Duration and Calendar Time Dependence of the Exit Rate out of Unemployment in Belgium. Is it True or Spurious?*

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Abstract

In this paper, we investigate what causes the aggregate exit rate out of unemployment estimated in Wallonia (Belgium) to decline over duration and to vary over calendar time. For that purpose, we specify a mixed proportional hazard (MPH) model where the mixing distribution depends on seasons and business cycle at the time of entry. Given its too restrictive nature, we relax the proportionality assumption in three ways. First, we allow the baseline hazard to vary non-proportionally between a boom and a recession in order to test the ranking hypothesis. Second, the variance of the mixing distribution needs not to fluctuate proportionally to its mean over calendar time at entry. Finally, we allow for random deviations from the MPH framework by introducing random cohort-specific business cycle effects at the time of exit. We estimated our model by Minimum Chi-Squares on quarterly data of male workers entering unemployment between June 1989 and February 1994. We find that the negative duration dependence of the aggregate exit rate is largely spurious. Moreover, for prime-aged, but not for young male workers, true duration dependence varies over the cycle, a finding consistent with employers ranking candidates according to unemployment duration in their recruitment decision. Changes in the composition of workers entering unemployment explain an important part of the seasonal variation of the exit rate, but not of its variation over the business cycle.

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1 Introduction

Finding an explanation for the rise and persistence of European unemployment has been one of the main research programmes of labour economists the last decennia. This study aims at contributing to this literature by questioning the causes of unemployment dependency in Belgium, more specifically in Wallonia, the French speaking region in the South[1]. The case of Belgium is particularly interesting, because long-term unemployment is especially important in this country: The share of long-term unemployment is one of the highest in Europe. During the 1983-1996 period this share has peaked to a level of 75% in 1988 and has only been slightly below 60% during the 1991-1993 recession[2] (see OECD 1997).

It is particularly important to understand what drives this persistence. Does unemployment dependency by itself increase the likelihood of future dependency? Prolonged unemployment may induce a process of skill deterioration and demotivation or may be used as a recruitment criteria by the employers (for a survey of the 'true' negative duration dependence explanations, see Machin and Manning 1999). Or is the negative duration dependence that we observe for any cohort of unemployed 'spurious', i.e. generated by a process of sorting? The individuals with the most favourable characteristics leave unemployment rapidly leaving behind the 'low-skilled' workers. This sorting process causes the aggregate exit rate to decrease spuriously with duration, as the aggregate exit rate is simply equal to the average exit rate of those remaining unemployed. These questions are old (see Salant 1977, Nickell 1979, Lancaster 1979), but disentangling true from spurious duration dependence remains highly relevant from a policy point of view.

The first aim of this paper is to investigate what causes the aggregate hazard estimated in Wallonia to decline. A number of researchers (see Spinnewyn 1982, Plasman 1993 and Mahy 1994) have studied this question for Belgium. They find that the negative duration dependence is completely spurious. The hazard rate increases significantly once unobserved heterogeneity is taken into account. However, in view of the strong parametric assumptions regarding both the baseline hazard (Weibull) and the mixing distribution (Gamma), these results are likely to be biased. The evidence from other European studies on duration dependence and heterogeneity seems to converge to the same conclusion (for a recent review, see Machin and Manning 1999): once controlling for (observed and unobserved) heterogeneity, there is no marked evidence of 'true' negative duration dependence of the exit rate out of unemployment in most European countries, like France, the Netherlands, Germany, Austria, Spain, Denmark and the Scandinavian countries. One exception to this conclusion is the United Kingdom where individual unemployment duration distributions appear to exhibit strong negative duration dependence and to be not significantly heterogeneous.

The second aim of this paper is to study the cyclical and the seasonal behaviour of the exit rate out of unemployment in Wallonia. The hazard rate out of unemployment is generally found to be procyclical. This dynamic fluctuations in the average unemployment

[1] Belgium is divided into three regions: Wallonia, Flanders and Brussels.

[2] These figures are somewhat higher in Wallonia.

duration can be explained by variations in the quality of entrants into unemployment rather than by the effect of the business cycle on the exit rate of all currently unemployed. For instance, if workers with more favourable labour market characteristics, say 'high-skilled' workers, are less (more) likely to enter unemployment in a downturn (upturn), while the 'low-skilled' workers face always the same risk of loosing their job, then this change in the composition of the unemployed could partly explain the procyclical variation in the hazard rate[3]. If this compositional effect is important, then the 'low-skilled' workers benefit less from an economic recovery than what aggregate statistics on the cyclical evolution of the hazard rate out of unemployment suggests. In order to answer this question we try to disentangle the general effect of the business cycle (and the seasons) on the hazard, affecting all unemployed workers in the same proportion, from its compositional effect. Given the recent interest of European researchers in this question, there are few studies on the business cycle effect on unemployment duration in Europe[4]. Both Abbring *et al.* (1994, 1999) and Rosholm (1997), respectively for France and Denmark, conclude that compositional effects are of minor importance.

The analysis of this study is based on aggregate data. We observe the quarterly exit rates of unemployed male workers between June 1989 and February 1994. Van den Berg and van Ours (1994) developed a method of estimation that, assuming a Mixed Proportional Hazard (MPH) specification[5], is adapted to this type of aggregate data. The advantage of this method is that it is very flexible, allowing to identify both, the distribution of duration and unobserved characteristics, non-parametrically. Nevertheless, we will use another method of estimation in this paper and this for three reasons.

First, the method proposed by van den Berg and van Ours (1994) is based on a discrete-time model. Such a specification implies that the parameters are not invariant to the time unit (see Flinn and Heckman 1982, p.53-56). Consequently, consistency requires that the timing of the underlying stochastic duration process coincides with the actual grouping of the data[6]. In order to avoid this problem, we follow van den Berg and van der Klaauw (1998) and specify the discrete-time process as a continuous-time model. Second, their model specification assumes that, apart from measurement error, the observed aggregate exit probability coincides with its theoretical counterpart in the population. Since the observed exit probability is calculated on the basis of a finite sample, this is not correct. We show below that a correct specification leads to a statistical foundation of the model residuals. This provides a firmer basis for hypothesis testing and suggests a more efficient estimator, since the residuals are heteroskedastic. Finally, the computational complexity of the method increases considerably as one augments the number of duration

[3] Darby *et al.* (1985) and Rosholm (1997) refer to changing proportions of voluntary quitters ('job shoppers') and laid off workers ('career makers') over the cycle rather than to proportions of 'high' and 'low-skilled' workers.

[4] However, this question has puzzled American researchers since the mid 1980s already (see Darby *et al.* 1985, Sider 1985, Dynarski and Sheffrin 1990, Baker 1992, Imbens *et al.* 1992).

[5] In a MPH model both, the observed and unobserved explanatory variables, enter the hazard multiplicatively (see e.g. Ridder 1990).

[6] The authors are aware of this problem and test the validity of this assumption (see e.g. van den Berg and van Ours 1994, p.437). The power of this test can, however, be questioned.

intervals. This is not the case for the estimator used in this paper.

We follow Cockx (1997) and estimate a duration model by means of the Minimum Chi-Square method. In a first step, the method constructs, for each duration interval, the Kaplan-Meier estimator of the hazard for a group of individuals, homogenous with respect to the observed explanatory variables, i.e. the calendar time at the moment of inflow in and outflow out of unemployment. Subsequently, (a transformation of) these empirical hazards are regressed against their theoretical counterparts in the population. The latter are at first assumed to be of the MPH form. For this assumption, together with the condition that at least one regressor varies continuously over the set of real numbers[7], allows the mixing and duration distribution to be identified non-parametrically from grouped duration data (see Ridder 1990). The baseline hazard is specified as piecewise-constant. In the benchmark model the mixing distribution is assumed to be Gamma. We compare our findings with those found with a non-parametric specification of the mixing distribution, as approximated by one with a discrete number of points of support (see Heckman and Singer 1984).

The MPH is standard in the literature. We relax it in three ways. First, we allow the hazard to vary non-proportionally between two sub-periods, i.e. between a boom and a recession. The reason for doing so, is that if 'true' negative duration dependence is caused by ranking, a recruitment rule which consists in hiring the (unemployed) candidate with the shortest unemployment duration, the individual exit rate is predicted to vary non-proportionally over the business cycle: It will decline more rapidly the more depressed is the labour market (see Blanchard 1991, Blanchard and Diamond 1994, and Abbring *et al.* 1994, 1999). By considering an interaction effect between the duration and the cyclical dependence of the hazard, we can test the ranking hypothesis. Moreover, we show that ignoring such a non-proportionality may lead to an underestimation of the unobserved heterogeneity. Note that the mixing distribution is identified by the assumption of proportionality within the sub-periods and the proportionality of seasonal effects at the time of exit.

Second, related to our objective to disentangle compositional from general effects of the cycle on the exit rate out of unemployment, we propose a specification in which the composition at the time of entry in unemployment may vary non-proportionally over calendar time. More specifically, the variance of the (Gamma) mixing distribution need not vary proportionally to its mean over seasons and the business cycle, such as imposed by Abbring *et al.* (1994, 1999). Identification of the mixing distribution at each entry date requires that the conditional baseline hazard is proportional in the calendar time of exit (at least within sub-periods).

Finally, the MPH specification assumes that the business cycle at the time of exit influences the hazard of all cohorts, i.e. of all duration classes at this instant, with the same factor of proportionality. We generalise this specification by allowing for random deviations from this specification, i.e. by introducing random cohort-specific business cycle effects at the time of exit. Moreover, suppose that cohorts are each other's imperfect substitutes, then an increase (decrease) in the hazard of one particular cohort spills over

[7] This is assured by introducing a polynomial in the calendar time at the outflow as regressor.

to the other cohorts. If we assume that the degree of substitutability decreases with the difference of the elapsed duration between the affected and non-affected cohorts, then this substitution induces, for any fixed exit time, the model residuals to be positively auto-correlated with duration. We will show below that for our data the correlation structure of the residuals is compatible with this type of specification error and not with the type of measurement error introduced by Abbring *et al.* (1994, 1999) and van den Berg and van der Klaauw (1998).

The plan of the paper is as follows. The next section describes the data and introduces the main notations and assumptions. In a third section we test whether the MPH specification is compatible with our data. The fourth section is devoted to the derivation of our generalisation of the MPH model. The estimation results are discussed in Section 5. The concluding part summarizes our findings.

2 Data, Notations and Assumptions

Our analysis exploits quarterly census data relative to the male unemployed in Wallonia and stratified by a limited number of characteristics: the quarter of inflow, the unemployment duration and the age group (less than 29 years old, and between 29 and 44 years old).

Workers are defined to be unemployed if they are officially registered as full-time unemployed and if a sufficiently long employment record entitles them to unemployment benefits. The inflow in a given quarter is equal to the number of workers who entered unemployment for the first time or after an exit of at least three months[8] and who are still unemployed at the end of the quarter in which they enter. The observation period consists of 19 quarterly intervals[9], the first interval starting on the 1^{th} of June 1989, the last one ending on the 28^{th} of February 1994. So there are 18 cohorts of unemployed[10] (a cohort being defined by its quarter of inflow), stratified by age-group. For each cohort, the outflows out of unemployment are counted on a quarterly basis, from the time of inflow until the end of February 1994, date at which all spells are right censored. The data do not allow us to distinguish between unemployment spells ending in employment, participation in labour market programmes or withdrawal from the labour force. Outflows from unemployment are therefore treated globally. This is not likely to bias our results given that employment is the most frequent state of exit for the prime-aged unemployed (see Bardoulat *et al.* 1998).

For each age group, the data are consequently grouped into $N = \sum_{n=1}^{18} n = 171$ homogeneous cells. This calls for an estimation by Minimum Chi-Squares (see Berkson 1944, Amemiya 1981, Cockx 1997). The method consists in regressing (a transformation of) the Kaplan-Meier estimate of the hazard, calculated for each cell, on the discrete equivalent of a theoretically specified hazard rate.

[8] This restriction allows to neglect temporary exits (for administrative reasons for example).

[9] Four quarters are defined: (Jun,Jul,Aug); (Sep,Oct,Nov); (Dec,Jan,Feb); (Mar,Apr,May).

[10] There are 18 cohorts instead of 19 as there is, by definition, no exit defined for those entering the unemployment pool in the 19^{th} quarter.

In the sequel, the variables l and t denotes respectively the calendar time at the moment of inflow and unemployment duration. These variables are measured in quarters. The way the inflow is constructed in our data requires us to model calendar time at the moment of inflow, l, as a discrete time process. We have that $l \in \{0, 1, ..., 17\}$ and by definition, that $t \equiv 0$ at the moment of inflow l.

We treat unemployment duration, t, as a continuous-time process. So, $t \in R^{+}$. Otherwise, the specification would be sensitive to the chosen duration interval (see Flinn and Heckman 1982). Misspecified duration intervals, i.e. not consistent with the unemployed behaviour, would then lead to non-proportionality, violating the MPH specification imposed below. However, even if duration is modeled in continuous time, the underlying process is assumed to be discrete. For, otherwise the specification would complicate substantially, since a genuine continuous time process requires modeling spells that start and end within the same quarter (see van den Berg and van der Klaauw 1998).

We then denote the hazard of an individual unemployed for t quarters and at risk of leaving unemployment at calendar time $l + t$, conditional on unmeasured characteristics v, by:

$$h(t \,| l + t, v) \tag{1}$$

and the survivor function at unemployment duration t by:

$$S(t \,| v) = \exp \left[- \int_0^t h(s \,| l + s, v) \, ds \right] \tag{2}$$

Here and in the sequel, the calendar time dependence is implicit in the notation of the survivor function.

We now impose the mixed proportional hazard (MPH) specification. Since calendar time and duration are generated by a discrete time process, we can impose without loss of generality that both, the baseline hazard and the calendar time effects are constant within quarterly intervals:

$$\forall t \in [k - 1, k) : h(t \,| l + t, v) = \exp \left[\varphi_1 (k) + \varphi_2 (l + k) \right] v \equiv h_{kl} v \tag{3}$$

where $v > 0$, $k \in \{1, ..., 18\}$ and the functions $\varphi_1 (.)$ and $\varphi_2 (.)$ represent respectively the duration and calendar time dependence of the individual hazard.

We assume that calendar time at the moment of inflow affects the shape of the mixing distribution (see Abbring *et al.* 1994, 1999). Using (2) and (3), the mixture survivor function at the end of quarter k can then be found to be:

$$S^m (k \,| l) = \int_0^\infty \exp \left[-v \sum_{j=1}^{k} h_{jl} \right] dF_l (v) \tag{4}$$

where $F_l(.)$ is the heterogeneity distribution. Below, we will specify this distribution as well as how it depends on calendar time at the inflow.

We parametrise $\varphi_1(k)$ as a piecewise-constant function:

$$\varphi_1(k) = c + \sum_{j=2}^{18} (\gamma_j - c)\, \delta_{jk}, \tag{5}$$

where δ_{jk} is the Kronecker delta and where we impose that $\forall j \geqslant 12 : \gamma_j = \gamma_{12}$. The latter restriction is imposed to avoid erratic behaviour of the parameters induced by a too small number of observations at the tail of the duration distribution.

If $\varphi_2(l+k)$ were to be specified piecewise-constant, the calendar time parameters would share the properties of incidental parameters (see Neyman and Scott 1948). Indeed, there would only be a limited number of observations that contain information to estimate them, i.e. the $l+k$ duration classes observed at each quarter. The number of duration classes increases with calendar time, but typically with some limit: beyond this limit the information is lacking or unreliable. Consequently, an increase in the number of calendar time intervals would not contain additional information about these parameters.

We therefore follow Abbring *et al.* (1994, 1997) and introduce the following flexible parametric specification, where we decompose $\varphi_2(l+k)$ into a cyclical part, $\varphi_{2c}(l+k)$, and a seasonal part, $\varphi_{2s}(l+k)$:

$$\begin{aligned} \varphi_{2c}(l+k) &= \sum_{i=1}^{5} \beta_{ci} p_i (l+k) \\ \varphi_{2s}(l+k) &= \sum_{a=2}^{4} (\beta_{sa} - c)\, I_{N^+}\left(\frac{l+k-a}{4}\right), \end{aligned} \tag{6}$$

where $I_A(.)$ is the characteristic function of set A. The effect of calendar time at the outflow on the hazard is represented by a flexible fifth degree polynomial in calendar time, $p_i(l+k)$, capturing business cycle effects[11], and by dummy variables capturing seasonal effects. To avoid multi-collinearity problems, we follow Abbring *et al.* (1997) and use the orthogonal Chebyshev polynomial instead of an ordinary polynomial[12].

[11] A fifth degree polynomial should track the business cycle dependence of the hazard in a flexible way. Note, in order to avoid the incidental parameter problem, the number of degrees should be constant or at least increase at a slower rate than the number of calender time points. In the latter case, the 'good' asymptotic properties of the estimator cannot be guaranteed (see Gourieroux and Monfort 1995, p.189). However, this does not imply that the number of parameters should necessarily be fixed, such as Merz (1999, p.333) claims in her critique on van den Berg and van der Klaauw (1998).

[12] The series of Chebyshev polynomials is obtained as follows (see Abbring *et al.* 1997, p.16). First, linearly transform the domain of calendar time to the domain of orthogonality of the Chebyshev Polynomial, $[-1, 1]$, by means of ($x = l + k$ and $x_0 = 1$):

$\hat{x}(x) = 2\frac{x-x_0}{n-1} - 1$, where n $(= 18)$ is the number of calendar time intervals considered.

Then generate the series of orthogonal polynomials, $p_i(\hat{x})$, by means of:

$p_i(\hat{x}) = \frac{i}{2} \sum_{i=0}^{\frac{i}{2}} (-1)^j \frac{(i-j-1)!}{j!(i-2j)} (2\hat{x})^{i-2j} + 1$, for $j = 1, 2, ..., n_x$.

3 Testing the Proportionality Assumption

3.1 Statistical Model

Intuitively, the presence of heterogeneity in a proportional hazard model, such as defined in (3), implies a decrease in the observed hazard (i.e. unconditional on v) with duration which is slower for low value of $\varphi_2(l+k)$ (e.g. in downturn) and faster for high value of $\varphi_2(l+k)$ (e.g. in upturn). In a tight labour market, the individuals with a high value of v leave unemployment at a very fast rate. So the group of survivors is rapidly made of 'low-skilled' individuals, inducing a strong negative duration dependence of the observed hazard. However, in a depressed labour market, even the unemployed with the best characteristics are likely to stay some time in that state. The observed exit rate declines only slowly over duration.

Formally, this intuition is, however, only correct if the duration is small (see van den Berg 1999, p.44). For larger durations, the sign of this interaction depends on the form of the heterogeneity distribution. For instance, Lancaster (1979) shows that if the unobserved heterogeneity is distributed Gamma, the interaction remains always negative. On the other hand, for a discrete distribution with a finite number of points of support, it is clear that the interaction must be positive on some range, since, as $t \to \infty$, the group of survivors becomes homogenous[13] and the interaction goes back to its value at $t = 0$ (see van den Berg 1999).

The MPH model implies, however, that the cumulative interaction of the unconditional hazard over the duration interval $[0, t]$ is always negative (see Abbring *et al.* 1997). In our notation, $\forall k \in \{2, 3, ..., 17\}$[14], we must have that:

$$\frac{\partial}{\partial \varphi_{2i}(l+k)} \left(\log \frac{h_{kl}^u}{h_{1(k+l-1)}^u} \right) < 0 \quad for \quad i = c, \ s \tag{7}$$

where $h_{1(k+l-1)}^u$ is the unconditional hazard in the first duration quarter at calendar time $l+k$.

We can therefore test whether the MPH assumption is compatible with our data by testing whether such a cumulative interaction effect is negative. This amounts to adding an interaction effect, $\varphi_3(k, l+k)$, to a proportional specification of the unconditional hazard, h_{kl}^u:

$$\log\left(h_{kl}^u\right) = \varphi_1(k) + \varphi_2(l+k) + \varphi_3(k, l+k) \tag{8}$$

where $\varphi_3(k, l+k)$ is specified in the following way:

$$\varphi_{3i}(k, l+k) = \left(\psi_i \log(k) \sum_{j=2}^{18} \delta_{jk} \right) \varphi_{2i}(l+k) \quad for \ i = c, s \tag{9}$$

[13] All survivors having the lowest value v of the points of support.

[14] The derivative is not defined for $k = 18$ as there is only one observation for this duration quarter.

Note that the interaction with the cyclical component, c, is defined separately from the seasonal component, s. We test whether $\psi_i < 0$[15].

There are theoretical reasons to believe that the proportionality assumption stated in (3) does not hold. The ranking model (see Blanchard 1991, Blanchard and Diamond 1994) implies that the effects of duration on the individual exit rate are stronger the more depressed is the labour market. As the state of the labour market deteriorates, the employers posting vacancies receive many applications of unemployed workers. If employers rank applicant according to their elapsed unemployment duration, competition among the long-term unemployed to occupy a vacancy is increased as compared to the situation in a tight labour market. Formally, Abbring *et al.* (1997) show that, contrary to the MPH model, the ranking model implies a positive cumulative interaction effect, i.e. $\psi_i > 0$ in (9).

The sign of ψ_i can therefore only be informative on the *relative* importance of sorting as compared to ranking. If it is significantly negative, sorting dominates and the data are compatible with a MPH specification. However, it does not exclude that ranking is at work simultaneously. In such circumstances, a MPH specification, even if it will identify some spurious negative duration dependence, will underestimate the extent to which the duration dependence is spurious. We will illustrate this below by introducing an interaction term between duration and two sub-periods, one covering an upturn and the other a downturn of the business cycle.

We now turn to a description of the estimation procedure. We do not observe the unconditional hazard, but the empirical probability that a worker leaves unemployment within the next quarter, conditional on not having left it earlier. The theoretical counterpart of this probability at the k^{th} duration interval for a worker who is at risk of leaving unemployment within the $(l+k)^{th}$ quarter is:

$$P_{kl} \equiv \Pr(k-1 \leq T < k \,|T \geq k-1, l+k) \tag{10}$$

Using (2), we then link this probability to the unconditional hazard rate:

$$P_{kl} = \frac{S^u\,(k-1) - S^u\,(k)}{S^u\,(k-1)} = 1 - \exp\left[-h^u_{kl}\right] \tag{11}$$

where $S^u\,(.)$ is the unconditional survivor function. Inverting this relationship gives us:

$$z_{kl} = \log\left[-\log\left(1 - P_{kl}\right)\right] = \log\left(h^u_{kl}\right) \tag{12}$$

We now relate the theoretical probability to the empirical probability. Let r_{kl} be the number of individuals who entered into unemployment at l, are still in that state at

[15]This specification imposes that the cumulative interaction effect is monotonically decreasing in duration. As already stated, this is compatible with a Gamma, but not with a discrete heterogeneity distribution. A specification that allows the interaction to vary non-monotonically with duration, could therefore guide us with respect to the specification of the heterogeneity distribution. We therefore also estimated a model in which we include a second interaction parameter in $\log^2 k$. The coefficient of this second term is, however, always very imprecisely estimated.

the start of the k^{th} duration interval and are therefore at risk of leaving unemployment within the $(l+k)^{th}$ quarter. Let q_{kl} be the number of these individuals who leaves unemployment within the k^{th} duration interval. We can then estimate the probability of leaving unemployment, P_{kl}, by the Kaplan-Meier estimator of the hazard adapted to grouped data:

$$\hat{P}_{kl} = \frac{q_{kl}}{r_{kl}} \tag{13}$$

If we replace the probability of leaving unemployment by its estimate, $\hat{P}_{kl}$, in (12), the equality of this equation does no longer hold exactly. The analysis initiated by van den Berg and van Ours (1994) neglects this. This leads to an incorrect specification of model residuals and will consequently affect both, the efficiency of the estimator and the statistical theory on which hypothesis testing is to be based. We follow Cockx (1997) and expand $\log\left[-\log\left(1-\hat{P}_{kl}\right)\right]$ in a Taylor series around P_{kl}:

$$\hat{z}_{kl} = \varphi_1(k) + \varphi_2(l+k) + \varphi_3(k, l+k) + u_{kl} \tag{14}$$

with the approximation error $u_{kl} = \dfrac{\hat{P}_{kl} - P_{kl}}{(1-P_{kl})\log(1-P_{kl})}$

There is an additional term, but since it is of order less or equal than r_{kl}^{-1}, it can be ignored for large r_{kl}[16] (see Amemiya 1985, pp.276-77). Cockx (1997) shows that $E(u_{kl}) = 0$ and that a consistent estimate of the variance of u_{kl} is[17]:

$$\hat{s}_{kl}^2 = \hat{P}_{kl}\left[\left(1-\hat{P}_{kl}\right)\left[\log\left(1-\hat{P}_{kl}\right)\right]^2\right]^{-1}\frac{1}{r_{kl}} \tag{15}$$

The Minimum Chi-square estimator is then defined as the weighted least squares estimator as applied to (14).

It is important to notice that these approximation errors, u_{kl}, do not correspond to the measurement errors such as introduced by Abbring *et al.* (1994) nor to specification errors. They reflect the stochastic nature of the empirical exit rates, $\hat{P}_{kl}$. Taking the heteroskedastic approximation errors into account, does not only improve the efficiency of the estimators, it also provides a firmer basis for hypothesis testing.

[16] The size of our cells is indeed quite large. The lowest and the average r_{kl} are respectively 266 and 1649 for the men aged between 29 and 44 years old, and respectively 155 and 1973 for the men aged less than 29 years old.

[17] The covariance is zero.

3.2 Empirical Results

The estimation results for the model specified in (14) are reported in the first column of Table 1 and Table 2, respectively for men aged 29-44 and for men aged less than 29 years old. For both demographic groups, the interaction parameters, ψ_c and ψ_s, are negative: duration dependence of the unconditional hazard is steeper for high value of $\varphi_2(l+k)$ than for low value of $\varphi_2(l+k)$. This result is consistent with the presence of heterogeneity in a MPH model such as specified in (3). Abbring *et al.* (1994) conclude the same for France. This finding implies that we can identify heterogeneity within a proportional framework in the next stage.

Note that for the men aged between 29 and 44 years old, the parameter ψ_c is small in absolute value and insignificant. One possible reason of this finding is that ranking according to unemployment duration is present for the prime-age men. As mentioned above, the interaction parameter ψ_c would then 'underestimate' the importance of heterogeneity in the data, unlike the parameter ψ_s. In the next stage, we therefore relax the proportionality assumption between two calendar time sub-periods (a boom and a recession), but maintain it within these two sub-periods. We maintain the proportionality in the seasonal component.

4 The Mixture Models

4.1 The Gamma Mixing Distribution

Insofar as we showed that the proportionality assumption of the hazard in duration and the state of the business cycle might be too restrictive for the oldest men, we decide to relax this assumption between two calendar time sub-periods. In order to contrast the two periods considered, we retain for the first sub-period calendar time intervals relative to the peak, i.e. between June 1989 and November 1990, and for the second sub-period, those relative to the slack period starting in December 1990 and continuing up to February 1994. This amounts to add in the conditional hazard (3) an interaction term $\tilde{\varphi}_3(k, l+k)$:

$$\forall t \in [k-1, k) : h(t\,|l+t, v) = \exp\left[\varphi_1(k) + \varphi_2(l+k) + \tilde{\varphi}_3(k, l+k)\right] v \equiv h_{kl} v \qquad (16)$$

which is specified as follows[18]:

$$\tilde{\varphi}_3(k, l+k) = \phi I_{\{1,2,3,4,5\}}(l+k) \sum_{j=2}^{18} \left|\gamma_j - c\right| \delta_{jk} \qquad (17)$$

The interaction parameter, ϕ, is only defined for the boom period and is assumed to affect the logarithm of the baseline hazard in absolute value multiplicatively. We take

[18] Since the first sub-period spans only 5 quarters, a separate piecewise-constant specification of the baseline hazard would yield too imprecise estimates. We therefore summarise the information into one interaction parameter.

the absolute value to avoid that the sign of the duration dependence affects the sign of the interaction term. Ranking implies that $\phi > 0$.

When unobserved heterogeneity is taken into account, we have to replace the survivor function in (11) by the mixture survivor function as defined in (4), yielding:

$$P_{kl} = \frac{S^m(k-1\,|l) - S^m(k\,|l)}{S^m(k-1\,|l)} = 1 - \frac{\int_0^\infty \exp\left[-v\sum_{j=1}^{k} h_{jl}\right] dF_l(v)}{\int_0^\infty \exp\left[-v\sum_{j=1}^{k-1} h_{jl}\right] dF_l(v)} \tag{18}$$

We assume that V (random variable) is a Gamma variate[19] of mean, $\mu_l = \frac{\lambda_l}{\delta_l}$, and variance, $\sigma_l^2 = \frac{\lambda_l}{\delta_l^2}$. As such, we allow both the mean and the variance of the distribution of V to depend on calendar time at the moment of inflow, l. By normalisation, the mean is equal to one for $l = 0$. We therefore impose $\delta_0 = \lambda_0$. Since the moment generating function of this Gamma variate is (see Lancaster 1990, p.328):

$$M_v \equiv E\left(e^{sV}\right) = \left(1 - \frac{s}{\delta_l}\right)^{-\lambda_l} \tag{19}$$

we are able to simplify greatly the last expression in (18).

Before deriving the mixture regression model, we specify how the variables δ_l and λ_l depend on calendar time at the inflow. We first introduce the following notations: $\delta_l = \exp(-\varphi_{4c}^{\delta}(l) - \varphi_{4s}^{\delta}(l))$ and $\lambda_l = \exp(\varphi_{4c}^{\lambda}(l) + \varphi_{4s}^{\lambda}(l))$ where $\varphi_{4c}^{i}(l)$ and $\varphi_{4s}^{i}(l))$, $\forall i \in \{\delta, \lambda\}$, denote the cyclical and seasonal component, respectively. Unlike for the effect of calendar time on the hazard at the moment of exit, we do not specify a polynomial to capture the effect of calendar time at the moment of entry. For, the linear term of this polynomial cannot be identified (see Abbring *et al.* 1997, 1999). We therefore choose to characterise the effect of calendar time at the moment of inflow by a business cycle indicator and by the season at inflow. This leads us to specify $\varphi_{4c}^{i}(l)$ and $\varphi_{4s}^{i}(l)$, $\forall i \in \{\delta, \lambda\}$, as follows:

$$\begin{aligned} \varphi_{4c}^{i}(l) &= \omega_c^i b(l) \\ \varphi_{4s}^{i}(l) &= \omega_{s1}^i + \sum_{a=2}^{4}\left(\omega_{sa}^i - \omega_{s1}^i\right) I_{N^+}\left(\frac{l+1-a}{4}\right) \end{aligned} \tag{20}$$

The business cycle indicator, $b(l)$, is the deseasonalised logarithm of the number of

[19] The choice of a Gamma distribution for $F(v)$ can be justified by the result that, for a continuous v and under mild regularity conditions, the unobserved heterogeneity distribution among survivors at t converges to a Gamma distribution if $t \to \infty$ (see Abbring and van den Berg 1998). This result does not hold, however, if v is discrete and justifies therefore our specification of a discrete heterogeneity distribution in the sensitivity analysis below.

quarterly flows into unemployment[20]. By imposing $b(0) = 0$ and $\omega_{s1}^{\delta} = \omega_{s1}^{\lambda}$, we normalise the mean of the mixing distribution to be one at $l = 0$.

Combining (18), (19) and (20), we then obtain the following non-linear heteroskedastic regression model:

$$1 - \hat{P}_{kl} = \left[1 - \frac{\exp\left[\varphi_1(k) + \varphi_2(l+k) + \tilde{\varphi}_3(k, l+k) + \varphi_4^{\delta}(l)\right]}{1 + \sum_{j=1}^{k} \exp\left[\varphi_1(j) + \varphi_2(l+j) + \tilde{\varphi}_3(j, l+j) + \varphi_4^{\delta}(l)\right]}\right]^{\exp\left(\varphi_4^{\lambda}(l)\right)} + u_{kl} + e_{kl} \tag{21}$$

where $u_{kl} \equiv \hat{P}_{kl} - P_{kl}$ is the approximation error. We have that $E(u_{kl}) = 0$ and its variance can be consistently estimated by (see Cockx 1997):

$$\hat{s}_{kl}^2 = \left[\left(\hat{P}_{kl}\right)\left(1 - \hat{P}_{kl}\right)\right] \frac{1}{r_{kl}} \tag{22}$$

The errors e_{kl} are unobserved random variables which can either be specification or measurement errors. We assume that they have a distribution such that $E(e_{kl}) = 0$ and $E\left(e_{kl}^2\right) = s_e^2$.

We now show that the correlation structure of these residuals is informative about whether these errors are to be interpreted as specification or measurement errors. First, we follow Abbring *et al.* (1994, 1999) and van den Berg and van der Klaauw (1998) and take them to be measurement errors. In this interpretation, the errors are made in counting the number of unemployed at a particular duration interval and/or calendar time interval. Consequently, they introduce a difference between the true and the observed value of r_{kl} in (13) and, indirectly, between P_{kl} and $\hat{P}_{kl}$. Following Abbring *et al.* (1994, p.6), the correlation between the residuals of adjacent duration classes for any fixed calendar time at the outflow, i.e. the correlation between e_{kl} and e_{k-1l+1}, denoted by ρ_{l+k}, is negative if individuals are sometimes classed in the wrong duration interval adjacent to the right interval. It is positive if the definition of unemployment used to count individuals at $l + k$ is less restrictive than the definition used at another calendar time.

Measurement errors of this type, whether they are independent or not, always imply that the correlation between the residuals of adjacent duration classes for any fixed calendar time at the inflow, i.e. the correlation between e_{kl} and e_{k-1l}, denoted by ρ_l, is equal to $-\frac{1}{2}$. This means that we can test, on the basis of the empirical correlation coefficients, whether the residuals of regression model (21) can be interpreted as measurement errors. We will explain below how we calculate such a statistic. We find that for both groups analysed, i.e. prime aged men, between 29 and 44 years old, and men younger than 29,

[20] The inflow rate would be a more appropriate indicator. This statistic is not available on a quaterly basis. However, if the number of employed workers remains approximately constant over the observation period, we can approximate it by the number of workers flowing into unemployment.

the empirical correlation between e_{kl} and e_{k-1l} is not significantly different from zero according to the LM-test statistic (see Godfrey 1978 and Breusch and Pagan 1980). Its value is -0.02 for the prime-aged men and 0.03 for the young men.

On the other hand, ρ_{l+k} is significantly positive both, for the men aged 29-44 and for those aged <=28: respectively, 0.65 and 0.77[21]. These results suggest an alternative interpretation of the regression residuals. We can interpret them as random cohort-specific business cycle effects at the time of exit. On average these deviations from the MPH specification cancel out. However, to the extent that cohorts with a different elapsed duration are imperfect substitutes, then an increase (decrease) in the hazard of one particular cohort will spill over to the other cohorts. If we assume that the degree of substitutability decreases with the difference of the elapsed duration between the affected and non-affected cohorts, then this substitution induces, for any fixed exit time, the model residuals to be positively auto-correlated with duration. Note that, if cohorts are not substitutable, then the coefficient of auto-correlation is zero. On the other hand, if substitution is perfect, the cohort-specific business cycle effect affects each cohort by a common factor.

We might depart from our general mixture model in (21) by testing various restrictions on the parameters:

$$R1 \quad : \quad F_l\left(\exp\left[\varphi_4^{\delta}(l)\right]v\right) = F_0(v) \Leftrightarrow \forall a \in \{2,3,4\} : \omega_c^{\lambda} = \omega_{sa}^{\lambda} = 0 \tag{23}$$

$$R2 \quad : \quad \phi = 0 \tag{24}$$

$$R3 \quad : \quad \forall i \in \{\delta, \lambda\} : \omega_c^{i} = 0 \tag{25}$$

With $R1$, the specification of the mixing distribution corresponds to the one retained by Abbring *et al.* (1994, 1999). They allow a scale parameter of the mixing distribution, in our notations $\exp\left[\varphi_4^{\delta}(l)\right]$, to depend on calendar time at that moment of inflow. This specification is more restrictive than ours, since it imposes the mean and the variance of the mixing distribution to vary proportionally. $R2$ restricts the pattern of duration dependence not to vary over the business cycle. Finally, $R3$ imposes a fixed heterogeneity distribution over the business cycle: the mean and the variance of the unmeasured characteristics, v, of those entering unemployment are constant over the cycle. Note that $R3$ does not imply $R1$, since under $R3$ the variance of the mixing distribution can still vary non-proportionally over seasons.

The estimation procedure consists in two-steps (see Amemiya and Nold 1975). In a first step we estimate the model (21) by Ordinary Least Squares (OLS). On the basis of the OLS residuals ($\hat{n}_{kl}$) and of the estimated variance of the approximation error ($\hat{s}_{kl}^2$), we can calculate a consistent estimate of s_e^2:

[21] We also test whether e_{kl} follows an AR(1) process over l and in the dimension k. We found that the empirical correlation coefficient between e_{kl} and e_{kl-1} is not significantly different from zero for both age-groups.

$$\hat{s}_e^2 = \frac{1}{N}\left\{\sum_{l=0}^{17}\sum_{k=1}^{18-l}\left[(\hat{n}_{kl})^2 - \hat{s}_{kl}^2\right]\right\} \tag{26}$$

Using this statistic and the empirical auto-covariance of the OLS residuals, we can also calculate a consistent estimate of the auto-correlation coefficients, ρ_{l+k} and ρ_l, of the higher mentioned specification errors, e_{kl} (see Appendix 1). In a second step, we estimate the statistical model (21) by Generalised Least Squares (GLS), explicitly allowing for the AR(1) disturbances (e_{kl}) over k, for any fixed $l+k$ (see Appendix 2).

Because we have grouped data, we can use a χ^2-goodness-of-fit test to evaluate the model specification. The weighted sum of squared residuals ($WSSR$) is distributed χ^2_{N-p} if the model is correctly specified, where N denotes the number of observations and p is the number of parameters. Moreover, we can test the acceptability of the higher mentioned restrictions, $R1-R3$. If the constrained model is correctly specified, then the difference between the weighted sum of squared residuals of the constrained and the unconstrained model ($WRSS_0 - WRSS$) is distributed $\chi^2_{(p-p_0)}$.

4.2 A Non-Parametric Specification of the Mixing Distribution

In the benchmark model we chose a Gamma mixing distribution. Monte Carlo analysis realised by Ridder and Verbakel (1983) and Ridder (1987) suggests that if the baseline hazard is sufficiently flexible, the parameters of the conditional hazard are robust to a misspecification of the mixing distribution. Empirical studies confirm this result (see Kerckhoffs *et al.* 1994 and Cockx 1997)[22]. However, in these studies regressors are time-constant. One may therefore question whether these findings are confirmed for the case of time-varying regressors.

Heckman and Singer (1984) propose a non-parametric estimation method of the mixing distribution. In this method the mixing distribution is approximated by one with a discrete number of points of support. We follow this approach, as to test the sensitivity of our results to the parametrisation of the mixing distribution. In this approach the number of points of support to be estimated is a priori unknown. However, in the empirical application we find that if we increase the number of points of support beyond two, the third point always converges to one of the two others. We therefore restrict the number of points of support to two in the model specification below.

If the mixing distribution is discrete with two points of support, v_1 and v_2, the non-linear heteroskedastic regression model becomes:

$$\begin{aligned} 1-\hat{P}_{kl} \quad = \quad & \frac{\pi \exp\left[-v_1 \exp\left(\varphi_4^\delta(l)\right)\sum_{j=1}^{k} h_{jl}\right] + (1-\pi)\exp\left[-v_2 \exp\left(\varphi_4^\delta(l)\right)\sum_{j=1}^{k} h_{jl}\right]}{\pi \exp\left[-v_1 \exp\left(\varphi_4^\delta(l)\right)\sum_{j=1}^{k-1} h_{jl}\right] + (1-\pi)\exp\left[-v_2 \exp\left(\varphi_4^\delta(l)\right)\sum_{j=1}^{k-1} h_{jl}\right]} \\ & + u_{kl} + e_{kl} \end{aligned} \tag{27}$$

[22] Note that the study of Baker and Melino (1997) refutes this result with a discrete-time model.

where $v_1 > 0$, $v_2 > 0$, $0 \leq \pi \leq 1$, π being the probability assigned to v_1, and $v_2 = \frac{1-\pi v_1}{1-\pi}$ since we normalise the mean of the discrete distribution to one at calendar time $l = 0$. We specify h_{kl} as in (16). The function $\varphi_4^\delta(l)$ describes the evolution of the mean (and variance) of the mixing distribution over calendar time. For purposes of comparability, we impose restriction $R1$, such that the mean and variance vary proportionally. It is unclear how we should specify a 'comparable' non-proportional variation in the variance in the model with a discrete mixing distribution.

It is not only interesting to verify the sensitivity of the parameter estimates of the conditional hazard, but also to be able to reject the model that is incorrectly specified. This requires a non-nested test procedure. We follow Chow's (1985) suggestion and base a comparison on Schwarz's (1978) approximation of the Jeffrey-Bayes posterior-probability criterion[23]. According to this criterion, the preferred model is the one that minimises the following statistic:

$$WSSR + N_\theta \ln\left(\sum_{l=0}^{17}\sum_{k=1}^{18-l} r_{kl}\right) \tag{28}$$

where the weighted sum of squared residuals, $WSSR$, replaces minus twice the log likelihood function, a result derived by Amemiya (1981), and where N_θ is the number of estimated parameters. The expression in brackets represents the cumulative number of individuals at risk of leaving unemployment at each duration interval and for all quarters of inflow.

4.3 Identification

The MPH specification ensures that the conditional hazard is non-parametrically identified from a large number of observations on two conditions. First, the mean of the mixing distribution has to be finite. The second condition depends on the nature of the data and on the way in which they are modeled. If duration data are continuous, the regressor function needs to take on at least two values (see Elbers and Ridder 1982). If duration data are grouped, we need to distinguish between two cases. If duration is modeled as a continuous time process, as it is done in this paper, Ridder (1990) proves that the presence of a continuous explanatory variable is sufficient. If duration is modeled as a discrete time process, the mixing distribution is identified up to its moments, in so far as the support of the heterogeneity distribution is bounded[24] and the regressor function is non-constant (see van den Berg and van Ours 1994, 1996b and Abbring *et al.* 1999).

If we impose $R1$ and $R2$ on our specification (21), we obtain, apart from the random specification errors, the standard MPH model. To see this, note that $R2$ implies that calendar time at the outflow influences the baseline hazard proportionally throughout the observation period. $R1$ implies that the business cycle and seasonal indicators at the time

[23] See Cockx, Van der Linden and Karaa (1998) for an application of this criterion.

[24] The finite mean is implied by this condition.

of entry enter the specification multiplicatively. However, even with such assumption an exponential trend in the inflow cannot be identified from an exponential trend in the outflow (see Section 4.1). We avoid this problem because entry effects are assumed to be completely captured by seasonal effects and a business cycle indicator at the time of entry, i.e. the number of entrants. If this indicator does not vary according to an exponential trend, identification is assured. Nevertheless, entry effects still have two indistinguishable interpretations, i.e. either compositional or competition effects (see Abbring *et al.* 1999). Until now, we interpreted them as compositional effects, by assuming that calendar time at the moment of inflow affects the shape of the distribution of v in the inflow. Calendar time at the inflow could, however, also influence the individual exit rate directly, leaving the composition of inflow constant over time. In such an interpretation, seasonal and cyclical fluctuations in the number of workers entering the unemployment pool may alter the intensity of the job-search competition faced by the newly unemployed and, therefore, their exit rate. So, the inflow into unemployment creates a negative intra-group externality corresponding to congestion effects. In that case, the multiplicative effect of the indicators at the time of inflow should be taken to affect the conditional hazard rather than the form of the mixing distribution. We rule this out by assumption. The reader can, however, validly interpret the empirical findings below differently, in terms of competition rather than compositional effects.

For the model in which assumptions $R1$ and $R2$ are imposed, we can therefore rely on the non-parametric identification results of Ridder (1990). The mean of the mixing distribution is restricted to be finite and equal to one in the quarter beginning in June 1989. This is achieved by the normalisation that $b(0) = 0$ and $\omega_{s1}^{\delta} = \omega_{s1}^{\lambda}$. Both, the polynomial capturing the business cycle effects at the time of exit and the business cycle indicator at the time of entry ensure that the regressor function is continuous.

If we relax $R2$ the specification is no longer MPH, since the baseline hazard is then allowed to vary non-proportionally between two calendar time sub-periods at the time of exit. As long as the number of sub-periods does not increase with the number of observations[25], identification is, however, assured by the MPH assumption within each sub-period.

If $R1$ is violated, the mean and the variance of the mixing distribution vary non-proportionally over calendar time at entry. This specification is equivalent to make the hazard rate dependent on an interaction term between unemployment duration and the calendar time indicators at entry. However, we can still identify the mixing distribution at each entry date, because the conditional baseline hazard is proportional in the polynomial at the calendar time of exit (at least within sub-periods). Note that it more natural to interpret this non-proportionality as compositional effects rather than as competition effects. Indeed, it is unclear why fluctuations in the number of entrants into unemployment over time should influence the pattern of the exit rates over duration.

[25] This is feasible if observations are classified to one of the subperiods according to whether they are realised in an upturn or a downturn.

5 Empirical Results

5.1 Specification Tests

In Tables 1 and 2 we report the estimation results of the mixture regression model (21), respectively for men aged between 29 and 44 years old and for those aged less than 29 years old. The second column refers to the model without any restrictions. The third column tabulates the estimates on which restriction $R1$ is imposed, i.e. the restriction that the variance of the mixing distribution varies proportionally to the mean over calendar time. In the last column we report the findings for the discrete mixture with two points of support (and on which restriction $R1$ is imposed). The constant term is, after an exponential transformation, the estimated hazard of a reference individual with average unmeasured characteristics (i.e. $v = 1$).

Consider first the performance of the models on the basis of the goodness-of-fit statistic. At a significance level of 1% no model is to be rejected against the saturated model for both age-groups. However, for the young workers all specifications are rejected at a significance level of 5%. We therefore need to be cautious in interpreting the estimation results regarding the young unemployed workers.

On the basis of the approximation of the Jeffrey-Bayes posterior probability criterion (see the third and the fourth columns), the model with a Gamma mixing distribution is preferred for both age cohorts. This conclusion does affect the interpretation of the results. For, the parameter estimates relative to the baseline hazard of the discrete mixture model systematically exhibit a more negative duration dependence. However, this merely reflects our uncertainty regarding the true parameter values. In Figure 1 we observe that the 95%-confidence intervals of the two models overlap to a great extent, at least for the age group 29-44. This uncertainty is particularly large for the Gamma specification as applied to the younger age group. Moreover, the overlap of the confidence intervals is less important. We should therefore be especially careful in interpreting the duration dependence of the hazard of the young unemployed workers. Moreover, the finding that the estimated conditional hazard is robust to the misspecification of the mixing distribution (see e.g. Ridder and Verbakel 1984), might only hold to the extent that the conditional hazard is correctly specified. Finally, notice that the other parameter estimates are not sensitive to the form of the mixing distribution, generalising the empirical findings of Ridder (1987), Kerckhoffs *et al.* (1994) and Cockx (1997) to the case of time-varying regressors and heterogeneity distribution.

INSERT FIGURE 1 APPROXIMATELY HERE

Since the discrete mixture specification is rejected against the Gamma mixture model, we only retain the latter specification in the subsequent discussion. Before entering into a more detailed interpretation of the estimation results with respect to duration and calendar time dependence, we now first question whether we can impose the three restrictions proposed in Section 4.1.

According to the χ^2-test, we cannot reject restriction $R1$ for the men aged 29-44 at a significance level of 27%, but we do reject it for the young male workers with a risk of 3%

of an error of Type I. For neither group, the parameter estimates change significantly, apart from the inflow seasonal effects (see the second and the third columns). The inflow cyclical effect are hardly affected because compositional effects over the business cycle are unimportant. Neither the mean nor the variance of the mixing distribution varies over the cycle: $R3$ cannot be rejected at a significance level of 5%, both for the young and older workers. The non-proportional variation of the variance to the mean for the young unemployed workers is therefore entirely due to seasonal effects.

The estimated interaction parameter, ϕ, is significantly positive for men aged between 29 and 44 years old (ϕ =1.99). Consequently, restriction $R2$ is rejected. This result means that duration dependence becomes more negative when the labour market state deteriorates (i.e. after 1990). This provides evidence in favour of the ranking model. It also explains why the interaction effect ψ_c estimated in the first stage (see the first column of Table 1), although negative and thereby suggesting the presence of heterogeneity, is small in absolute value: ranking has an opposite effect than sorting on the duration dependence of the aggregate outflow rate within the business cycle. As expected, we underestimate the variance of the Gamma distribution in a model ignoring this interaction[26]. For the youngest age-group, the sign of ϕ also points to ranking (ϕ =0.08). Yet, given the size of its standard deviation, this coefficient is not significantly different from zero and restriction $R2$ is not rejected.

Finally, note that standard deviation of the specification errors is small: of the order of .01 for both groups and over all specifications. For the adult population, the specification error accounts only for 1.2% of the variation in the dependent variable. For the young unemployed workers this figure is 1.6%. Cohort specific calendar time effects are thus unimportant.

To conclude, for both groups the procyclical variation in the hazard rates is general and cannot be explained by compositional effects. Ranking can partly explain the negative unemployment duration of prime aged unemployed workers. A neglect of this phenomenon causes the variance of the mixing distribution to be under-estimated. Ranking is not important for young unemployed workers. Seasonal effects only induce a non-proportional variation of the variance to the mean of the mixing distribution of the young population, but not for the prime-aged men.

5.2 True versus Spurious Duration Dependence

The results for the estimated variance of the heterogeneity distribution indicate an important disparity between the characteristics of those flowing into unemployment. For men aged between 29 and 44 years old, the estimated variance is significantly positive at the reference calendar time of inflow ($\hat{\sigma}_0^2 = 0.89$). The variance is somewhat, but not significantly, lower for the young unemployed workers ($\hat{\sigma}_0^2 = 0.83$).

Figure 2 shows, for men aged 29-44, the duration pattern of the hazard resulting from three different model specifications: a model with neither unmeasured heterogeneity nor

[26] The estimation is available upon request.

a calendar time interaction at the time of exit[27], the mixture model (21) under $R2$, i.e. without interaction, and the general mixture model (21). In the general model, the duration dependence in the upturn is positive while it is negative in the downturn. We attribute this to the theoretical prediction that in the hiring process, ranking according to unemployment duration is less important or is even absent in an upturn. Notice that the 'true' negative duration dependence in the downturn is over-estimated when ignoring the interaction.

INSERT FIGURE 2 APPROXIMATELY HERE

If we focus on the duration dependence pattern estimated in downturn, the nature of the negative duration dependence of the aggregate hazard in Wallonia is largely spurious: the sorting process due to unobserved heterogeneity explains most of the sharp decline in the estimated aggregate exit rate with unemployment duration for the men aged 29-44. There is a 7% decrease in the individual hazard between the first and the second quarter of unemployment, and then a slight increase up to fifth quarter where the hazard nearly reaches its initial level. Given the level of parameters significance, we can argue that individual exit probabilities are, if anything, slightly decreasing over the first 1.5 years of unemployment and exhibit significant negative duration dependence afterwards. After two years and a half of unemployment the conditional hazard has dropped by 20%.

We now turn to the estimated duration dependence patterns for the young unemployed. As the interaction parameter is insignificantly different from zero, the estimated duration dependence of the exit rate does not vary over the business cycle. So ranking is apparently unimportant in the hiring process of young unemployed workers. After correcting for unobserved heterogeneity, the estimated duration dependence is strongly positive. The baseline hazard is, however, very imprecisely estimated. We cannot reject duration to follow an exponential distribution at a significance level of 66%. Nevertheless, we can conclude that the observed negative duration dependence is completely spurious.

How explain the differences in the duration pattern between the distinct age groups? First, unlike for the adult unemployed, there is no evidence of ranking for the young people. Why is it that the ranking rule is not relevant for the young unemployed? The employer has an important piece of reliable information at his disposal to infer the productivity of young workers, i.e. their level of educational attainment. Conditional on this level, the elapsed unemployment duration is unlikely to signal additional information. The employer cannot therefore increase the productivity of his recruits by ranking candidates according to unemployment duration. This explanation is reinforced by the observation that the conditional hazard is not decreasing. On the other hand, the level of educational attainment is likely to be a very noisy signal of the productivity of older workers. If it is difficult and costly to obtain reliable information on the worker's productivity, unemployment duration is a cheap and reliable signal, even if it is completely

[27] In order to take into account inflow effects in this model, we assume that the individual hazard is multiplicative in calendar time at the moment of inflow.

spurious. The reliability of this signal is reinforced, because the conditional hazard exhibits true negative duration dependence after 1.5 years that is unlikely to be completely explained by the ranking in the recruitment procedure[28].

The depreciation of human capital during unemployment is likely to be more important for the older workers than for younger. This is because (i) the level of human capital is simply higher for older workers[29] and (ii) the skills that older workers have acquired on their previous job may require more maintenance than the general skills learnt at school. This higher rate of human capital depreciation can also lead to a more rapid 'demotivation' of older workers in their search for a job. Observe that the net expected returns to the on-the-job investments required in a new job are lower for older than for younger workers, simply because older workers face a shorter horizon. This may not only affect the search intensity level, but also its pattern over duration. The more human capital depreciates, the larger the on-the-job investments required in the new job.

Differential participation in active labour market programmes (ALMP) can also explain the different pattern of duration dependence between the two age groups. For, participation in ALMP in Belgium is often targeted to young and long-term unemployed workers. Besides, young people are likely to be more involved in ALMP given that they expect a higher return of these programs than older people who have a lower time span to amortize their investment. However, we do not have any figures to corroborate the fact that the young unemployed participate more to ALMP than the prime-aged unemployed in Belgium. If it is actually the case, this may induce the baseline hazard of the younger workers to increase with unemployment duration since in our dataset participants in these programmes are recorded to leave unemployment[30] if they do not return within the next quarter[31].

Finally, the rules governing the unemployment benefit scheme may induce younger workers to search more intensively as they are longer on the dole. For, the likelihood that young male workers are head of a family is lower than for the older age group. Since unemployment benefits for those who are not head of a family drop after 1 year and once more after 18 months if one is cohabitant, e.g. living with once parents, the young will decrease their reservation wage and increase their search intensity gradually with unemployment duration (see van den Berg 1990). By contrast, the heads of households are entitled to a constant unemployment benefit for an indefinite duration. Moreover, since the drop in the level of unemployment benefits after 18 months can be postponed with a factor that is proportional to past work experience, the more experienced and

[28] We cannot infer this from our data, because the observation period in the upturn is too short, i.e. only 5 quarters. If the negative duration dependence of the conditional hazard would not be observed in the upturn, the negative duration dependence would be completely induced by ranking.

[29] This argument has been used by van den Berg and van Ours (1996a, p.11) to explain the difference in the duration dependence pattern between young male and female in France. As these former have on average a higher schooling level than the female workers, "a certain loss of human capital during unemployment leaves long-term unemployed men with still a higher average level of human capital than long-time unemployed women".

[30] An exception to this rule is the participation in counseling programmes: the worker remains registered as unemployed.

[31] This is the so-called 'tautological' effect of ALMPs (see Calmfors 1994).

therefore older cohabiting workers will also be less affected by the declining profile of unemployment benefits.

We finish the discussion of our estimation results on duration dependence and heterogeneity by comparing them to those obtained in other studies. For purpose of comparison with our analysis, we restrict our discussion to recent European studies on unemployment duration applying a MPH framework and a flexible functional form for the duration dependence (for a more complete survey, see Machin and Manning 1999).

In view of our results Belgium belongs to the large pool of European countries where there is both, no marked evidence of 'true' negative duration dependence of the exit rate out of unemployment and important 'spurious' dependence. So the United Kingdom seems to remain the exception, with individual unemployment duration distributions exhibiting strong negative duration dependence and not being significantly heterogeneous (see Nickell 1979 or van den Berg and van Ours 1994).

With respect to the prime-aged men, the duration dependence of the conditional hazard in Wallonia resembles much the one that is found for the Netherlands and France, where there is evidence of non-monotonic true duration dependence, first constant, or even slightly increasing, then decreasing. Using a non-parametric specification of the mixing distribution, Van den Berg *et al.* (1998a) estimate a slightly increasing trend of the individual outflow probabilities over the first year of unemployment for the men aged 25-49, while these exhibit significant negative duration dependence onwards[32]. Although they treat the population of male unemployed globally, van den Berg and van Ours (1994) and Kerckhoffs *et al.* (1994) obtain the same kind of non-monotonicity in the Netherlands, using a discrete mixing distribution. Yet, the estimated hazard is overall constant over the first year of unemployment (first increasing, then decreasing) and declines very mildly onwards. Notice that unlike Belgium, France and the Netherlands, there is a slight positive dependence of the exit rate over all durations in Germany (see Steiner 1997), Spain (see Bover *et al.* 1996) and Norway (see Hernaes and Strom 1996).

Concerning the young job-seekers, most of the studies tend to estimate a constant, or weakly negative (after some quarters of inactivity), duration dependence of the exit rate. Van den Berg and van Ours (1996a) as well as van den Berg *et al.* (1998a) found that young unemployment duration distributions in France exhibit no significant duration dependence during the first year of unemployment and a moderate negative duration dependence thereafter[33]. Specifying a Gamma mixing distribution, D'Addio (1999) found no evidence of negative true duration dependence of the exit rate of young French workers unlike van den Berg *et al.*. Besides, an exponential distribution for the duration dependence pattern cannot be rejected as in our analysis.

We should, however, keep in mind that none of the reviewed studies allow the pattern

[32] Only the first four quarters of unemployment are explicitly introduced in their empirical analysis. They use an informal procedure to deduce the duration dependence pattern beyond. They estimate non-parametrically the moments of the mixing distribution, and show that these are compatible with a two points of support distribution. The estimate of this mixing distribution on data regarding the first four quarters only and the aggregate observed exit rates are then used to infer the duration dependence of the conditional exit rate for the intervals beyond one year.

[33] see the preceeding footnote.

of the duration dependence to vary over the business cycle. As is shown in this study, this potentially biases their findings regarding duration dependence downwards. Rosholm (1997) does allow for an interaction effect with the business cycle. He estimates that the duration dependence of the hazard becomes less negative, but insignificantly so, when unemployment increases for adult male workers[34], even after controlling for unobserved heterogeneity. He interprets this as evidence against the ranking model.

Our study does not only show that ignoring an interaction between the duration dependence and the business cycle may bias the estimations. It also suggests that the duration dependence may not be similar across age groups. Consequently, the common[35] assumption that age affects the baseline hazard proportionally, may accordingly lead to incorrect conclusions.

Our findings cast serious doubt on the reliability of some micro-econometric studies attempting to disentangle true from spurious duration dependence in Belgium (see Spinnewyn 1982 and Mahy 1994). Using strong parametric assumptions (Weibull) regarding the baseline hazard, they estimate a significant positive duration dependence of the conditional baseline hazard. Note that, assuming a Gamma mixing distribution, Kerckhoffs *et al.* (1994) estimate for the Netherlands a strong positive duration dependence with a Weibull baseline hazard specification while they obtain a similar result as ours when allowing for a flexible duration dependence pattern. These findings confirm that the importance of specifying the baseline hazard with sufficient flexibility (see also Heckman and Singer 1984). Finally, note that the positive duration dependence found by Plasman (1993) is not inconsistent with our findings. For, he restricts his analysis to young school-leavers, excluded from our analysis.

5.3 Decomposition of Unemployment Duration over Calendar Time

The outflow rate from unemployment appears to be procyclical for men in Wallonia, as observed in comparing a Belgian business cycle indicator (the Kredietbank indicator, see Kredietbank 1997) and the estimated five degrees polynomial function in Figure 3. The exit rate of the young unemployed is more heavily hit by the recession in 1993 than the one of the adult unemployed: there is a nearly 40% (resp. 50%) drop in the hazard in February 1993 compared to its level in November 1989 for the men aged 29-44 (resp. men aged <=28). This contrasts with the findings of van den Berg *et al.* (1998a) who estimated that the exit rate of young workers is less affected by the cycle then the one of the adult workers in France.

INSERT FIGURE 3 APPROXIMATELY HERE

Figure 4 shows the estimated deseasonalised variance and mean of the Gamma distribution at each calendar time of our observation period for men aged 29-44 and for

[34] The interaction between the baseline hazard and the unemployment rate is not significant for the young men.

[35] Rosholm (1997) and van den Berg *et al.* (1998a) deviate from this common rule and specify a distinct baseline hazard by age groups.

those aged <=28. For the former age-group, the mean and the variance vary proportionally over the cycle (restriction $R1$) while for the latter, they vary independently. We observe that the quality and the dispersion of male entrants has declined, although not significantly, from the cyclical peak at the end of 1989 to the downturn in 1993, while the number of inflows into unemployment was increasing. This result suggests a slightly rising share of entrants with poor re-employment prospects as labour market conditions deteriorate in Wallonia. However, since this effect is small and insignificant, we conclude that compositional variation cannot explain the procyclical variation of the hazard. This finding is in line with the results obtained with French data by Abbring *et al.* (1994, 1999) and van den Berg and van der Klaauw (1998). Finally, notice that we only observe data in the descending phase of a business cycle. We should therefore be cautious when generalising our findings to the complete cycle. For instance, Rosholm (1997) finds for Danish data that the compositional effect varies across the cycle.

INSERT FIGURE 4 APPROXIMATELY HERE

There is also some seasonal variation in the average quality of the inflow, mainly in the young population as we observe in Figure 5. The average characteristics of new entrants slightly worsen in autumn and spring, and their dispersion largely increases, compared to those observed in the other seasons.

INSERT FIGURE 5 APPROXIMATELY HERE

We also find significant seasonal variations in the outflow rate that remain unexplained by the seasonal variation in the quality of the inflow (see Table 1 and Table 2). These are about the same for both age groups. As expected, the summer time seems to impede a lot the exit from unemployment, while the labour market conditions are the most favourable during the spring time.

6 Conclusion and Policy Recommendations

In this paper, we investigated what causes the aggregate exit rate out of unemployment estimated in Wallonia to decline strongly over duration and to vary over calendar time. For that purpose, we proposed to relax the commonly used MPH specification in three ways. First, we allowed the individual hazard to vary non-proportionally between two sub-periods, i.e. a boom and a recession, in order to test the ranking hypothesis. Second, the variance of the mixing distribution needs not to fluctuate proportionally to its mean over calendar time at entry. Finally, we allowed for random deviations from the MPH framework by introducing random cohort-specific business cycle effects at the time of exit.

We estimated our model by Minimum Chi-Squares on quarterly data of male workers entering unemployment between June 1989 and February 1994. We distinguished between two age groups, those less than 29 and workers between 29 and 44 years old. For both age-group, we found that heterogeneity induces significant spurious negative duration dependence of the aggregate hazard. During a recession, the conditional hazard of prime-aged men is, if anything, slightly decreasing over the first 1.5 years of unemployment, and exhibits significant negative duration dependence onwards. When the labour market conditions ameliorate, duration dependence is slightly positive. So, there is evidence of ranking for the adult unemployed. For the young men, the individual exit rate is significantly constant over all durations, whatever the state of the business cycle. Ranking is therefore not important for the young unemployed workers.

On the basis of these results, we conclude that negative duration dependence of the exit rates out of unemployment, even if it plays a role, cannot be the main channel of unemployment persistence in Wallonia. The hysteresis diagnosis of unemployment persistence originates from the United Kingdom where individual exit rates exhibit strong negative duration dependence (see e.g. Layard *et al.* 1991). According to this theory, the presence of 'true' negative duration dependence explains why the unemployment rate did not return to its initial level after a succession of negative economic shocks in the eighties. Two crucial factors play a role here. Unemployment dependency leads to labour shortages in case of economic recovery, although unemployment stays high. Second, it reinforces the bargaining power of insiders with respect to wage demands, tempering by this way employment growth. Empirical studies on unemployment duration and heterogeneity in Europe have proven that the United Kingdom remains the exception in a large pool of countries where there is no marked evidence of true negative duration dependence. Among this group, the duration dependence of the conditional hazard in Wallonia resembles much the one that is found in the Netherlands and in France.

Our findings also suggest that public outlays to active labour market policies should not primarily focus on temporary work experience schemes with little training content. These schemes are often aimed at preventing or countering the process of demotivation and skill deterioration likely to arise after a prolonged unemployment. Our results show that this process is of little importance to explain the low employability of the long-term unemployed in comparison with the importance of their intrinsic skills (used in a broad sense). Given this diagnosis, it is unlikely that temporary work programs are by themselves sufficient to upgrade durably the employability of the long duration unemployed in Wallonia.

For both age-group, the pro-cyclical variation of the aggregate exit rate in Wallonia is driven by a cyclical fluctuation in the individual exit rate of all currently unemployed rather than by a change in the average quality of the new entrants within the economic cycle. This finding is in line with the results obtained with French data. As we only observe data in the descending phase of a business cycle, we should, however, be cautious when generalising our findings to the complete cycle. Seasonal fluctuations in the exit rate are the result of large seasonal variations both, in the individual exit rate and in the average characteristics of the inflow. The variance of these characteristics changes non-proportionally to their mean in the young population, but not in the adult population.

We significantly improve our statistical model in departing from the 'pure' proportionality assumption. On the one hand, we show that the variance of the mixing distribution can be underestimated in a model ignoring the non-proportionality of the hazard in duration and calendar time at the outflow, i.e. the ranking hypothesis. On the other hand, we found that ignoring random cohort-specific business cycle effects at the time of exit can lead to an efficiency loss in the estimates. Indeed, these deviations from the proportionality framework induces, for any fixed exit time, the model residuals to be positively auto-correlated with duration under two reasonable assumptions : (i) cohorts are each other's imperfect substitute and (ii) the degree of substitutability decreases with the difference of the elapsed duration between the affected cohort and the non-affected cohorts.

References

Abbring, J.H. and G.J. van den Berg (1998), "Limit results for unobserved heterogeneity distributions in mixed proportional hazard models", Working paper, Free University Amsterdam, Amsterdam.

Abbring, J.H., G.J. van den Berg, and J.C. van Ours (1994), "The anatomy of unemployment dynamics", Working paper n°9437, Tinbergen Institute.

Abbring, J.H., G.J. van den Berg, and J.C. van Ours (1997), "Business cycles and compositional variation in U.S. unemployment", Discussion paper n°1702, Centre for Economic Policy Research.

Abbring, J.H., G.J. van den Berg, and J.C. van Ours (1999), "The anatomy of unemployment dynamics", mimeo, Vrije Universiteit Amsterdam.

Amemiya, T. (1981), "Qualitative response models: A survey", *Journal of Economic Literature*, 19, 1483-1536.

Amemiya, T. (1985), *Advanced Econometrics*, Basil Blackwell, Oxford.

Amemiya, T. and F. Nold (1975), "A modified logit model", *Review of Economics and Statistics*, 57, 255-57.

Baker, M. (1992), "Unemployment duration: Compositional effects and cyclical variability", *American Economic Review*, 82, 313-321.

Baker, M. and A. Melino (1997), "Duration dependence and nonparametric heterogeneity: A Monte Carlo study", Working paper, University of Toronto, Toronto.

Bardoulat, I., M. Dejemeppe, Y. Saks, B. Cockx, and B. Van der Linden (1998), Marché du travail et chômage. Valorisation de banques de données existantes: la STAT. 92., Rapport final du contrat SSTC n°DB/10/035, "Programme de valorisation des banques de données socio-économiques fédérales", IRES, Université Catholique de Louvain, décembre.

Berkson, J. (1944), "Application of the logistic function to bio-assay", *Journal of the American Statistical Association*, 39, 357-365.

Blanchard, O.J. (1991), "Wage bargaining and unemployment persistence", *Journal of Money, Credit, and Banking*, 23, 277-292.

Blanchard, O.J. and P.A. Diamond (1994), "Ranking, unemployment duration, and wages", *Review of Economic Studies*, 61, 417-434.

Bover, O., M. Arellano, and S. Bentolila (1996), "Unemployment duration, benefit duration, and the business cycle", Estudios Economicos n°57, Banco de Espana - Servicio de Estudios.

Breusch, T.S. and A.R. Pagan (1980), "The Lagrange multiplier test and its applications to model specification in econometrics", *Review of Economic Studies*, 47, 239-253.

Calmfors, L. (1994), "Active labour market policy and unemployment: Framework for analysis of crucial design features", *OECD Economic Studies*, 22, 7-52.

Chow, G.C. (1985), *Econometrics*, Mc Graw-Hill.

Cockx, B. (1997), "Analysis of transition data by the Minimum Chi-Square method: An application to welfare spells in Belgium", *The Review of Economics and Statistics*, 79 (3), 392-405.

Cockx, B., B. Van der Linden, and A. Karaa (1998), "Active labour market policies and job tenure", *Oxford Economic Papers*, 50, 685-708.

D'Addio, A.C. (1999), "Unemployment durations of French young people", Discussion Paper n°9821, Institut de Recherches Economiques et Sociales, Université Catholique de Louvain.

Darby, M.R., J. Haltiwanger, and M. Plant (1985), "Unemployment rate dynamics and persistent unemployment under rational expectations", *American Economic Review*, 75, 614-637.

Dynarski, M. and S.M. Sheffrin (1990), "The behavior of unemployment durations over the cycle", *Review of Economics and Statistics*, 72, 350-356.

Elbers, C. and G. Ridder (1982), "True and spurious duration dependence: The identifiability of the proportional hazard model", *Review of Economic Studies*, 49, 403-410.

Flinn, C.J. and J.J. Heckman (1982), "Models for the analysis of labor force dynamics", in Basmann, R. and G. Rhodes (eds.), *Advances in Econometrics*, 1, 35-95.

Godfrey, L.G. (1978), "Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables", *Econometrica*, 46, 1293-1302.

Gourieroux, C. and A. Monfort (1995), *Statistics and Econometric Models*, Cambridge University Press, Cambridge.

Heckman, J.J. and B. Singer (1984), "A method for minimizing the impact of distributional assumptions in econometric models for duration data", *Econometrica*, 52, 271-320.

Hernaes, E. and S. Strom (1996), "Heterogeneity and unemployment duration", *Labour*, 10, 269-296.

Imbens, G.W. and L.M. Lynch (1992), "Labor market transitions over the business cycle", *Review of Economics and Statistics*, 72, 350-356.

Kerckhoffs, C., C. de Neubourg, and F. Palm (1994), "The determinants of unemployment and jobsearch in the Netherlands", *De Economist*, 142, 1, 21-42.

Kredietbank (1997), "La conjoncture guette l'évolution chez nos partenaires commerciaux", Bulletin Hebdomataire Kredietbank, 52ème année, n°19.

Lancaster, T. (1979), "Econometric methods for the duration of unemployment", *Econometrica*, 47, 939-956.

Lancaster, T. (1990), *The econometric analysis of transition data*, Cambridge University Press, Cambridge.

Layard, R., S.J. Nickell, and R. Jackman (1991), *Unemployment*, Oxford University Press, Oxford.

Machin, S. and A. Manning (1999), "The causes and consequences of long-term unemployment in Europe", *The Handbook of Labor Economics*, Volume 3C, 3085-319.

Mahy, M. (1994), "Politiques et recherche d'emploi: évaluation microéconométrique", *Reflets et Perspectives de la Vie Economique*, 33, n°1/2, 87-102.

Merz, M. (1999), "Time series evidence of unemployment flows: The sample period matters", *Journal of Business and Economic Statistics*, 17, 3, 324-334.

Neyman, J. and E.L. Scott (1948), "Consistent estimates based on partially consistent observations", *Econometrica*, 16, 1-32.

Nickell, S. (1979), "Estimating the probability of leaving unemployment", *Econometrica*, 47, 1249-1266.

OECD (1997), *The public employment service. Belgium*, Paris.

Plasman, R. (1993), Efficacité des Programmes Publics d'Emploi, Colloque de l'A.E.A. sur l'Evaluation des Politiques d'Emploi, Paris.

Ridder, G. (1987), "The sensitivity of duration models to misspecified unobserved heterogeneity and duration dependence", Working paper, Groningen University, Groningen.

Ridder, G. (1990), "The non-parametric identification of generalized accelerated failure-time models", *The Review of Economic Studies*, 57, 167-181.

Ridder, G. and W. Verbakel (1983), "On the estimation of the proportional hazard model in the presence of heterogeneity", University of Amsterdam, Faculty of Actuarial Science and Econometrics, A&E Report 22/83.

Rosholm, M. (1997), "Cyclical variations in unemployment duration: A decomposition", mimeo, Centre for Labour Market and Social Research, University of Aarhus.

Salant, S.W. (1977), "Search theory and duration data : A theory of sorts", Quarterly Journal of Economics", 91, 39-57.

Schwarz, G. (1978), "Estimating the dimension of a problem", *Ann. Satisti.*, 6, 461-464.

Sider, H. (1985), "Unemployment duration and incidence: 1968-82", *American Economic Review*, 75, 461-472.

Spinnewyn, F. (1982), "De statistische analyse van gegevens in verband met de werkloosheid", mimeo, Centrum voor Economische Studien, Katholieke Universiteit Leuven.

Steiner, V. (1997), "Extended benefit-entitlement periods and the duration of unemployment in West Germany", Zentrum für Europäische Wirtschaftsforschung Discussion Paper n°97-14, Germany.

van den Berg, G.J. (1990), "Nonstationarity in job search theory", *Review of Economic Studies*, 57, 255-277.

van den Berg, G.J. (1999), "Duration models: Specification, identification, and multiple durations", Working paper, Free University Amsterdam, Amsterdam, to appear in Heckman, James J. and Edward Leamer (eds.), *The Handbook of Econometrics*, Volume V, Amsterdam: North Holland.

van den Berg, G.J., A. Gijsbert, C. van Lomwel, and J.C. van Ours (1998a), "Unemployment dynamics and age", Discussion Paper n°9897, Center for Economic Research.

van den Berg, G.J. and B. van der Klaauw (1998b), "Combining micro and macro unemployment duration data", Research Memorandum 1998-41, Free University, Amsterdam.

van den Berg, G.J. and J.C. van Ours (1994), "Unemployment dynamics and duration dependence in France, The Netherlands and The United Kingdom", *Economic Journal*, 104, 432-443.

van den Berg, G.J. and J.C. van Ours (1996a), "Duration dependence and heterogeneity in French youth unemployment durations", Discussion paper n°96-151/3, Tinbergen Institute.

van den Berg, G.J. and J.C. van Ours (1996b), "Unemployment dynamics and duration dependence", *Journal of Labor Economics*, 14, 100-125.

Appendix

Appendix 1

In this appendix, we derive the empirical correlation coefficients between e_{kl} and, respectively, e_{k-1l+1} and e_{k-1l}.

Let us define the total errors v_{kl} as the sum of the approximation errors and the specification (or measurement) errors:

$$v_{kl} = u_{kl} + e_{kl} \tag{a1}$$

and make the following assumptions on the covariance structure of these errors:

$$E\left(u_{kl}u_{k-sl+s}\right) = E\left(u_{kl}u_{k-sl}\right) = E\left(u_{kl}e_{kl}\right) = E\left(u_{k-sl+s}e_{kl}\right) = E\left(u_{k-sl}e_{kl}\right) = 0 \quad \forall s \neq 0 \tag{b1}$$

First, consider that in (a1), e_{kl} follows an AR(1) process over k and for $l+k$ fixed:

$$e_{kl} = \rho_a e_{k-1l+1} + w_{kl}, \text{ where } \left|\rho_a\right| < 1 \tag{c1}$$

where it is assumed that:

$$E\left(e_{k-1l+1}w_{kl}\right) = 0 \tag{d1}$$

Upon substitution of (c1) in (a1) and expressing e_{k-1l+1} as a function of v_{kl} and u_{kl}, we obtain:

$$v_{kl} = \rho_a v_{k-1l+1} + w_{kl} + u_{kl} - \rho_a u_{k-1l+1} \tag{e1}$$

Multiplying both sides by v_{k-1l+1} and taking the expectation give:

$$\begin{aligned} E\left(v_{kl}v_{k-1l+1}\right) \quad = \quad & \rho_a E\left(v_{k-1l+1}^2\right) + E\left(w_{kl}v_{k-1l+1}\right) + E\left(u_{kl}v_{k-1l+1}\right) \\ & -\rho_a\left[E\left(u_{k-1l+1}e_{k-1l+1}\right) + E\left(u_{k-1l+1}^2\right)\right] \end{aligned} \tag{f1}$$

By using the assumptions stated in (b1) and in (d1), we then find that the covariance of v_{kl} in the dimension $l+k$ and for varying k is given by:

$$E\left(v_{kl}v_{k-1l+1}\right) = \rho_a s_e^2 \tag{g1}$$

From (g1), we can finally derive a consistent estimate of ρ_a:

$$\hat{\rho}_a = \frac{\frac{1}{N}\sum_{l=0}^{16}\sum_{k=2}^{18-l}\hat{v}_{kl}\hat{v}_{k-1l+1}}{\hat{s}_e^2} \tag{h1}$$

where $\hat{v}_{kl}$ is the OLS residual of the regression (21) and $\hat{s}_e^2$ is the estimate of s_e^2 given in (26). In fact, $\hat{\rho}_a$ is a generalisation of the empirical autocorrelation coefficient found in the literature to the case of two errors terms, one of them following an AR(1) process. The LM-test statistics for $\hat{\rho}_a$ takes the form (see Godfrey 1978 and Breusch and Pagan 1980):

$$LM = (\hat{\rho}_a)^2 N \backsim_{\alpha}^{H_0} \chi^2(1) \tag{i1}$$

where the null hypothesis is $H_0 : \rho_a = 0$ against $H_1 : \rho_a \neq 0$ and α is the significance level of the test.

If in (a1), e_{kl} follows an AR(1) process over k and in the dimension l:

$$e_{kl} = \rho_b e_{k-1l} + w_{kl}, \text{ where } |\rho_b| < 1 \tag{j1}$$

where it is assumed that:

$$E(e_{k-sl}w_{kl}) = 0 \;\; \forall s \neq 0 \tag{k1}$$

we can similarly find a consistent estimate of $\hat{\rho}_b$:

$$\hat{\rho}_b = \frac{\frac{1}{N}\sum_{l=0}^{17}\sum_{k=2}^{18-l}\hat{v}_{kl}\hat{v}_{k-1l}}{\hat{s}_e^2} \tag{l1}$$

and apply the same LM-test statistic than in (i1).

Appendix 2

In this appendix, we give the estimation procedure of the mixture model (21) where the disturbances, e_{kl}, follows an AR(1) process over k and in the dimension $l+k$.

When e_{kl} follows an AR(1) process across k and for $l+k$ fixed such that:

$$e_{kl} = \rho e_{k-1l+1} + w_{kl} \tag{a2}$$

the mixture model in (21) becomes a non-linear regression model with heteroskedastic and correlated disturbances. Assuming that $E(u_{kl}e_{kl}) = 0$, the variance-covariance matrix of the N total disturbances, v_{kl}, is then block-diagonal. The block-matrix, idempotent and of dimension $l+k$ (for simplicity, we denote $l+k$ by c), takes the following form:

$$\underset{(c,c)}{\begin{bmatrix} s^2_{1c-1}+s^2_e & \rho s^2_e & \rho^2 s^2_e & ... & \rho^{c-1}s^2_e \\ \rho s^2_e & s^2_{2c-2}+s^2_e & \rho s^2_e & ... & \rho^{c-2}s^2_e \\ \rho^2 s^2_e & \rho s^2_e & s^2_{3c-3}+s^2_e & ... & \rho^{c-3}s^2_e \\ ... & ... & ... & ... & ... \\ \rho^{c-1}s^2_e & \rho^{c-2}s^2_e & \rho^{c-3}s^2_e & ... & s^2_{c0}+s^2_e \end{bmatrix}} \tag{b2}$$

The estimation procedure consists then in two-steps. The first step consists in using OLS to estimate the residuals $\hat{v}_{kl}$. These allow us to construct a consistent estimate of the specification errors, $\hat{s}^2_e$, and to calculate the empirical correlation coefficient ρ (see (h1) or (l1) in Appendix 1). In a second step, we estimate the variance-covariance matrix in (b2) and estimate the parameters of the mixture model (21) by GLS.

Tables and Figures

Table 1: Hazard model estimates for men aged 29-44

Variables	TEST	SD	GAMMA	SD	GAMMA R1	SD	2 POINTS OF SUPPORT	SD
c	-0.58	0.05	-0.36	0.05	-0.36	0.05	-0.46	0.05
1. Duration (in quarters)								
2 $(\gamma_2 - c)$	-0.33	0.03	-0.06	0.03	-0.07	0.03	-0.15	0.03
3 $(\gamma_3 - c)$	-0.55	0.05	-0.04	0.03	-0.05	0.03	-0.16	0.05
4 $(\gamma_4 - c)$	-0.73	0.07	-0.03	0.04	-0.04	0.04	-0.15	0.07
5 $(\gamma_5 - c)$	-0.87	0.08	-0.01	0.05	-0.02	0.05	-0.11	0.08
6 $(\gamma_6 - c)$	-1.08	0.09	-0.07	0.06	-0.07	0.06	-0.16	0.10
7 $(\gamma_7 - c)$	-1.28	0.10	-0.15	0.06	-0.16	0.07	-0.26	0.11
8 $(\gamma_8 - c)$	-1.44	0.12	-0.20	0.07	-0.21	0.08	-0.34	0.12
9 $(\gamma_9 - c)$	-1.47	0.13	-0.15	0.08	-0.15	0.08	-0.32	0.12
10 $(\gamma_{10} - c)$	-1.67	0.14	-0.27	0.09	-0.27	0.10	-0.49	0.14
11 $(\gamma_{11} - c)$	-1.67	0.15	-0.17	0.10	-0.18	0.10	-0.46	0.14
12 $(\gamma_{12} - c)^{*}$	-1.96	0.14	-0.31	0.11	-0.31	0.11	-0.70	0.15
2. Calendar time at outflow								
Cycle								
β_{c1}	-0.21	0.02	-0.22	0.05	-0.22	0.05	-0.22	0.05
β_{c2}	0.08	0.02	0.06	0.02	0.06	0.02	0.06	0.02
β_{c3}	0.01	0.01	0.03	0.02	0.03	0.02	0.02	0.02
β_{c4}	0.03	0.01	0.04	0.02	0.04	0.02	0.04	0.02
β_{c5}	0.04	0.01	0.04	0.02	0.05	0.02	0.04	0.02
Seasons								
Winter $(\beta_{s2}\text{-}c)$	-0.35	0.03	-0.32	0.03	-0.31	0.03	-0.30	0.03
Spring $(\beta_{s3}\text{-}c)$	0.00	0.02	0.00	0.03	0.01	0.03	0.02	0.03
Summer $(\beta_{s4}\text{-}c)$	-0.35	0.03	-0.31	0.03	-0.31	0.03	-0.31	0.03
3. Interaction terms								
ψ_c	-0.08	0.12						
ψ_s	-0.14	0.06						
ϕ			2.13	0.86	1.99	0.81	0.87	0.35
4. Calendar time at inflow								
$\omega^{\delta}_{s1} = \omega^{\lambda}_{s1}$			0.16	0.08	0.12	0.06		
Cycle								
ω^{δ}_{c1}			-0.11	0.35	-0.18	0.18	-0.11	0.15
ω^{λ}_{c1}			-0.05	0.20				
Seasons								
Autumn $(\omega^{\delta}_{s2} - \omega^{\delta}_{s1})^{**}$			-0.02	0.08	-0.09	0.03	-0.07	0.03
Winter $(\omega^{\delta}_{s3} - \omega^{\delta}_{s1})^{**}$			0.08	0.09	-0.04	0.03	-0.03	0.03
Spring $(\omega^{\delta}_{s4} - \omega^{\delta}_{s1})^{**}$			-0.16	0.09	-0.09	0.03	-0.07	0.03
Autumn $(\omega^{\lambda}_{s2} - \omega^{\lambda}_{s1})$			-0.04	0.05				
Winter $(\omega^{\lambda}_{s3} - \omega^{\lambda}_{s1})$			-0.08	0.05				
Spring $(\omega^{\lambda}_{s4} - \omega^{\lambda}_{s1})$			0.04	0.06				
5. Points of support								
π							0.55	0.05
v_1							1.60	0.09
6. Empirical correlation coefficients of e_{kl}								
ρ_{l+k}			0.65		0.65		0.70	
ρ_l			-0.02		0.03		0.01	
7. Standard deviation of e_{kl}								
s_e			0.01		0.01		0.01	
Number of observations	171		171		171		171	
Number of estimated parameters	22		30		26		27	
Weighted sum of squared residuals	478.32		169.78		170.44		171.20	
P-value of the goodness-of-fit test	0		0.05		0.073		0.06	
Jeffrey-Bayes posterior-probability statistics					496.73		510.04	

* $\gamma_{18} = ... = \gamma_{12}$ ** ω^{δ}_{s1} is replaced by c in the fourth column.

Table 2: Hazard model estimates for men aged <=28

Variables	TEST	SD	GAMMA	SD	GAMMA R1	SD	2 POINTS OF SUPPORT	SD
c	-0.33	0.04	-0.04	0.09	-0.07	0.08	-0.23	0.05
1. Duration (in quarters)								
2 $(\gamma_2 - c)$	-0.32	0.03	0.09	0.08	0.07	0.07	-0.09	0.02
3 $(\gamma_3 - c)$	-0.54	0.04	0.20	0.14	0.16	0.12	-0.07	0.04
4 $(\gamma_4 - c)$	-0.76	0.05	0.24	0.20	0.18	0.17	-0.08	0.06
5 $(\gamma_5 - c)$	-0.89	0.06	0.35	0.25	0.28	0.21	0.00	0.08
6 $(\gamma_6 - c)$	-1.03	0.07	0.43	0.29	0.34	0.25	0.03	0.10
7 $(\gamma_7 - c)$	-1.21	0.08	0.46	0.33	0.36	0.29	0.01	0.12
8 $(\gamma_8 - c)$	-1.38	0.09	0.44	0.37	0.33	0.32	-0.07	0.13
9 $(\gamma_9 - c)$	-1.54	0.11	0.42	0.40	0.31	0.34	-0.17	0.14
10 $(\gamma_{10} - c)$	-1.64	0.12	0.46	0.42	0.35	0.37	-0.20	0.15
11 $(\gamma_{11} - c)$	-1.68	0.14	0.56	0.45	0.43	0.39	-0.19	0.15
12 $(\gamma_{12} - c)^*$	-1.92	0.13	0.58	0.48	0.44	0.42	-0.37	0.15
2. Calendar time at outflow								
Cycle								
β_{c1}	-0.29	0.02	-0.32	0.04	-0.32	0.04	-0.31	0.03
β_{c2}	0.06	0.01	0.04	0.02	0.04	0.02	0.06	0.02
β_{c3}	0.01	0.01	0.03	0.02	0.03	0.02	0.02	0.02
β_{c4}	0.04	0.01	0.03	0.02	0.03	0.02	0.04	0.02
β_{c5}	0.07	0.01	0.07	0.02	0.07	0.02	0.06	0.02
Seasons								
Winter $(\beta_{s2}\text{-}c)$	-0.36	0.03	-0.30	0.04	-0.31	0.04	-0.31	0.03
Spring $(\beta_{s3}\text{-}c)$	0.00	0.02	0.01	0.04	0.01	0.03	0.01	0.03
Summer $(\beta_{s4}\text{-}c)$	-0.33	0.03	-0.26	0.04	-0.26	0.04	-0.26	0.04
3. Interaction terms								
ψ_c	-0.30	0.07						
ψ_s	-0.17	0.05						
ϕ			0.08	0.27	0.05	0.35	0.72	0.57
4. Calendar time at inflow								
$\omega^{\delta}_{s1} = \omega^{\lambda}_{s1}$			0.19	0.22	0.27	0.23		
Cycle								
ω^{δ}_{c1}			-0.23	0.46	-0.21	0.22	0.04	0.15
ω^{λ}_{c1}			-0.02	0.23				
Seasons								
Autumn $(\omega^{\delta}_{s2} - \omega^{\delta}_{s1})^{**}$			-0.21	0.07	-0.11	0.03	-0.07	0.02
Winter $(\omega^{\delta}_{s3} - \omega^{\delta}_{s1})^{**}$			-0.01	0.07	-0.07	0.03	-0.06	0.02
Spring $(\omega^{\delta}_{s4} - \omega^{\delta}_{s1})^{**}$			-0.13	0.07	-0.15	0.04	-0.11	0.02
Autumn $(\omega^{\lambda}_{s2} - \omega^{\lambda}_{s1})$			0.06	0.04				
Winter $(\omega^{\lambda}_{s3} - \omega^{\lambda}_{s1})$			-0.04	0.04				
Spring $(\omega^{\lambda}_{s4} - \omega^{\lambda}_{s1})$			-0.02	0.04				
5. Points of support								
π							0.63	0.05
v_1							1.40	0.06
6. Empirical correlation coefficients of e_{kl}								
ρ_{l+k}			0.77		0.75		0.76	
ρ_l			0.03		0.05		-0.02	
7. Standard deviation of e_{kl}								
s_e			0.01		0.01		0.01	
Number of observations	171		171		171		171	
Number of estimated parameters	22		30		26		27	
Weighted sum of squared residuals	677.79		176.4		178.45		178.84	
P-value of the goodness-of-fit test	0		0.023		0.031		0.026	
Jeffrey-Bayes posterior-probability statistics					509.43		522.55	

* $\gamma_{18} = ... = \gamma_{12}$ ** ω^{δ}_{s1} is replaced by c in the fourth column.

Figure 1: Confidence intervals of the baseline hazard for men aged 29-44 (top) and <=28 (bottom)

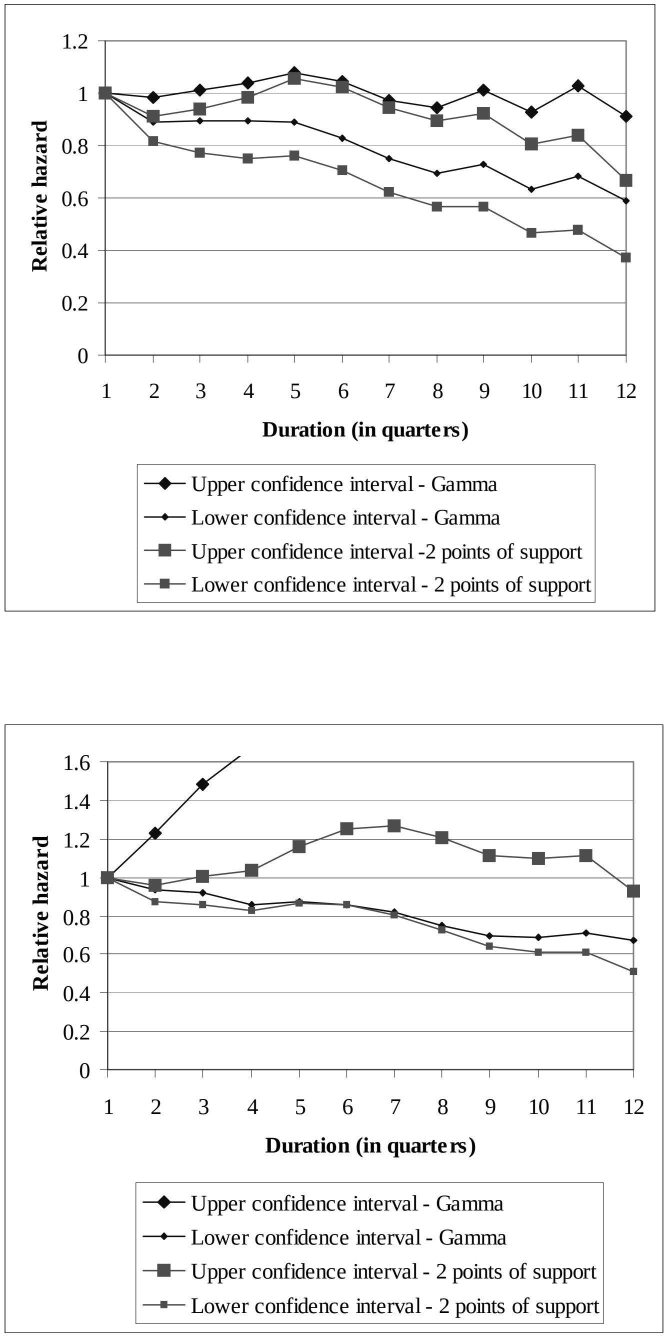


Figure 2: Baseline hazard (Gamma mixing distribution) for men aged 29-44

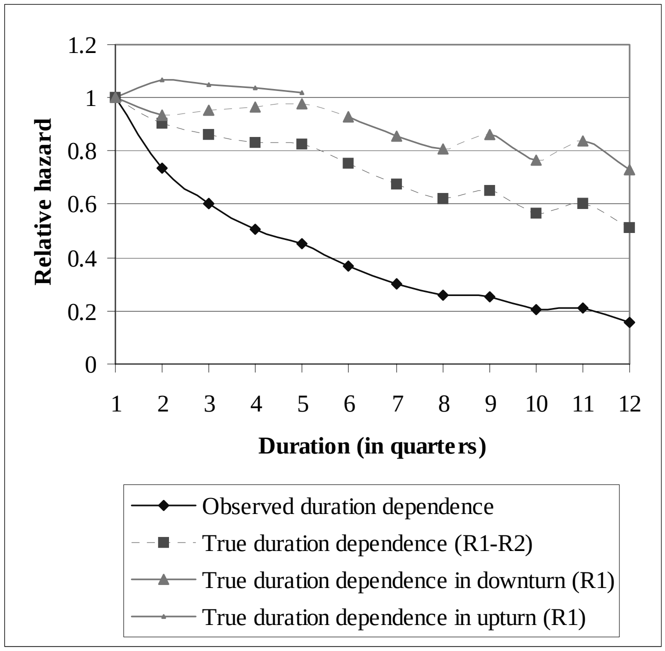


Figure 3: Cyclical dependence of the hazard for men aged 29-44 and <=28 and the Kredietbank indicator (right scale)

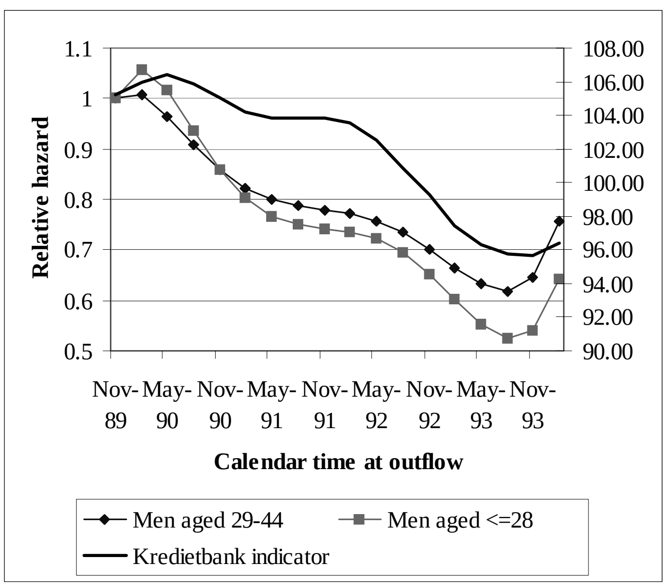
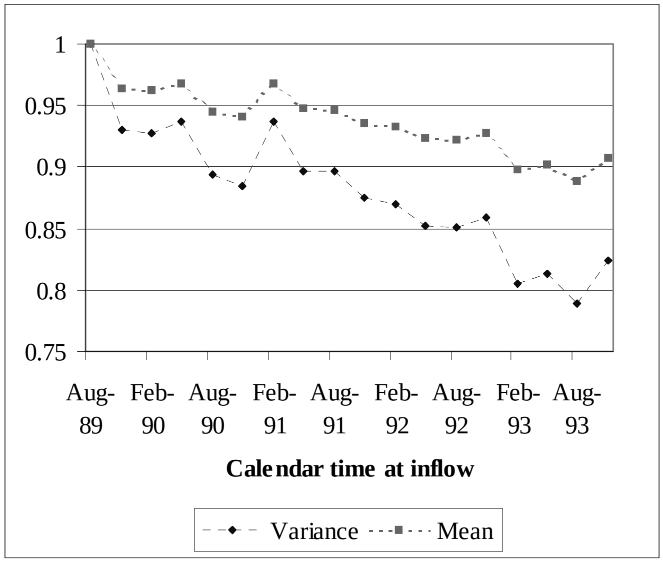


Figure 4: Mean and variance of the Gamma over the cycle at inflow for men aged 29-44 (top) and <=28 (bottom)



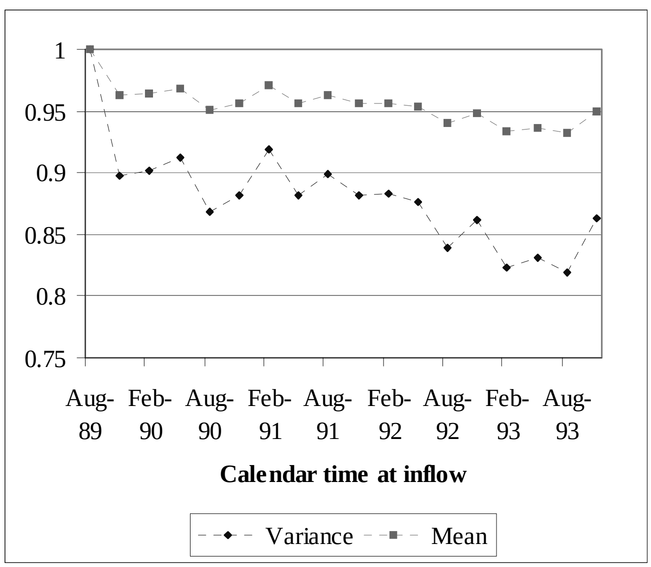


Figure 5: Mean and variance of the Gamma over seasons at inflow - men aged 29-44 (top) and <=28 (bottom)