 7 and 9 we demonstrate how taking into account the observable characteristics of our respondents changes the estimates of the hazard rates by quarter as shown in Figures 1 and 2. The estimates are calculated by assuming that the hazard rate, $\lambda(t, t^0, x(t))$, is equal to $\lambda_0(t) \cdot \omega(t - t^0, x(t); \hat{\beta})$, using the third specification of the hazard rate depending on the local unemployment rate. Given the estimates $\hat{\beta}$ we estimated $\lambda_0(t)$ using maximum likelihood techniques, by assuming that it is constant within quarters. If some of the regressors are strongly seasonal, in the sense that their distribution in the flow into nonemployment changes considerably over the year or the cycle, one might expect significant changes in Figures 7 and 9 compared to 1 and 2. There is some evidence of this, but not much. The shape of the hazard function is only slightly affected by the inclusion of the observable characteristics. Note that the scale changes, because the regressors do not have zero mean, but this has no interpretable consequences.

Figures 8 and 10 show how the systematic part of the hazard controlling for personal characteristics and duration dependence, $\omega(t - t^0, x(t); \hat{\beta})$, changes over time. In Figures 8 and 10 the solid line gives $\bar{\omega}(t)$, the average of $\omega(t-t^0, x(t); \hat{\beta})$:

$$\bar{\omega}(t) = \sum_{n \in R(t)} \omega(t-t^0, x_n(t); \hat{\beta}) \Big/ \sum_{n \in R(t)} 1$$

Multiplied with the estimate of the baseline hazard $\lambda_0(t)$ given in Figures 7 and 9 this is equal to the average hazard given in Figures 1 and 2. It is clear that the average systematic part of the hazard, $\bar{\omega}(t)$, changes over time for men but seems to follow a general downward trend for women. We can further decompose this time path by including in the average only those in the first week of their non–employment spells. Inspection of the timepath of this average shows that the quality of the inflow into non–employment did not substantially change over the business cycle. There is some seasonal variation in the characteristics of those entering non–employment, but nothing that could explain longterm changes in the unemployment rate.

In the end it is always possible that we left out a crucial characteristic of the nonemployed that would explain the cyclical and seasonal behavior. However, such unobserved characteristic would not only need to have a strong effect on hazard rates, it would also have to exhibit strong seasonal and cyclical behavior to explain Figures 7-10. Note as well, that in Tables 2 and 3 while the coefficients on our duration dependence terms drop when we include a wide range of characteristics the duration dependence terms remain strongly significant. If all the observed heterogeneity results in a relatively small decrease in duration dependence it is hard to imagine that there exists an unobserved variable that would totally eliminate this effect. Suppose, however, that there is such a variable that has a strong effect on the hazard rate and whose distribution in the inflow into unemployment varies considerably within a year. This implies that the hazard rates would depend upon the month nonemployment was entered, since that would be highly correlated with this unobserved variable. While we can specify the hazard rate to be a function of the date in which the spell was started, $t^0$, to capture any unobserved heterogeneity correlated with the time of entry, we do not think such an approach would be fruitful. It is clear that any hazard rate that can be written as a function of calendar time $t$ and duration $t - t^0$, can also be written as a function of duration $t - t^0$ and time of entry $t^0$. The effects of time of entry and calendar time are therefore not separately non-parametrically identified in the presence of duration dependence.

## 6. Summary.

In this paper we analyze the distributions of nonemployment spells. In particular, we investigate the seasonal and cyclical variation in these distributions. We find that there is considerable variation in the durations both over time and within a year. This variation cannot be explained by the covariates we measure. Unobserved heterogeneity seems an unlikely explanation as it would have to have a stronger effect than even all our included observable variables, as well as exhibit considerable seasonal and business cycle variation to account for our findings. Our main findings are, first, that policies targeted at specific demographic groups will change individuals' positions within the queue of job seekers but will not have much impact on overall re-employment probabilities. Second, scarring occurs if individuals experience long spells of non-employment but the damage is reduced if they are in an area of high unemployment. This implies that pure ranking models of unemployment appear to be rejected in case of young workers in the labor market. Finally, static models of re–employment probabilities that do not take into account business and seasonal cycle effects will ignore an important factor in the determination of the duration of a jobless spell.

Table 1: SAMPLE CHARACTERISTICS AT ENTRY

| Males, Total Sample Size is 2276 | | | | | | | |
|---|---|---|---|---|---|---|---|
| Variable | 1979 | 1980 | 1981 | 1982 | 1983 | 1984 | 1985 |
| Education | 11.0 | 11.6 | 12.0 | 12.5 | 12.8 | 13.3 | 14.3 |
| Age | 18.3 | 18.8 | 19.3 | 20.0 | 20.3 | 21.6 | 23.2 |
| Number of Observations | 417 | 388 | 322 | 369 | 330 | 265 | 185 |

| Females, Total Sample Size is 2682 | | | | | | | |
|---|---|---|---|---|---|---|---|
| Variable | 1979 | 1980 | 1981 | 1982 | 1983 | 1984 | 1985 |
| Education | 11.4 | 11.9 | 12.4 | 12.6 | 12.9 | 13.5 | 14.3 |
| Age | 18.5 | 18.8 | 19.4 | 19.8 | 20.4 | 21.7 | 22.9 |
| Number of Observations | 493 | 428 | 458 | 423 | 413 | 271 | 196 |

Table 2: PROPORTIONAL HAZARD ESTIMATES, MEN, ALL YEARS.

| 5661 Spells, 5285 Uncensored | | | | | | |
|---|---|---|---|---|---|---|
| Covariates | Coeff. | (s.e.) | Coeff. | (s.e.) | Coeff. | (s.e.) |
| Personal Characteristics | | | | | | |
| HISP (1 if Hispanic) | | | -0.101 | (0.041) | 0.021 | (0.039) |
| BLACK (1 if Black) | | | -0.263 | (0.035) | -0.294 | (0.034) |
| AGE (in years at start of spell) | | | -0.005 | (0.010) | -0.005 | (0.010) |
| EDUC (in years) | | | 0.090 | (0.010) | 0.085 | (0.010) |
| KIDHOM (number of children at home) | | | 0.036 | (0.062) | 0.040 | (0.062) |
| PARHOM (1 if living with parents) | | | -0.024 | (0.038) | -0.014 | (0.034) |
| MARSTA (1 if married) | | | 0.059 | (0.033) | 0.060 | (0.033) |
| UCOMP (1 if received unemploym benefits) | | | 0.164 | (0.045) | 0.173 | (0.046) |
| URBRUR (1 if living in urban area) | | | 0.066 | (0.035) | -0.018 | (0.034) |
| DISABL (1 if disabled) | | | -0.368 | (0.075) | -0.395 | (0.075) |
| GOVTRN (1 if received government training) | | | -0.024 | 0.085) | 0.052 | (0.083) |
| PRITRN (1 if received private training) | | | 0.150 | (0.052) | 0.120 | (0.051) |
| Previous Labor Market History | | | | | | |
| FIRSTSP (1 if first spell) | | | -0.662 | (0.064) | -0.651 | (0.065) |
| LAGDUR (length of prev spell) | | | -0.079 | (0.028) | -0.081 | (0.027) |
| AVDUR (av duration of all prev spells) | | | -0.156 | (0.033) | -0.140 | (0.032) |
| NUSPEL (number of prev spells) | | | 0.017 | (0.012) | 0.014 | (0.011) |
| Regional Differences | | | | | | |
| NORTH EAST | | | -0.091 | (0.046) | | |
| NORTH CENTRAL | | | -0.216 | (0.044) | | |
| SOUTH | | | 0.025 | (0.42) | | |
| LOCRAT (local unenmpl rate in percentage) | | | | | -0.071 | (0.011) |
| Duration Dependence | | | | | | |
| DUR (log (duration+1)) | -0.072 | (0.078) | 0.128 | (0.079) | 0.043 | (0.066) |
| DURDUR (square of log (dur+1)) | -0.091 | (0.011) | -0.093 | (0.012) | -0.076 | (0.012) |
| DURLOC (log (dur+1) × local unempl rate) | | | | | 0.014 | (0.004) |
| DURNAT (log (dur+1) × national unempl rate) | 0.031 | (0.007) | 0.018 | (0.008) | | |
| Log of Partial Likelihood | -29490.8 | | -29218.2 | | -29212.3 | |

Table 3: PROPORTIONAL HAZARD ESTIMATES, WOMEN, ALL YEARS.

| 6221 Spells, 5342 Uncensored | | | | | | |
|---|---|---|---|---|---|---|
| Covariates | Coeff. | (s.e.) | Coeff. | (s.e.) | Coeff. | (s.e.) |
| Personal Characteristics | | | | | | |
| HISP (1 if Hispanic) | | | −0.327 | (0.043) | −0.227 | (0.041) |
| BLACK (1 if Black) | | | −0.349 | (0.038) | −0.436 | (0.037) |
| AGE (in years at start of spell) | | | −0.012 | (0.009) | −0.011 | (0.009) |
| EDUC (in years) | | | 0.116 | (0.009) | 0.117 | (0.010) |
| KIDHOM (number of children at home) | | | -0.222 | (0.037) | −0.214 | (0.038) |
| PARHOM (1 if living with parents) | | | 0.053 | (0.032) | 0.065 | (0.032) |
| MARSTA (1 if married) | | | −0.063 | (0.025) | -0.076 | (0.024) |
| UCOMP (1 if received unemploym benefits) | | | 0.227 | (0.057) | 0.249 | (0.057) |
| URBRUR (1 if living in urban area) | | | 0.113 | (0.034) | 0.071 | (0.034) |
| DISABL (1 if disabled) | | | −0.205 | (0.058) | −0.206 | (0.058) |
| GOVTRN (1 if received government training) | | | 0.218 | (0.093) | 0.239 | (0.093) |
| PRITRN (1 if received private training) | | | 0.200 | (0.050) | 0.192 | (0.050) |
| Previous Labor Market History | | | | | | |
| FIRSTSP (1 if first spell) | | | −0.612 | (0.067) | −0.594 | (0.067) |
| LAGDUR (length of prev spell) | | | -0.051 | (0.028) | −0.049 | (0.028) |
| AVDUR (av duration of all prev spells) | | | −0.126 | (0.032) | −0.122 | (0.032) |
| NUSPEL (number of prev spells) | | | 0.024 | (0.013) | 0.025 | (0.013) |
| Regional Differences | | | | | | |
| NORTH EAST | | | −0.037 | (0.046) | | |
| NORTH CENTRAL | | | −0.207 | (0.044) | | |
| SOUTH | | | −0.059 | (0.040) | | |
| LOCRAT (local unenmpl rate in percentage) | | | | | −0.027 | (0.011) |
| Duration Dependence | | | | | | |
| DUR (log (duration +1)) | 0.076 | (0.074) | 0.138 | (0.075) | 0.082 | (0.061) |
| DURDUR (square of log (dur+1)) | −0.105 | (0.010) | -0.086 | (0.010) | −0.074 | (0.010) |
| DURLOC (log (dur+1) × local unempl rate) | | | | | -0.001 | (0.004) |
| DURNAT (log (dur+1) × national unempl rate) | 0.007 | (0.007) | -0.001 | (0.007) | | |
| Log of Partial Likelihood | -32469.8 | | -32062.1 | | -32047.3 | |

Fig 1: Weekly Hazard Rate (Men)

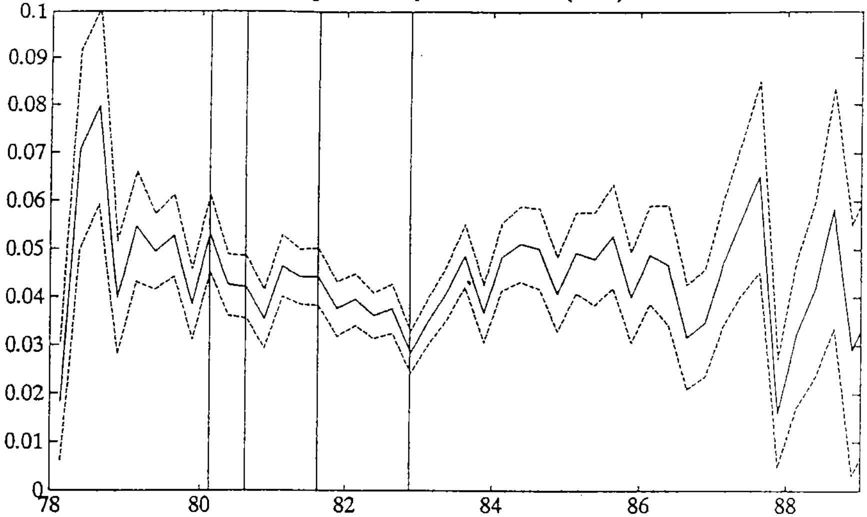



Fig 2: Weekly Hazard Rate (Women)

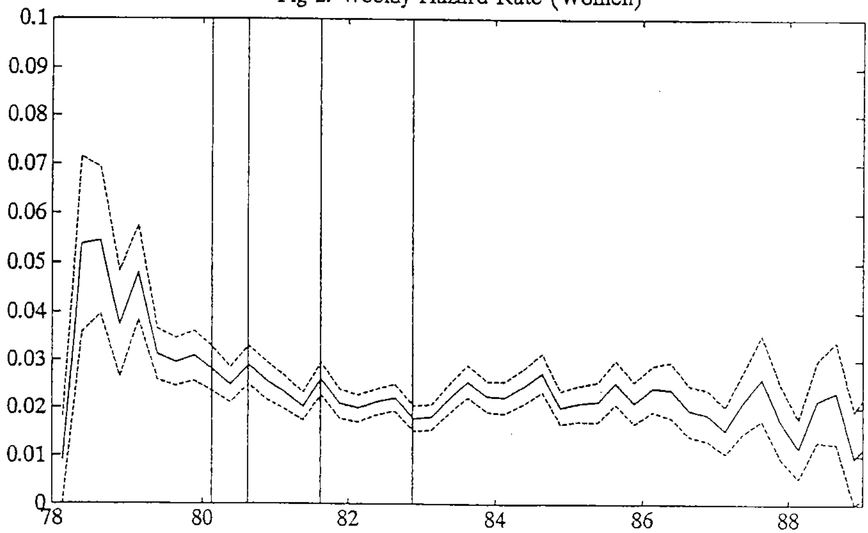


Fig 3: Quartiles of Duration Distribution by Year (Men)

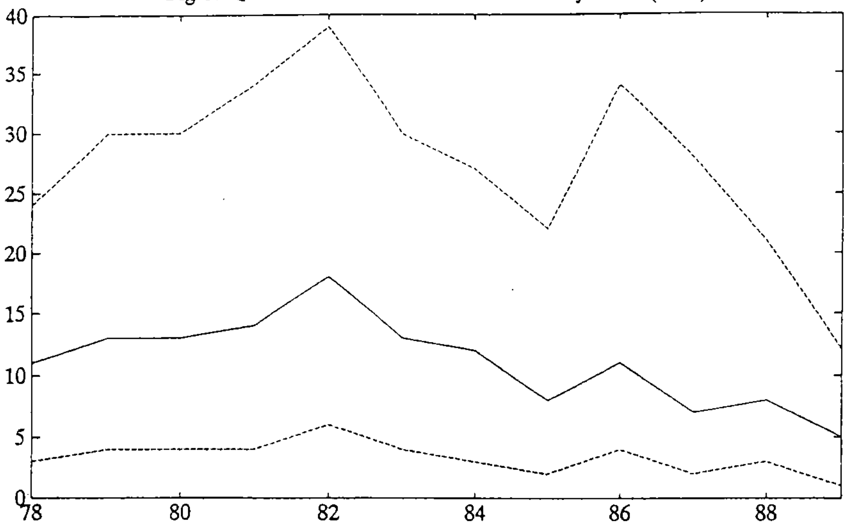



Fig 4: Quartiles of Duration Distribution by Year (Women)

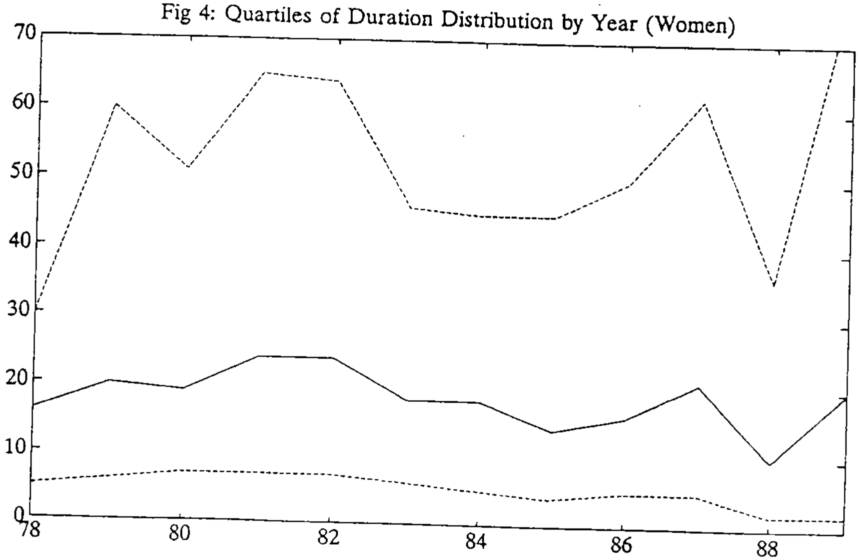


Fig 5: Hazard Rate as a Function of Duration (Men)

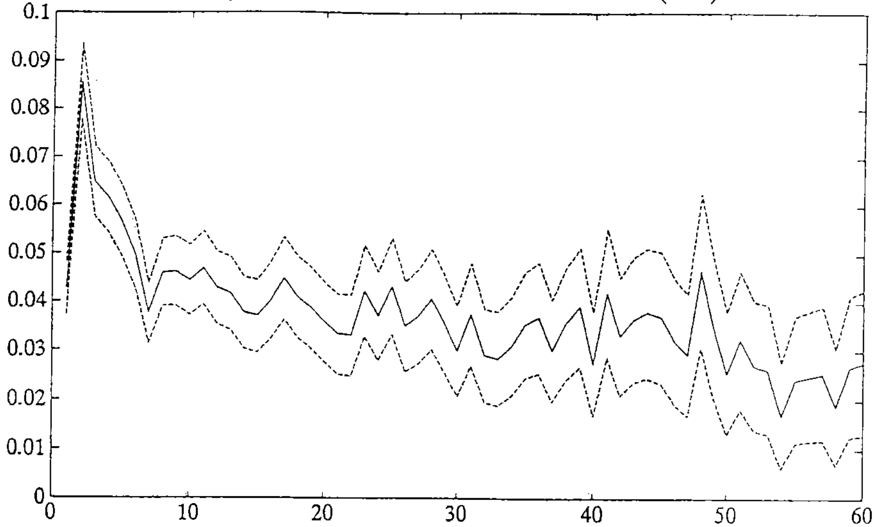



Fig 6: Hazard Rate as a Function of Duration (Women)

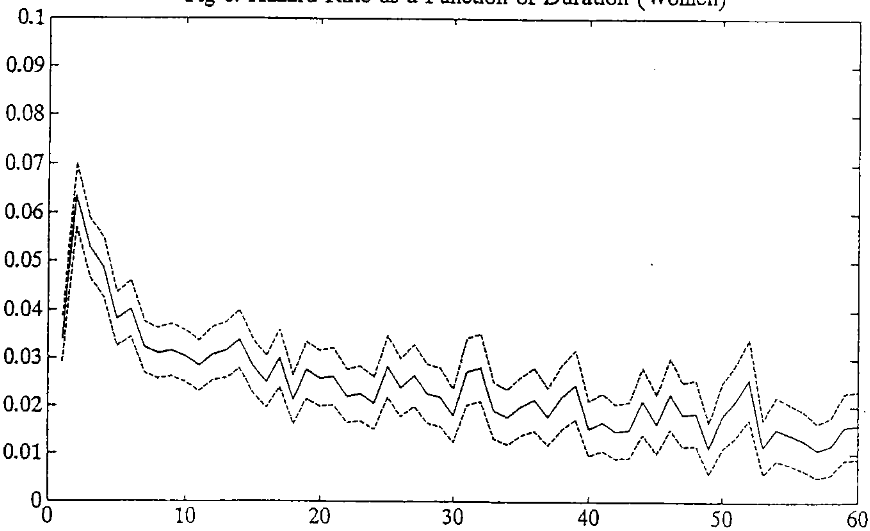


Fig 7: Weekly Hazard Rate Controlling for Regressors (Men)

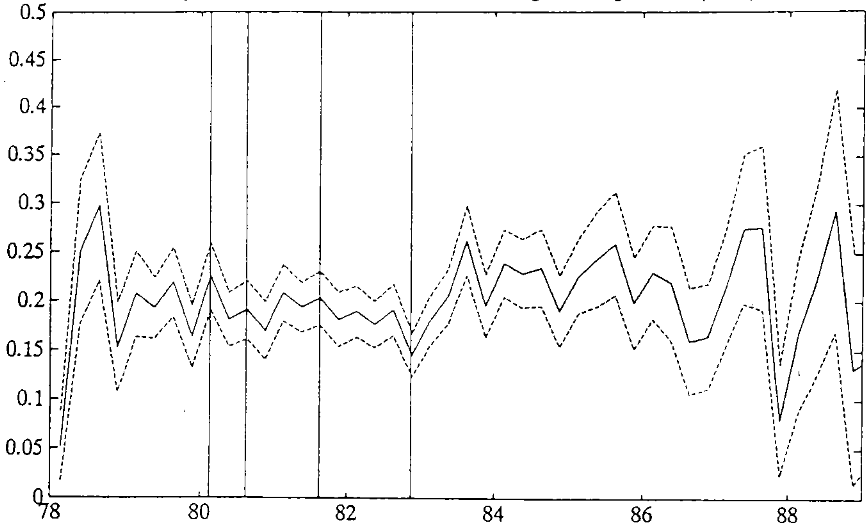



Fig 8: Systematic Part of the Hazard Function (Men)

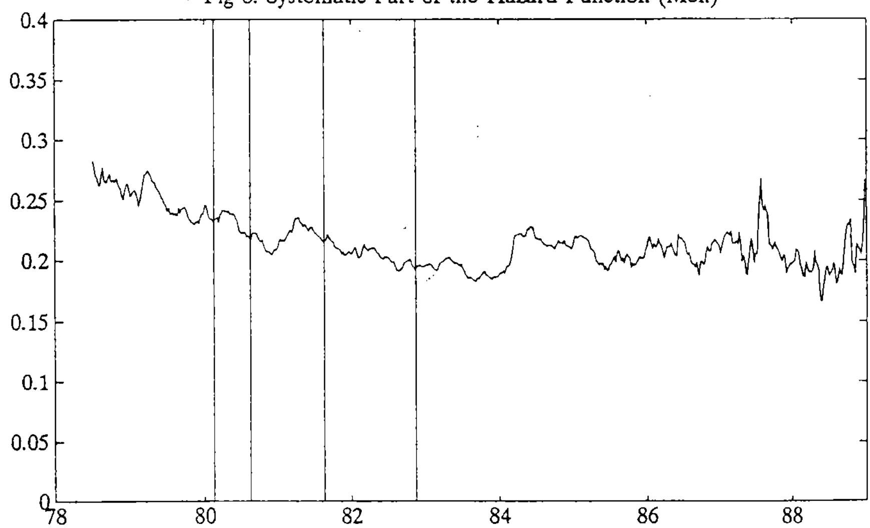


Fig 9: Weekly Hazard Rate Controlling for Regressors (Women)

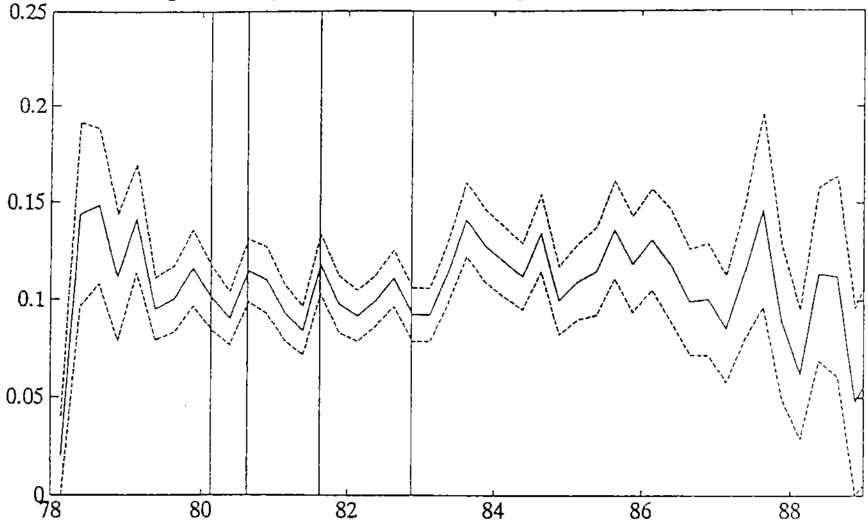
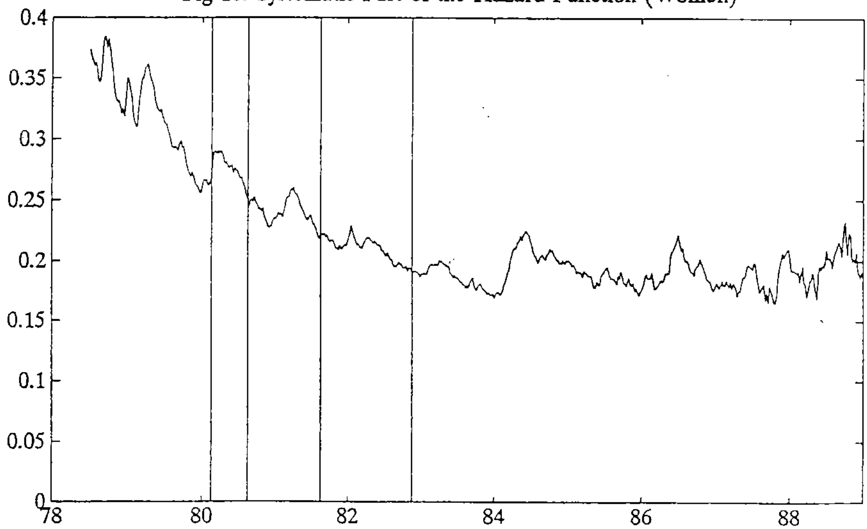



Fig 10: Systematic Part of the Hazard Function (Women)



# Appendix

Fig A1: Quartiles of Duration Distribution by Month (Men)

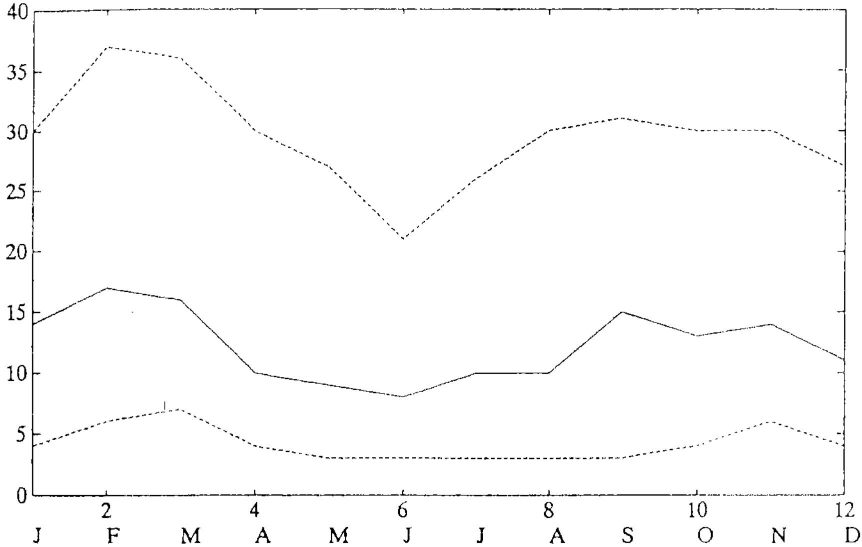



Fig A2: Quartiles of Duration Distribution by Month (Women)

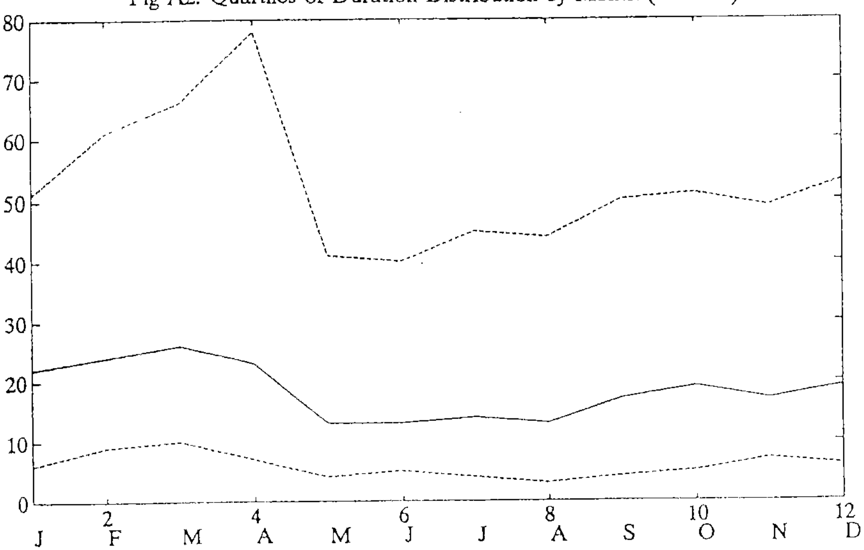


Fig A3: Hazard Rate with Local Unempl. Rate 5 and 15 Percent (Men)

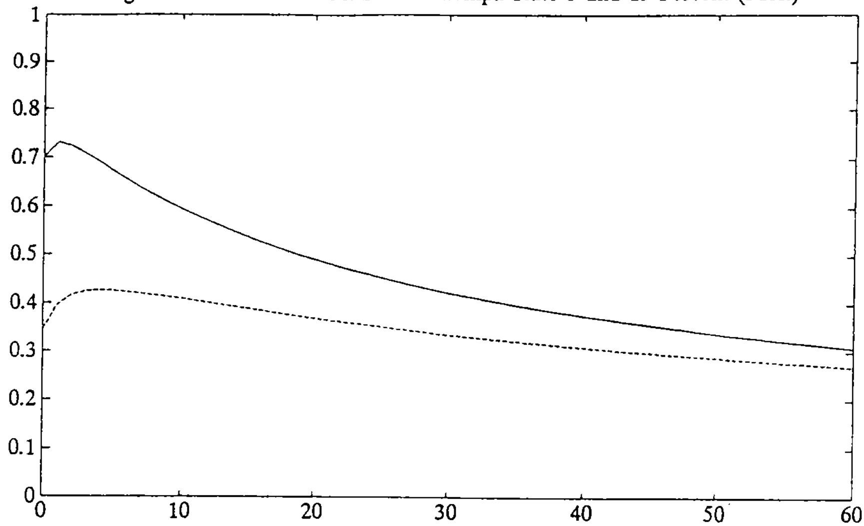
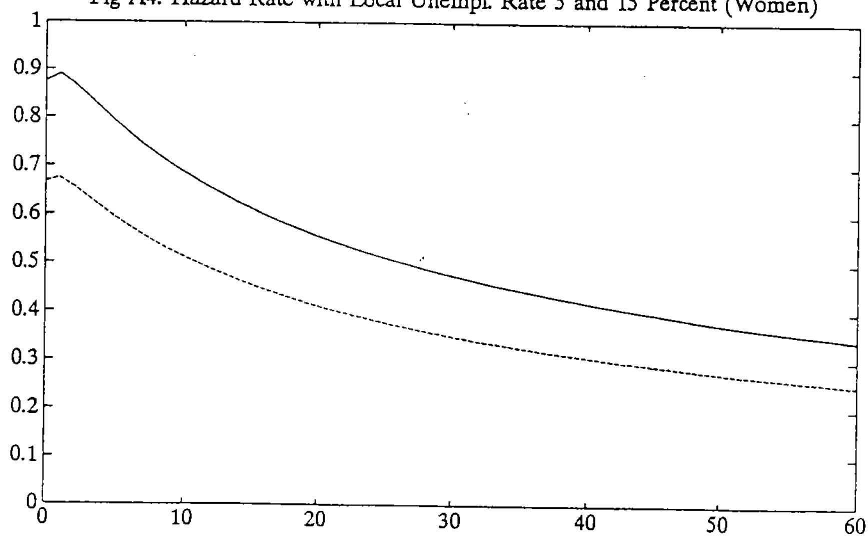



Fig A4: Hazard Rate with Local Unempl. Rate 5 and 15 Percent (Women)



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