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Re-employment probabilities over the business cycle

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Abstract Using a Cox proportional hazard model that allows for a flexible time dependence in order to incorporate business cycle effects, we analyze the determinants of re-employment probabilities of young workers in the USA from 1978–1989. We find considerable changes in the chances of young workers finding jobs over the business cycle despite the fact that personal 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 may only have a more limited impact on average re-employment probabilities. Living in an area with high local unemployment reduces re-employment chances as does being in a long spell of non-employment. However, the damage associated with being in a long spell seems to be reduced somewhat if a worker is unemployed in an area with high overall unemployment.

Keywords Unemployment · Duration dependence · Business cycle

JEL Classification E24 · E32 · J2 · J6

1 Introduction and background discussion

Much of the debate on the relationship between the length of unemployment spells and the business cycle can be summarized by two distinct empirical research strategies. Macro-economists have explored how changes in employment and

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unemployment durations over time affect changes in the aggregate unemployment rate. The issue, as discussed by Mortenson and Pissarides (1994), is whether changes over time in the aggregate unemployment rate are driven my changes in the rate at which jobs end or are destroyed (the separation rate) or by changes in the average duration of unemployment spells (the outflow of job-finding rate). Blanchard and Diamond (1990) using the gross flow data from the US Current Population Survey, CPS, find 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. They conclude that for the USA, variation in incidence is relatively more important in explaining fluctuations in the unemployment rate than variations in duration. Davis et al. (1996), using gross flows data from US manufacturing establishments, conclude that job destruction rises sharply in a recession while job creation declines by a modest amount. All these studies suggest that recessions are characterized by high separation rates, or are countercyclical, while the job-finding rate is acyclical. More recently, Shimer (2005) argues just the opposite; that the job-finding rate for the unemployed is strongly procyclical whereas the separation rate is acyclical.

In all of this work, relatively little is or can be done to control for changing characteristics of the unemployed over the business cycle. If the characteristics of the inflow into unemployment change over the cycle, one could confound pure business cycle effects with demographic effects. An early paper that tried to incorporate limited demographic effects using the CPS and a synthetic-cohort estimation framework is Baker (1992). He examined the relationship between the expected duration of unemployment and the unemployment rate. He reported separate elasticities for various demographic groups but he was not able to control for demographic characteristics simultaneously. Therefore, empirical work that combines 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.

Micro economists have pursued an alternative strategy and focused on estimating the determinants of the length of an individual's spell of joblessness or unemployment using detailed spell data from administrative records or longitudinal surveys. Researchers model the instantaneous probability of finding a job, the hazard rate, given a person's characteristics and the length of the current spell of unemployment. Since these micro-based studies usually have data on single spells of unemployment that cover a limited period, they are unable to explore how aggregate changes in the economy affect re-employment probabilities. At best, controls for region or the current local unemployment rate are included to capture local demand conditions (see Van den Berg 2001 for a recent review of this literature).

The underlying theoretical model of most of these micro-based studies is job search theory (see Pissarides 2000 for a recent review of this literature). In the simplest job search model when a worker becomes unemployed, his/her re-employment probability will depend upon two probabilities—the probability of receiving a job offer and the probability of then accepting this offer. The probability of receiving a job offer will be determined by factors such as education, post-school training, and demand conditions. The probability that an individual will then accept this job offer will be determined by his/her reservation wage. Factors that may influence the reservation 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.

Empirical work on US data by Lynch (1989) using local unemployment rates, and Dynarski and Sheffrin (1990) using the national unemployment rate, 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. Unfortunately, all of these studies examine relatively few years of data. Nevertheless, there does seem to be some ambiguity in the micro-empirical findings on the relationship between the business cycle and the duration of unemployment. It is important to note that the business cycle cannot be adequately controlled for by simply including dummy variables for the month in which workers lose their jobs. Since it is the economic conditions when searching for a job, not the conditions when one lost a job, that affect re-employment probabilities at an point during a spell, empirical work needs to allow for these types of time varying calendar effects.

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 be due to employers using the spell length as a proxy for some unobserved characteristics and not hiring workers with long spells of joblessness. It might also represent workers becoming more discouraged over time and a decrease in their search intensity. Finally, negative duration dependence could simply reflect unobservable heterogeneity. Sorting out "true" from "spurious" negative duration dependence has proven to be problematic without resorting to nonparametric methods.

Although it is difficult to identify the "true" nature of negative duration dependence, one can use the interaction of the local unemployment rate with the duration of a non-employment spell to try 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, Blanchard and Diamond theorize that an increasing proportion of the unemployed are those with the least skills. If this were the case, employers would use the length of a current spell of unemployment as a way to rank applicants for a position. Consequently, as local labor market conditions worsen, those with longer spells of unemployment would have more difficulty in finding employment. If instead, as the local unemployment rate 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. Without time series data that include detailed information on the characteristics of the unemployed, it is difficult to distinguish between these two explanations of unemployment.

Neither the macro-based nor the micro-based empirical strategies on their own can provide a complete answer on how re-employment probabilities vary over the business cycle. Specifically, it is possible that at the individual level re-employment probabilities are relatively constant over time, while changes in the composition of those who become unemployed over the business cycle lead to substantial 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 might be confounded if the analysis has not adequately controlled for changes in aggregate conditions. Specifically, it may appear that a particular characteristic reduces re-employment probabilities when in fact individuals with that characteristic are just more likely to lose their jobs during period of low average re-employment probabilities.

The distinction between the impacts of individual characteristics versus macroeconomic demand conditions to explain fluctuations in the unemployment experience has important 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 macroeconomic conditions are the main source of variation, such policies are likely to have a limited impact on overall unemployment. 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 by utilizing multiple spell data from a detailed longitudinal survey of individuals.

We focus on the determinants of the duration of non-employment spells of young workers using data from the National Longitudinal Survey of Youth 1979, NLSY79. We construct a sample of approximately 5,000 men and women who have just entered the labor market and observe them through two complete business cycles from 1978 to 1989. To analyze the determinants of the duration of non-employment spells for youths we use a Cox regression, or proportional hazard model (see Cox 1972) that allows for a flexible time dependence that can incorporate both seasonal and business cycle effects.

We examine the experience of youths for a variety of reasons. First, the share of total unemployment during this period that was represented by youths aged 16–24 was quite large in the USA. For example, Blank and Card (1991) show that in 1977 youths represented 46% of all those unemployed. There are several other reasons to focus on the determinants of the duration of unemployment or non-employment for youths. For example, an early spell of joblessness (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 addition, the early years of employment represent an important period for human capital development. Since most post school training in the USA, especially for non-college graduates, is acquired informally on-the-job, early spells of non-work may reduce human capital accumulation.

We find a large impact of the business cycle and seasonal effects within the year on the chances of young workers finding jobs over time. 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 the period 1978–1989. We also find evidence of negative duration dependence. This means that the longer an individual is not working the chances of their finding a job decline in a given period. Individuals living in areas with high unemployment, or who find themselves out of work 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 non-employment 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 The data

This study uses data from the National Longitudinal Survey Youth Cohort 1979, NLSY79. The NLSY79 originally consisted of 12,686 males and females who were 14 to 21 years of age at the end of 1978. These youths were first interviewed in 1979 and have been interviewed every year until 1994 about their education, jobs, military service, family characteristics, training, health and attitudes. Since 1994 they have been interviewed on a biennial basis. In 1985, 1,079 military respondents were dropped from the survey so we have excluded the military sub sample from our analysis. We have also restricted our sample to those youth who we observe finishing school and then not returning to school for five years. This allows us to observe the complete first five years of labor market experience for young people who have "permanently" left school. We use data from the NLSY79 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 that merges seven waves of "school leavers." Our sample pools 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.[1] This pooling means that jobless spells in a year such as 1984 could include respondents who entered the labor market in 1981, 1982, 1983, and 1984. While the decision to leave school is clearly endogenous, this selection rule gives us a sample of youths who are more permanently attached to the labor market. It is also 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.

[1] 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 of time than for later school leavers.

Table 1 presents some basic characteristics of our sample at the entry date into the labor market. Given the age structure of the NLSY79, 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 smaller than in any of the earlier years, again reflecting the age structure of the original NLSY79 cohort. This is also why we are not able to extend our analysis to the recession in the early 1990s because our sample size gets too small.

Besides detailed longitudinal information on individual characteristics, the NLSY79 had 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 NLSY79, spells of non-employment are not easily separable into spells of unemployment and out of the labor force but not in school. Therefore, the following analysis of re-employment probabilities focuses on the transition from non-employment to employment rather than unemployment to employment. The distinction between these two states is likely to be quite small, especially for males (see Flinn and Heckman 1982).

3 Cyclical effects in non-employment durations

Before estimating any models of non-employment 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 the non-employed in a given week who find a job in that week. This is an estimate of the hazard rate from non-employment to employment in that week. Since we have weekly data from January 1978 until 1989, the number of weeks is large relative to the number of observations. As a result, we smooth this hazard rate by estimating a constant hazard within each quarter.

Figures 1 and 2 present 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

Table 1 Sample characteristics at entry

Characteristics of the sample							
		Males, total sample size is 2,276					
Year of entry	1979	1980	1981	1982	1983	1984	1985
Mean education	11.0	11.6	12.0	12.5	12.8	13.3	14.3
Mean age	18.3	18.8	19.3	20.0	20.3	21.6	23.2
Number of obs.	417	388	322	369	330	265	185
		Females, total sample size is 2,682					
Year of entry	1979	1980	1981	1982	1983	1984	1985
Mean education	11.4	11.9	12.4	12.6	12.9	13.5	14.3
Mean age	18.5	18.8	19.4	19.8	20.4	21.7	22.9
Number of obs.	493	428	458	423	413	271	196

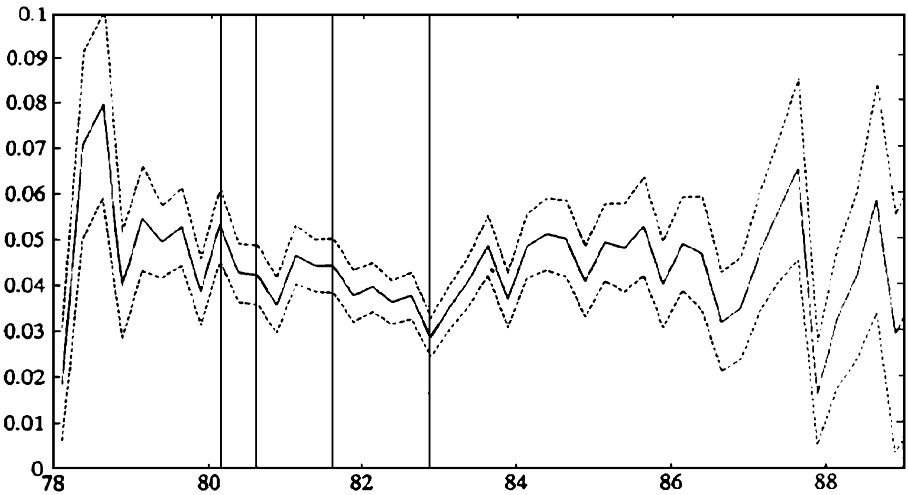

Fig. 1 Weekly hazard rate (men)

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 1980s with the hazard for young men dropping from over 5% in 1980 to about 3% at the end of 1982. Within years, the seasonal variation is smaller with the exception of 1987–89 where we have far fewer observations and the quality of our data in 1987 may be affected by a telephone interview rather than personal interview. 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 studies in terms of hazard functions.

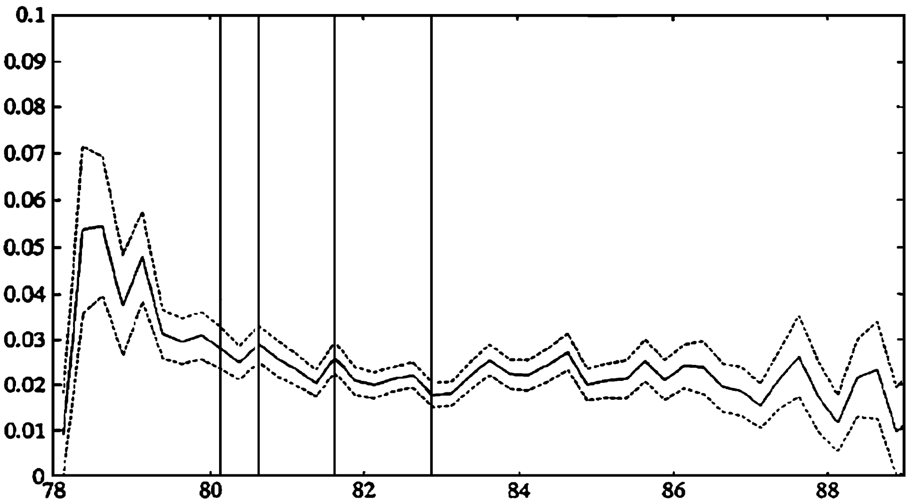

Fig. 2 Weekly hazard rate (women)

Nevertheless, there is another way of looking at these calendar effects that highlights even more the importance of the apparent cyclical and seasonal variation found in Figs. 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 quartiles allows for censored spells, and leads to more robust inference than looking at means that are very sensitive to censoring and tail behavior. In Figs. 3 and 4, we plot the quartiles of the distribution of the spells by year from 1978 to 1989. The differences by year are more pronounced than they are for the hazard rates. Ignoring 1989, for which we do not have many spells, the median duration of the non-employment spells for males reaches a low of about 7 weeks in 1987 and a high of 18 in the recession year of 1982. The comparable numbers for young females are 12 and 22 weeks. Not only does the median length of non-employment change over time but also the skewness varies over the cycle.

Barsky and Miron (1989) argue that we should consider the seasonal pattern of various macroeconomic variables as well as the behavior of these variables over the business cycle. Therefore, we also ordered the spells of non-employment by the month in which the spell was started. We find that the median duration for young men varies from 8 weeks in June to 17 weeks in February. [2] For women the median reaches a low of 13 weeks in May and a high in March of 26 weeks. The other quartiles tell a similar story.

Therefore, 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 non-employment because 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 drops by a small amount and then picks up again in the next quarter, it might be too late for people who did not find a job because of this drop if they have been "scarred" due to the length of their jobless spell. Another explanation is heterogeneity amongst individuals that appears as duration dependence. We therefore pay close attention to evidence of duration dependence and try to control for heterogeneity. We also see in Figs. 3 and 4 that the duration of non-employment for men during the 1982 recession at first increases (although it remains constant for women) and then falls for both men and women during the latter part of the recession. This suggests that during a long recession duration dependence may be less negative than in periods of economic expansion.

Figures 5 and 6 present 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 ith week of their non-employment spell to the number of people who have spells or 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% for men and more than 6% for women. After this peak, the hazard rate for men drops to a level of about 4% at 8–10 weeks. The hazard then continues to gradually decline until it reaches about 2% after a year of joblessness. While there is a lot of noise in the estimates, plotting confidence

[2] Plots of the quartiles are available from the authors on request.

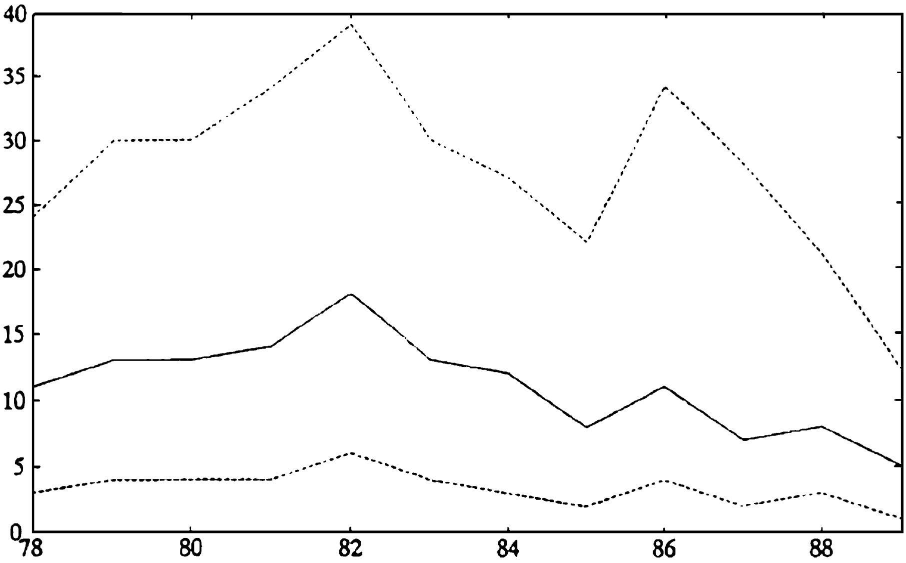

Fig. 3 Quartiles of duration distribution by year (men)

intervals around the estimates suggests that a steadily declining hazard 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 non-employed young men find a job within ten weeks. On the other hand, 20% are still not working after forty weeks. For young women the shape is very similar but the scale is different. The hazard drops after the

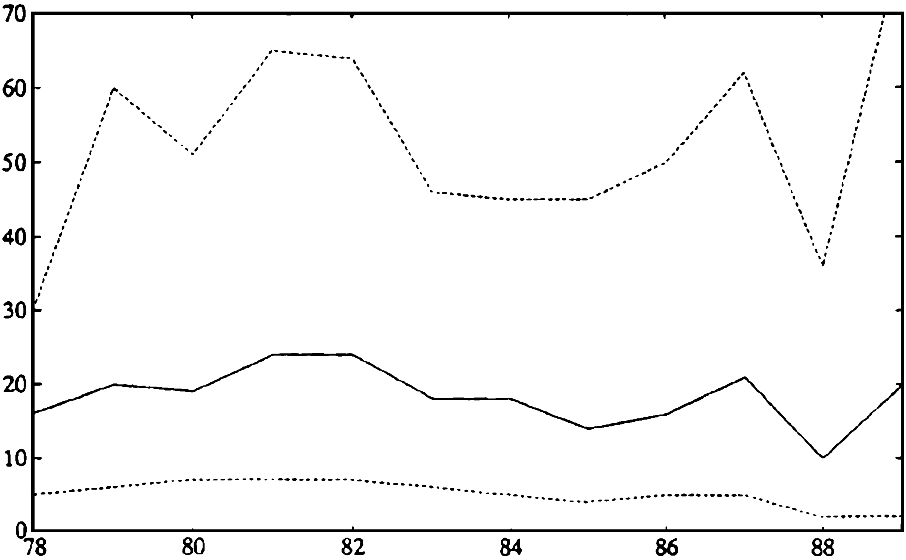

Fig. 4 Quartiles of duration distribution by year (women)

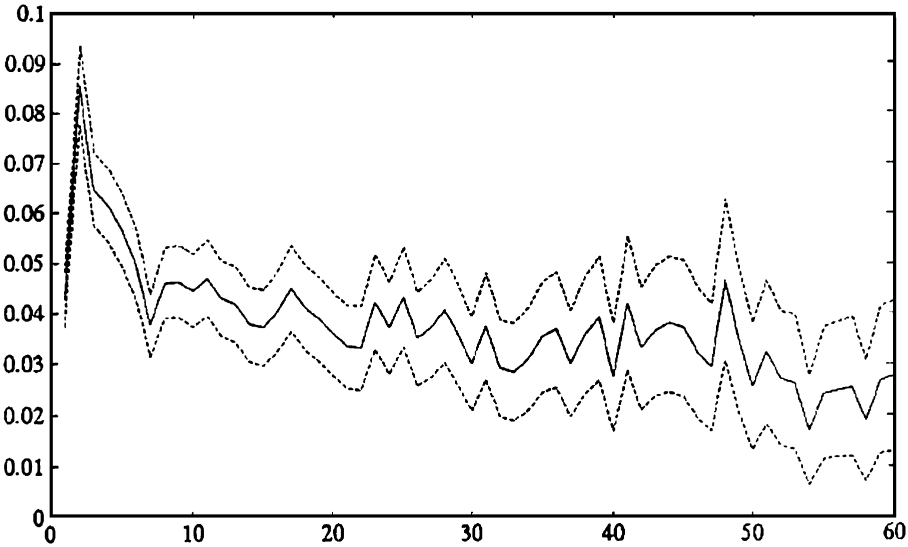

Fig. 5 Hazard rate as a function of duration (men)

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 suggest that there is considerable negative duration dependence: once someone has been out of work 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 over the business

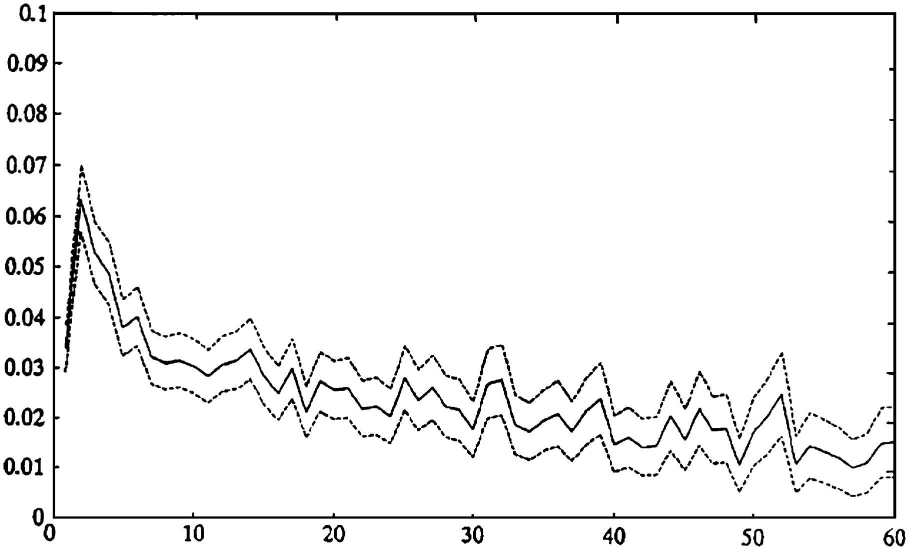

Fig. 6 Hazard rate as a function of duration (women)

cycle can and do, as shown in Figs. 3 and 4, lead to large changes in the median duration of non-employment spells. Similar results hold for changes within years.

Another interesting feature of Figs. 5 and 6 is that we do not find spikes around 25–29 weeks and 35–39 weeks that were found in earlier studies 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 see similar spikes is because our sample is drawn from the early years of work in the NLSY79. Most young people are unlikely to have worked long enough to become eligible for unemployment insurance. 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 non-employment over calendar time. There are a number of factors that could explain the cyclical behavior of the hazard rate found in Figs. 1 and 2. We know that given the way we have created our data set the characteristics at entry into the labor market are changing over time. In addition, due to the timing of the academic calendar, more of those seeking work in the second or third quarter of the year could be those with relatively high education. If a high level of education were associated with good chances of finding a job, i.e. a high hazard rate, one would expect to see higher hazard rates in the second or third quarter when graduates enter the labor market. It is critical, therefore, to control for the changing characteristics of the jobless to see how much of the variation in the hazard rate seen in Figs. 1 and 2 can be explained by personal characteristics rather than by changes in the calendar time.

4 Empirical framework: the proportional hazard model

We now estimate 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 and are just driven by changes in the composition of the pool of those out of work. Second, it allows us to determine whether taking account of calendar time alters conclusions reached in the literature concerning the dependence of the hazard rate on the duration of non-employment and individual characteristics. We accomplish this by comparing parameter estimates with those found in a specification that does not allow for flexible calendar time dependence. Third, we determine whether duration dependence varies according to the tightness of the labor market. If it does vary, we examine the direction of this variation to attempt to distinguish between ranking and signaling models of unemployment.

To pursue these goals we utilize duration models that allow for a more flexible time dependence that the models that are typically estimated. Specifically we use models developed in Imbens (1994) that do not restrict the time dependence other than by requiring it to be proportional to the systematic part of the hazard function. To formalize this, consider an individual at time t who has been unemployed since t^0, with characteristics at time t, $\chi(t)$. These characteristics may contain variables reflecting local labor market conditions, as well as personal characteristics such as education, age, marital status, number of children, etc... Let t^1 denote the date of re-employment. The hazard rate gives the probability of finding a job conditional on the individual's characteristics, and their history, $\{\chi(S)_{s\leq t}\}$, and given the time t that he or she is out of work. Formally the hazard rate λ, for $t>t^0$, is:

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

We assume that the only way in which the hazard depends on the history of the time-varying regressors is via the contemporaneous value $\chi(t)$. Thus, $\lambda=\lambda(t, t^0, \chi(t))$.

Economic applications of duration models have employed various specifications of the hazard rate $(t, t^0, \chi(t))$. Lancaster (1979) in an early example uses a Weibull form:

$$\lambda\left(t, t^0, \chi(t)\right) = \left(t - t^0\right)^{\alpha} \cdot exp\left(\beta_o + \beta'_1\chi(t)\right). \tag{2}$$

Where $(t-t^0)$ is the duration of the current spell and χ is a vector of individual characteristics that may vary with time. The generalizations of this model that have been estimated can be divided into two types. First, the restriction of a monotone duration dependence can be relaxed by using the Cox proportional hazards model:

$$\lambda\left(t, t^0, \chi(t)\right) = \lambda_0\left(t - t^0\right) \cdot exp\left(\beta'\chi(t)\right). \tag{3}$$

In this specification, the functional form of the baseline hazard $\lambda_0(t)$ need not be known for consistent estimation of the parameters of the systematic part of the hazard, β.

A substantial literature in econometrics going back to Lancaster (1979), Elbers and Ridder (1982), Heckman and Singer (1984), Honore (1990) and Meyer (1990) has considered alternative generalizations of this simple Weibull model by allowing for unobserved heterogeneity sometimes in combination with the previous generalization of the duration dependence. In this literature, it is assumed that conditional on some unknown individual specific factor ν, the hazard rate is:

$$\lambda\left(t, t^0, \chi(t)\right) = \left(t - t^0\right)^{\alpha} \cdot exp\left(\beta_o + \beta'_1\chi(t) + \nu\right). \tag{4}$$

Because ν is not known, it has to be integrated out in order to evaluate the likelihood function. Lancaster (1979) considered estimation assuming a gamma distribution for the unobserved heterogeneity factors ν. Later, Heckman and Singer (1984), Honore (1990), Meyer (1990), Ridder (1990), Van den Berg and Van Ours (1996), and others have investigated estimation procedures that do not require specification of the distribution of the heterogeneity factor.

In a Monte Carlo study Ridder and Verbakel (1983) show that while neglecting this unobserved component can significantly affect estimates of the duration dependence, there is typically little impact on estimates of the parameters of the regressors if the model allows for flexible duration dependence. As we do not allow for unobserved heterogeneity, we will be cautious in interpreting estimates of the duration dependence. However, one of the advantages of using the NLSY79 is that we are able to include a wealth of indicators for previous labor market experience such as length and number of previous spells of non-employment spells. This will capture some of the unobserved heterogeneity found in other studies that do not have as detailed information on the characteristics of the respondents.

We extend the general specification of the hazard rate given in Eq. (3). Instead of using the partial likelihood argument advanced originally by Cox (1972) to remove the duration dependence, we partial out the (calendar) time dependence. This implies that we allow for the very general time dependence observed in Figs. 1, 2, 3, and 4, while at the same time controlling for observed differences between individuals:

$$\lambda\left(t, t^0, \chi(t)\right) = \lambda_0(t) \cdot w\left(t - t^0, \chi(t); \beta\right). \tag{5}$$

We present estimates from the traditional Cox regression model given in Eq. (3) that allow for flexible duration dependence, but we go on to present three specification of Eq. (5) that incorporate calendar time dependence effects. In the first specification the hazard depends only upon the log of duration plus one of the spell, the log duration plus one squared, and the interaction of the duration and the national (monthly) unemployment rate:

$$\begin{aligned}\lambda(t, t^0, \chi(t)) = {} & \lambda_0(t) \cdot exp[\beta_0 \cdot ln(t - t^0 + 1) + \beta_1 \cdot ln^2(t - t^0 + 1) \\ & + \beta_2 \cdot ln(t - t^0 + 1) \cdot nu(t)].\end{aligned} \tag{6}$$

In the second specification, we add individual characteristics to Eq. (6):

$$\begin{aligned}\lambda(t, t^0, \chi(t)) = {} & \lambda_0(t) \cdot exp[\beta_0 \cdot ln(t - t^0 + 1) + \beta_1 \cdot ln^2(t - t^0 + 1) \\ & + \beta_2 \cdot ln(t - t^0 + 1) \cdot nu(t) + \beta_3^{'}\chi_0(t) + \beta_4^{'}d(t)].\end{aligned} \tag{7}$$

In Eq. (7) $\chi_0(t)$ is a vector of time-varying personal characteristics such as years of education, marital status, and number of children. The term $d(t)$ is a vector of dummy variables indicating the census region (North East, North Central, South and West) the individual is living in. The term nu(t) is the monthly national unemployment rate. We still allow the dependence of the hazard rate on calendar time to be very flexible, but we assume that it is proportional to the remainder of the hazard rate. We again 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 the business cycle and the 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 of this paper, 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 Figs. 1, 2, 5, and 6 we would need a much higher order polynomial to even begin to come close to capturing the calendar time effects, while the duration dependence follows a simple pattern of initially rising and then declining hazard rates.

In the third specification, Eq. (8), we let the systematic part of the hazard function depend on personal characteristics, duration and the local unemployment rate.

$$\lambda(t, t^0, \chi(t)) = \lambda_0(t) \cdot exp[\beta_0' \chi_0(t) + \beta_1 \cdot lu(t) + \beta_2 \cdot ln(t - t^0 + 1) \\ + \beta_3 \cdot ln^2(t - t^0 + 1) + \beta_4 \cdot ln(t - t^0 + 1) \cdot lu(t)]. \tag{8}$$

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 unemployment 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 good at capturing dynamic aspects of the labor market as the monthly national unemployment rate since it only changes yearly in our data set.

Although we use multiple spell data, 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 nth 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 and t_n^1 is the end of the observation period for that spell. If the spell ends with a job, the censoring indictor is equal to one. The full likelihood function for a set of N spells can then be written as:

$$\mathcal{L}(\beta) = \prod_{n=1}^{N} [\lambda_0(t_n) \cdot \omega(t - t_n^0, \chi_n(t); \beta)]^{c_n} \\ \cdot exp\left[- \int_{t_n^0}^{t_n^1} \lambda_0(s) \cdot \omega(s - t_n^0, \chi_n(s); \beta) ds \right]. \tag{9}$$

We estimate the parameters of this model using the Cox partial likelihood estimator (see 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 fuller detail in Imbens (1994). The estimator is based on comparing different individuals who are unemployed at the same calendar time. Assume the 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:

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

$R(t)$ can also be thought of as the set of individuals not employed at t. 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 rate 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 therefore the computational time increases substantially.

Formally, let $\iota(t)$ be the index of the spell that 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:

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

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

$$Pr(\iota(t) = n) = \frac{\lambda_0(t) \cdot \omega(t - t_n^0, \chi_n(t); \beta)}{\sum_{m \in R(t)} \lambda_0(t) \cdot \omega(t - t_m^0, \chi_m(t); \beta)} = \frac{\omega(t - t_n^0, \chi_n(t); \beta)}{\sum_{m \in R(t)} \omega(t - t_m^0, \chi_m(t); \beta}.$$

In this fashion we construct the partial likelihood 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]

5 Empirical results

Table 2 presents results from a standard Cox proportional hazards model as outlined by Eq. (3). In this and all subsequent tables, positive coefficients imply that an increase in the regressor is associated with an increase in the hazard rate and, consequently, with a decrease in the duration of non-employment. 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 non-employment. The number of children living at home has a strong negative effect on the chances of finding a job for women, but no impact on the re-employment probabilities for men. Living in the parental home has no effect on the re-employment probabilities for men or women while being married decreases the chances of finding a job for women. Interestingly, receiving unemployment compensation has a positive effect on the chances of *returning* to work for both men and women. This may be picking up greater attachment to the labor market for these relatively young workers since eligibility requirements for unemployment insurance in the USA require substantial labor market experience.[4] While some

[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. Since we have around 6,000 spells the optimization routines take a very long time. However, as suggested to us by Bruce Meyer, this may be reduced by averaging over a sample from the risk set, rather than averaging over the entire risk set.

[4] Therefore one might interpret the receipt of unemployment benefit as another measure of previous labor market experience that picks up whether or not the most recent employment spell was long enough to make the individual eligible for unemployment insurance.

Table 2 Cox proportional hazard estimates: men and women, 1978–1989

Covariates	Coeff. (s.e.) Males	Coeff. (s.e.) Females
	Personal characteristics	
Hispanic (1 if Hispanic)	0.025 (0.390)	−0.202 (0.041)
Black (1 if Black)	−0.294 (0.033)	−0.411 (0.035)
Age (at start of spell)	0.006 (0.008)	−0.002 (0.008)
Education (in years)	0.088 (0.009)	0.116 (0.009)
Number of children at home	0.059 (0.066)	−0.190 (0.039)
Live at home with parents	−0.022 (0.034)	0.037 (0.033)
Marital status (1 if married)	0.039 (0.034)	−0.098 (0.029)
Received unemployment benefits	0.085 (0.049)	0.210 (0.064)
Urban (1 if living in urban area)	−0.023 (0.034)	0.034 (0.034)
Disability status (1 if disabled)	−0.408 (0.074)	−0.097 (0.057)
Received government training	0.057 (0.096)	−0.052 (0.120)
Received private sector training	0.105 (0.055)	0.171 (0.057)
	Previous labor market history	
Is this the first spell (Yes=1)	−0.646 (0.063)	−0.584 (0.066)
Length of previous spell	−0.087 (0.027)	−0.049 (0.029)
Average duration of all previous spells	−0.129 (0.031)	−0.117 (0.034)
Number of previous spells	0.016 (0.011)	0.025 (0.013)
	Regional differences	
Local unemployment rate	−0.031 (0.004)	−0.026 (0.004)
Log of Partial Likelihood	−40528.957	−41959.977
Number of spells	5661	6221

states in the USA have experimented with re-employment bonuses to provide incentives to return to work this was not a factor in our sample. Participating in government training programs had no impact on re-employment probabilities, but having acquired some private sector training in the past did increase the chances of finding employment for both males and females. This suggests that some private sector training is general and portable (see Lynch 1991, 1992 and 1994 for more discussion on this). Finally, the dummy variable for disability has the expected sign. 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 as presented in Lynch (1989) using the early years of the NLSY79.

It should be noted that there is a potential endogeneity problem with all of the variables discussed so far. Therefore, for all time-varying regressors, we took the value of the regressor in the year preceding the year in which the current spell of non-employment took place. For example, if we are looking at a spell of non-employment 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 one source of private sector training) is equal to one during a particular spell of non-employment, it means that the individual received on-the-job training in the previous year. This strategy of using pre-determined values of the explanatory variables also helps address the endogeneity problem that can occur with the family status variables.

To capture heterogeneity and lagged duration dependence not accounted for by personal characteristics we included a number of regressors that depend upon previous non-employment experience. First, we included a dummy variable indicating whether the current spell is the first non-employment spell experienced by this individual. This regressor has a strongly significant and negative coefficient. Our interpretation of this result is that people who have not experienced any joblessness before are recent entrants into the labor market who have more difficulty finding a job than more experienced individuals. Their social/employment networks are more limited and so the first spell indicator proxies for attachment to and experience in the labor market. The second aspect we considered was lagged duration dependence. The variable we included to capture this was the logarithm of the previous spell length (plus1). This was set equal to one for first spells. We find that longer previous spells have a negative effect on the probability of leaving the current spell of non-employment. We also included the logarithm of the average length of all preceding completed spells of non-employment, including the most recent spell. This also comes in with a negative sign. The fact that the previous non-employment spell has a significant negative impact even after we include the average of all previous spells implies that experience with non-employment "hurts" more, in the sense of lowering the hazard, the more recent this experience is. We also included the total number of previous spells of non-employment. This is insignificant for men but has a positive effect on the hazard 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 signal of "negative" character. Alternatively it may reflect the fact that some women who have a lower labor force attachment are more likely to have more spells of joblessness and to seek jobs in which those spells are less detrimental. Finally, we included the local unemployment rate to capture local labor market effects. As shown in Table 2, poor labor market conditions reduce the re-employment probabilities for all young workers.

Tables 3 and 4 provide estimates using our extension of the Cox model (Eqs. 6–8) that allow for a very general time dependence while controlling for observed differences between individuals and duration dependence. The first column of results only includes the duration dependence term (Eq. 6) and an interaction between duration and the national unemployment rate. This gives us a baseline measure of duration dependence that should become smaller as we include other significant factors. In the second column we see how sensitive our results are to a different specification (Eq. 7) 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 (Eq. 8).

Most of the estimated coefficients in Tables 3 and 4 do not vary from those presented in Table 2. However, some coefficients change with this specification. Government training now has a positive and significant impact on re-employment probabilities of young women, as does living at home with parents. Marital status now becomes positive and significant for men while in Table 2 it was insignificant. The fact that the results presented in Tables 3 and 4 do not look wildly different from those presented in Table 2 suggests that our parameterization of duration dependence by a quadratic and the wealth of other regressors are soaking up much of the heterogeneity across our respondents. The advantage of the specifications presented

Table 3 Proportional hazard estimates, men, 1978–1989

Covariates	Coeff. (s.e.)	Coeff. (s.e.)	Coeff. (s.e.)
Personal characteristics			
Hispanic (1 if Hispanic)	–	−0.101 (0.041)	0.021 (0.039)
Black (1 if Black)	–	−0.263 (0.035)	−0.294 (0.034)
Age (at start of spell)	–	−0.005 (0.010)	−0.005 (0.010)
Education (in years)	–	0.090 (0.010)	0.085 (0.010)
Number of children at home	–	0.036 (0.062)	0.040 (0.062)
Live at home with parents	–	−0.024 (0.038)	−0.014 (0.034)
Marital status (1 if married)	–	0.059 (0.033)	0.060 (0.033)
Received unemployment benefits	–	0.164 (0.045)	0.173 (0.046)
Urban (1 if living in urban area)	–	0.066 (0.035)	−0.018 (0.034)
Disability status (1 if disabled)	–	−0.368 (0.075)	−0.395 (0.075)
Received government training		−0.024 (0.085)	0.052 (0.083)
Received private sector training	–	0.150 (0.052)	0.120 (0.051)
Previous labor market history			
Is this the first spell (Yes=1)	–	−0.662 (0.064)	−0.651 (0.065)
Length of previous spell	–	−0.079 (0.028)	−0.081 (0.027)
Avg. duration of all previous spells	–	−0.156 (0.033)	−0.140 (0.032)
Number of previous 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 (0.420)	–
Local unemployment rate	–	–	−0.071 (0.011)
Duration dependence			
Log (duration+1)	−0.072 (0.078)	0.128 (0.079)	0.043 (0.066)
Square of Log (duration+1)	−0.091 (0.011)	−0.093 (0.012)	−0.076 (0.012)
Log (duration+1) * local unemployment rate	–	–	0.014 (0.004)
Log (duration+1) * national unemployment rate	0.031 (0.007)	0.018 (0.008)	–
Log of partial likelihood	−29490.8	−29218.2	−29212.3
Number of spells: 5661 (5,285 uncensored)			

in Tables 3 and 4, however, is that we are now able to allow for a very general calendar time dependence.

In Table 3 a decrease in the local unemployment rate of 10 percentage points leads to an increase in the log of the hazard for young males of 0.71, or a 60% increase in the hazard rate. In addition, 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 non-employment 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 non-employment and the local unemployment rate for males has a positive sign. This suggest that while a high unemployment rate and a long spell of non-employment will each lower the re-employment probability, when individuals are in long spells in an area with high unemployment they may not be as stigmatized by their jobless spell as individuals in long spells of non-employment in areas with low overall unemployment rates. This finding might be interpreted as evidence against pure ranking models of unemployment as is argued in Layard et al. (1991). However, the size of this interaction term is small relative to the negative impact of high local unemployment

Table 4 Proportional hazard estimates, women, 1978–1989

Covariates	Coeff. (s.e.)	Coeff. (s.e.)	Coeff. (s.e.)
Personal characteristics			
Hispanic (1 if Hispanic)	–	−0.327 (0.043)	−0.227 (0.041)
Black (1 if Black)	–	−0.349 (0.038)	−0.436 (0.037)
Age (at start of spell)	–	−0.012 (0.009)	−0.011 (0.009)
Education (in years)	–	0.116 (0.009)	0.117 (0.010)
Number of children at home	–	−0.222 (0.037)	−0.214 (0.038)
Live at home with parents	–	0.053 (0.032)	0.065 (0.032)
Marital status (1 if married)	–	−0.063 (0.025)	−0.076 (0.024)
Received unemployment benefits	–	0.227 (0.057)	0.249 (0.057)
Urban (1 if living in urban area)	–	0.113 (0.034)	0.071 (0.034)
Disability status (1 if disabled)	–	−0.205 (0.058)	−0.206 (0.058)
Received government training		0.218 (0.093)	0.239 (0.093)
Received private sector training	–	0.200 (0.050)	0.192 (0.050)
Previous labor market history			
Is this the first spell (Yes=1)	–	−0.612 (0.067)	−0.594 (0.067)
Length of previous spell	–	−0.051 (0.028)	−0.049 (0.028)
Avg. duration of all previous spells	–	−0.126 (0.032)	−0.122 (0.032)
Number of previous 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)	–
Local unemployment rate	–	–	−0.027 (0.011)
Duration dependence			
Log (duration+1)	−0.076 (0.074)	0.138 (0.075)	0.082 (0.061)
Square of Log (duration+1)	−0.105 (0.010)	−0.086 (0.010)	−0.074 (0.010)
Log (duration+1) * local unemployment rate	–	–	−0.001 (0.004)
Log (duration+1) * national unemployment rate	0.007 (0.007)	−0.001 (0.007)	–
Log of partial likelihood	−32469.8	−32062.1	−32047.3
Number of Spells: 6,221 (5,342 uncensored)			

on the probability of leaving a spell of joblessness. Finally, our results vary from Dynarski and Sheffrin (1990) who find some evidence that being in a spell of more than three months when the national unemployment rate is high increased the duration of unemployment. However their finding holds only for those receiving unemployment insurance and they are not able to control for as many detailed personal characteristics and calendar time effects as we are.

In results available from the authors, we also redo the estimation 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 of our sample. We find that most of the coefficients seem relatively stable over time. One important exception is the coefficient on education. This coefficient changes considerably over the period of observations. This may reflect the fact that the distribution of this variable changes considerably over the period as shown in Table 1. During the first few years (1978–1981) there are few college graduates in our sample with most of the individuals only completing a high school degree. Slowly the sample changes to include more people with relatively higher education (1984–1989). However, when we plot the coefficient on education against time we find the major change in the value of the coefficient occurs during the 1982 recession when it drops dramatically. It then returns to its pre-1982 levels in the later 1980s.

Figures 1 and 2 presented the hazard rates of young males and females without controlling for any characteristics. In Figs. 7 and 9 we use our results from Tables 3 and 4 to demonstrate how taking into account the observable characteristics of our respondents change the estimates of the hazard rate by quarter. The estimates are calculated by assuming that the hazard rate, $\lambda(t, t^0, \chi(t))$, is equal to $\lambda_0(t) \cdot \omega(t - t^0, \chi(t); \widehat{\beta})$ using the results from the third specification of the hazard rate in each of these tables that also depends on the local unemployment rate. Given the estimates of $\widehat{\beta}$, we estimated $\lambda_0(t)$ using maximum likelihood techniques assuming that it is constant within quarters. As a result, Figs. 7 and 9 replot Figs. 1 and 2 now controlling for duration dependence and individual characteristics. If duration dependence and individual characteristics change over the business cycle we would expect to see Figs. 7 and 9 looking very different from Figs. 1 and 2. There is some evidence of this for women where the shape of the hazard in Fig. 9 now looks more similar to that of men in Fig. 7 (apart from a scale factor). However, this is not dramatic and for men the shape of the hazard 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, $\omega(t - t^0, \chi(t); \widehat{\beta})$, changes over time. In Figs. 8 and 10 the solid line is $\overline{\omega}(t)$, the average of $\omega(t - t^0, \chi(t); \widehat{\beta})$:

$$\overline{\omega}(t) = \sum_{n \in R(t)} \omega\left(t - t^0, \chi_n(t); \widehat{\beta}\right) \Bigg/ \sum_{n \in R(t)} 1$$

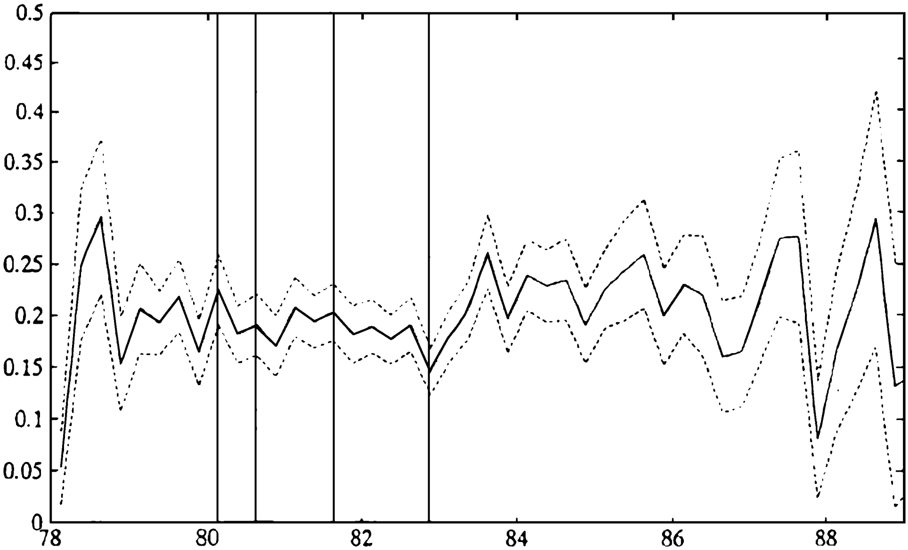

Fig. 7 Weekly hazard rate controlling for regressors (men)

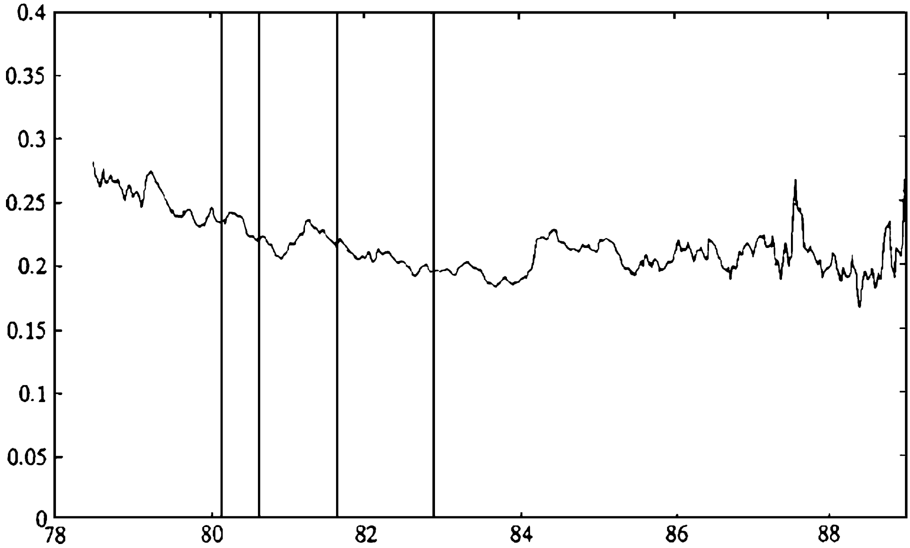

Fig. 8 Systematic part of the hazard function (men)

Multiplied with the estimate of the baseline hazard $\lambda_0(t)$ given in Figs. 7 and 9, this is equal to the average hazard presented in Figs. 1 and 2. It is clear that the average systematic part of the hazard, $\overline{\omega}(t)$, fluctuates somewhat over time for men and seems to follow a general downward trend for women. We have also decomposed this time path by including in the average only those in the first week of their non-employment spells in results not reported in this paper. Inspection of the time path of this average shows that the quality of the inflow into non-employment

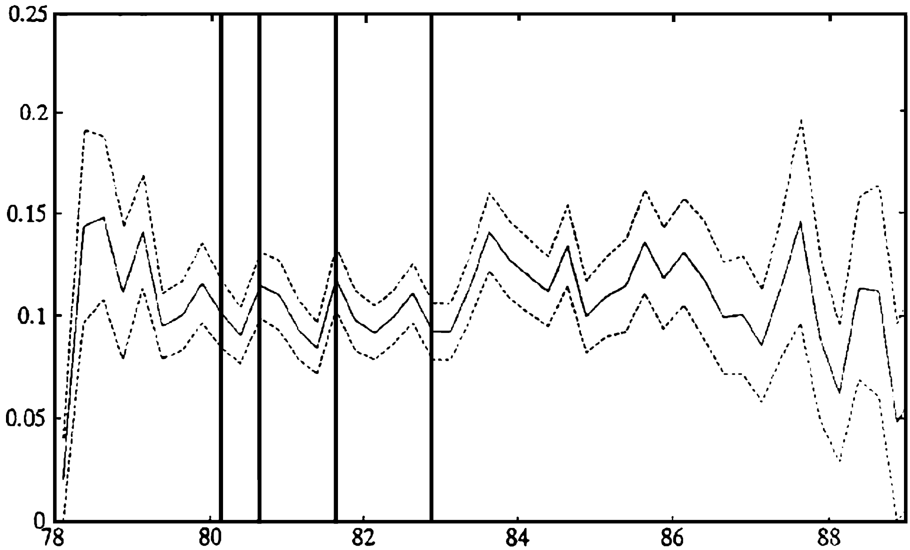

Fig. 9 Weekly hazard rate controlling for regressors (women)

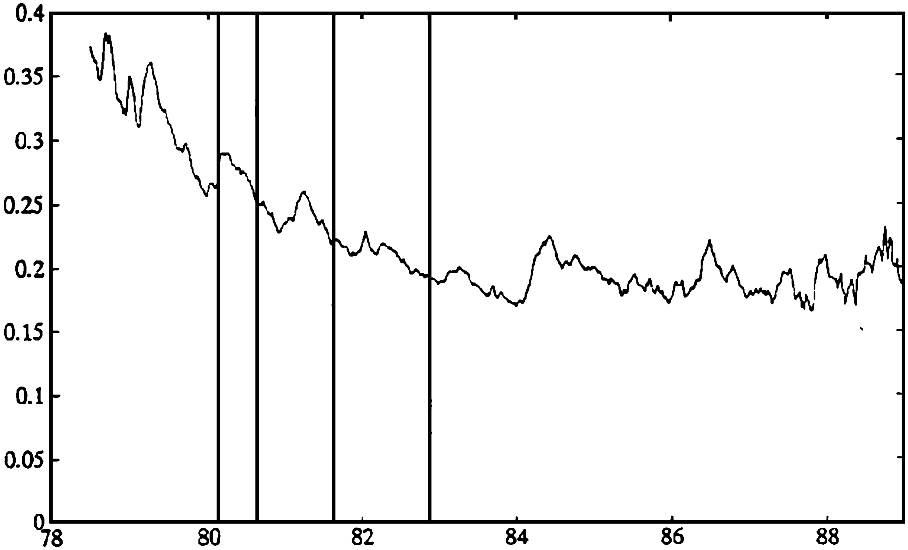

Fig. 10 Systematic part of the hazard function (women)

did not change substantially over the business cycle. There is some seasonal variation in the characteristics of those entering non-employment, but nothing that could explain long-term changes in the unemployment rate. In sum, while there are some changes in the characteristics of those who lose their job over the business cycle, a great deal of the variation in the hazard rates shown in Figs. 1 and 2 seem to be driven by business and seasonal cycles rather than by changes in the composition of job losers. These results are similar to those obtained for France by Van den Berg and Van der Klaauw (2001) using the same estimation technique utilized in this paper.

It is certainly possible that we have left out crucial characteristics of the non-employed that would explain the cyclical and seasonal patterns we see. However, such an unobserved characteristic would not only need to have a strong impact on the hazard rates, it would also have to exhibit strong seasonal and cycles behavior to explain Figs. 7, 8, 9, and 10. Note as well that in Tables 3 and 4 while the coefficients on our duration dependence terms drop when we include a wide range of characteristics, the duration dependence term remains strongly significant. If these controls for observed heterogeneity result in relatively small decreases in duration dependence, it is hard to imagine that there exists an unobserved variable that would eliminate this effect.

6 Summary

In this paper we have analyzed the distribution and determinants of spells of joblessness of youths over the period of 1978–1989 to distinguish between the relative contribution of personal characteristics, business cycle and seasonal cycles on the re-employment probability. Previous macro-based empirical work on the relationship between the expected duration of unemployment and the business cycle has been limited in its ability to control for the changing characteristics of those who become unemployed over the business cycle. At the same time, micro-based studies that are rich in personal characteristics of the unemployed have been unable to examine business cycle effects since they have had access to relatively few years of data. Using a unique longitudinal data set on youths we are able to observe both the impact of individual characteristics and business cycle effects on the probability of re-employment. We find that there is considerable variation in the duration of non-employment spells both over time and within a year. This variation cannot be explained by just the personal characteristics of those who become jobless. In fact, it appears that business cycle and seasonal cycle effects are more important than individual characteristics in explaining the time series variation in the probability of becoming re-employed, especially for men. Therefore, we conclude that policies that target specific demographic groups to raise their re-employment probabilities will alter individuals' position within the queue of job seekers, but are likely to have only a limited impact on aggregate average re-employment probabilities. This is not to say that government-training programs are fruitless. We do find that they raise the human capital of participants, especially for young women and result in higher re-employment probabilities. Our results also suggest that while the probability of becoming re-employed declines sharply as the spell of non-employment lengthens, the damage associated with a long spell of joblessness appears to be weakened somewhat if a young jobless worker is male and lives in an area of high unemployment. This may be because the stigma or signal attached to a long spell out of work is reduced if a young worker is in a community where many other individuals are in a similar situation. Our analysis has focused on the labor market transition experience of young workers. However, given the aging of the workforce future work should also examine the determinants of transitions for older workers and see if they are similar to what we have found on youths. In addition, the emergence of matched household-employer data sets, especially in Europe, will allow researchers to see if the results found in this paper hold for more recent recessions.

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