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Unemployment Dynamics and Age

Gerard J. VAN DEN BERG, Gijsbert VAN LOMWEL, Jan C. VAN OURS *

ABSTRACT. – In this paper we analyze unemployment dynamics for youths, adults, and elderly. We use French unemployment data over the period 1982-1994. We find that the inflow rate of male youths is more sensitive to the business cycle than the inflow rate of adults, but that the outflow of adults is more sensitive than the outflow of youths. After about one year of unemployment for youths there is negative duration dependence of the exit rate out of unemployment.

Dynamique du chômage et âge

RÉSUMÉ. – Dans cet article nous analysons la dynamique du chômage pour les jeunes, les adultes et les travailleurs âgés. Nous utilisons des données de chômage françaises sur la période 1982-1994. Nous trouvons que le flux entrant des hommes jeunes est plus sensible au cycle économique que celui des hommes adultes, mais que le flux sortant des adultes est plus sensible que celui des jeunes. Après environ un an de chômage, il apparaît pour les jeunes une dépendance de durée négative dans le taux de sortie du chômage.

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1 Introduction

There is hardly any study on youth unemployment that does not start by stating that governments are deeply concerned by high rates of youth unemployment. In France, the country we focus on in this paper, youth unemployment rates are double digit and much larger than those of adults. Moreover, French unemployment rates are higher than the OECD average. In 1994, the unemployment rate in France was 9.7 (13.1) percent for men (women) aged 25-54, and 24.2 (31.6) percent for men (women) aged 15-24 (OECD [1996]).

There are several economic explanations for the relatively great concern for youth unemployment compared to unemployment in general. First, an early spell of unemployment may increase the incidence and duration of future unemployment, because youths are not yet firmly rooted into the labor market and may be stigmatized by an early spell of unemployment. Second, this early spell of unemployment hampers the accumulation of human capital. Not only will human capital not increase due to the absence of on-the-job training, the human capital acquired at school is depreciated as well. Finally, commitment to society as a whole may reduce, the devil finding work for idle hands (OECD [1984a]).

This concern has led the French government to enact special youth programs and policies. In 1981 the "Future for youth plan" (Plan avenir jeunes) was brought into effect. The main objective of this plan was to stimulate the employment of young people by various economic premiums and exemptions for employers and by various training and workfare programs. The number of participants to such programs increased substantially after the 1986 "Emergency plan for youth employment" (Plan d'urgence pour l'emploi des jeunes), which introduced stronger incentives to participate and facilitated the development of new programs (see OECD [1984b], CSERC [1996] and BONNAL, FOUGÈRE and SÉRANDON [1997] for details on various programs and the numbers of individuals enrolled in them).

Our methodology is very suitable to study dynamics in unemployment and determine the relevance of duration dependence, unobserved heterogeneity for the exit rate out of unemployment and the effects of trend, cycle and season on both the inflow to and outflow from unemployment. In our analysis we use aggregate data on exit probabilities distinguished by duration class for different groups of unemployed workers. The variations in these exit probabilities both over the duration of unemployment and across calendar time enable us to study processes that cannot be studied easily when studying micro data. Whereas in micro data exit probabilities have to be inferred from observed duration data, our aggregate exit probabilities are observed directly. So, whereas we loose in terms of detail concerning the effect of observed characteristics we gain tractability in terms of observed interactions between internal unemployment dynamics and external trends and cyclical and seasonal effects.

In this paper we study unemployment dynamics among different age groups in a systematic way, focusing on business-cycle and calendar-time effects on the inflow and outflow rates of unemployment. These in turn determine the movement of the unemployment rate over time. Most of the previous studies on labor market dynamics have taken a micro approach (see DEVINE and KIEFER [1991] for an overview). This approach focuses on personal characteristics that affect individual re-employment probabilities. Macroeconomic conditions are at most included as an additional regressor (see for example DYNARSKI and SHEFFRIN [1990]). Recently, SIDER [1985], BAKER [1992], and BUTLER and MACDONALD [1986], amongst others, have stressed the effect of the business cycle on aggregate flows of individuals over a long period of time, using aggregate data. A few empirical studies on unemployment dynamics focus on the youth labor market. CLARK and SUMMERS [1982], by examining US data from the Current Population Survey of 1976, find that the high rate of joblessness among youths is a problem of job availability. Their data convey a picture of a dynamic labor market, where youth employment is very responsive to aggregate demand. The participation rate shows a large increase in the summer months, mainly due to summer-only workers. LYNCH [1985] examines duration data for a sample of London youths taken from a longitudinal survey of young workers in the greater London area who left school at age 16 in the summer of 1979. The determinants of re-employment probabilities are estimated using a Weibull proportional hazard model. The main conclusion concerns the evidence of negative duration dependence. LYNCH [1989] uses a US data set of young workers (both male and female) in the National Longitudinal Survey to estimate the determinants of re-employment probabilities. She finds strong negative duration dependence, and differences between men and women. Moreover she finds that local demand conditions play an important role. Chapter VI of the OECD 1983 Employment Outlook (OECD [1983]) also explores differences between youth and adult unemployment. Youths face a much higher risk of becoming unemployed, and most of the separations are involuntary. Moreover, youths have a higher propensity to terminate spells of unemployment by way of withdrawing from the labor force. The teenage labor force flows, in particular in North America, show a strong seasonal pattern. Finally, Chapter IV of the OECD 1996 Employment Outlook (OECD [1996]) examines the youth labor market over the 1980s and 1990s. Youth employment and unemployment seems to be exceptionally sensitive to the overall state of the labor market. From all these empirical studies we derive the following stylized facts on youth unemployment. First, youth unemployment is much more responsive to aggregate economic conditions than adult unemployment. Secondly, youth unemployment has a strong seasonal component. Thirdly, youth unemployment is heterogeneous with respect to gender.

In the present paper we examine whether these results are confirmed in a formal econometric analysis. For example, we examine to what extent youths are disproportionately affected by a recession. We estimate a model in which the business cycle affects the inflow and outflow into and out of unemployment. Concerning the latter we adopt a model in which the individual exit probability is duration dependent and also depends on the business cycle and on individual-specific characteristics. It is important to allow for the latter type of characteristics when dealing with cyclical effects on the exit rate out of unemployment. The weeding out of the individuals with the highest individual-specific effects occurs faster in the top of the cycle than in a recession (see VAN DEN BERG and VAN OURS [1996]). As a result, individual heterogeneity causes the duration dependence of the aggregate exit probability to be less negative in a recession than in the top of the cycle. If one does not take this into account then the business cycle effect in the recession will be overestimated; that is, the estimated effect on the individual exit probability will be less severe than the real effect. In our analysis, we estimate different models for different age groups and genders, and we allow for heterogeneity of unobserved individual characteristics. In sum, the estimates provide an econometrically more careful description of the business cycle effects than can be obtained from simply eyeballing the graphs of raw data. Note that previous studies on unemployment durations typically assume that duration dependence is invariant across age groups (some studies, however, restrict attention to data from just one age group, see *e.g.* the articles by LYNCH mentioned above). In the empirical analysis we use French administrative data which distinguish unemployment by elapsed duration and by gender. The data are quarterly and cover the period 1982.IV-1994.IV. Our model and estimation method are based on ABBRING, VAN DEN BERG and VAN OURS [2002].

The plan of the paper is as follows. In Section 2 we present the model and the empirical implementation. Section 3 describes the data. In Section 4, the estimation results are presented, and we decompose unemployment variation into the contributions of its determinants, notably business cycle effects. From a policy point of view, it is important to know differences across age groups of the instantaneous effect of the business cycle on inflow and outflow. For example, if exit probabilities of youths respond to business cycles at a later stage than the exit probabilities of adults, then this may help policy makers to anticipate cycles of youth unemployment. The results can also be used to predict, for a given state of the business cycle, which types of employed and unemployed workers suffer most from the cycle in terms of their chances on the labor market. In Section 5 we therefore discuss the policy implications of our results in some detail.

2 The model and the empirical implementation

In this section we describe the model for the exit probabilities out of unemployment. Since this model is described in detail in Abbring, VAN DEN BERG and VAN OURS [2002], the present exposition is brief. In the first subsection we start with a sketch of the type of data we use, and we discuss the role of measurement errors. The second subsection deals with the unemployment duration model. The parameterization of the model is discussed in the third subsection.

2.1 Observation of unemployment

We use two measures of time, each with a different origin. The variable t denotes the duration of a spell of unemployment for a given individual. The variable τ denotes calendar time. We take t and τ to have the same measurement scale, apart from the difference in origin. Both t and τ are discrete variables. For example, consider an individual who is unemployed for t periods at calendar time τ. If he fails to leave unemployment in period t, he will be unemployed for $t+1$ periods at calendar time $\tau+1$.

Aggregate data give the total numbers of individuals in the labor market who are unemployed for t periods of time ($t = 0,1,2,...$) at calendar times τ ($\tau = \tau_0, \tau_0+1, \tau_0+2,...$). By comparing the number of individuals who are unemployed for t periods of time at τ to the number unemployed for $t+1$ periods at $\tau+1$, we observe the fraction of the former who leave unemployment at t. This fraction of course equals the exit probability out of unemployment $\theta(t|\tau)$ of an individual who is unemployed for t periods, when calendar time equals τ at the moment of potential exit:

$$\theta(t|\tau) = \frac{U(t|\tau) - U(t+1|\tau+1)}{U(t|\tau)} \tag{1}$$

In reality we do not exactly observe the numbers $U(t|\tau)$, due to *e.g.* rounding-off errors and administrative errors. In addition, the unemployment definition changes over time. We capture this by way of stochastic errors. From now on, a tilde denotes an observed variable whereas the absence of a tilde denotes the true value of the corresponding model variable. We assume that

$$\widetilde{U}(t|\tau) = U(t|\tau)\varepsilon_{t,\tau} \tag{2}$$

with

$$\log\varepsilon_{t,\tau} \sim N(0,\sigma^2)$$

In the empirical analysis we allow for non-zero correlations between errors $\varepsilon_{t,\tau}$ at one single calendar moment. Thus, we specify the correlation between $\log\varepsilon_{t^*,\tau^*}$ and $\log\varepsilon_{t^{**},\tau^{**}}$ to be equal to $r^{|t^*-t^{**}|}$ if $\tau^* = \tau^{**}$, and 0 otherwise. Combining the equations (1) and (2), we obtain

$$\log(1-\widetilde{\theta}(t|\tau)) = \log(1-\theta(t|\tau)) + e_{t,\tau} \tag{3}$$

where

$$e_{t,\tau} := \log\varepsilon_{t+1,\tau+1} - \log\varepsilon_{t,\tau}$$

Equation (3) links the data to the true exit probabilities. In the next subsection we present a model for $\theta(t|\tau)$.

2.2 The model

The model expresses the true exit probabilities in terms of the (determinants of the) exit probabilities at the individual level. The relation is established by way of aggregating over individual unemployment duration distributions.

It is assumed that all variation in the individual exit probabilities out of unemployment can be explained by the prevailing unemployment duration t

and calendar time τ, and by observed and unobserved heterogeneity across individuals. The effect of t represents genuine duration dependence, *i.e.* dependence of individual exit probabilities on the elapsed unemployment duration. Calendar time is assumed to capture macro effects (including business cycle and seasonal effects) on individual exit probabilities, as well as structural changes influencing these probabilities. In the data we use, we have two observed individual characteristics that can be used as an explanatory variable x, namely the gender and age group (youth, adult, elderly). We estimate the model separately for both gender types and the three age groups, and in the sequel we suppress the conditioning on the prevailing value of x.

We denote the probability that an individual leaves unemployment right after t periods of unemployment, given that he is unemployed for t periods at calendar time τ, and conditional on his unobserved characteristics v, by $\theta(t|\tau,v)$. By definition, this is the exit probability out of unemployment (or hazard) at τ conditional on t and v. We assume proportionality of individual exit probabilities $\theta(t|\tau,v)$: there are functions ψ_1 and ψ_2 such that

$$\theta(t|\tau,v) = \psi_1(t)\cdot \psi_2(\tau)\cdot v \tag{4}$$

with ψ_1 and ψ_2 positive and uniformly bounded from above. The functions ψ_1 and ψ_2 represent the duration dependence and the calendar time dependence of the individual exit probabilities out of unemployment. Furthermore, the distribution of v is such that, for every t and τ,

$$Pr(0 < \theta(t|\tau,v) < 1) = 1.$$

We now turn to the effect of calendar time at the inflow into unemployment on the exit probabilities. We assume this to act by way of the composition of the inflow. This is modelled by a calendar time dependent scale parameter of the distribution function G_τ of v,

$$G_\tau(\psi_3(\tau)v) = G(v)$$

with $G(v)$ the distribution of the composition of the inflow at the calendar time base $\tau = 0$, and ψ_3 positive and uniformly bounded from above. If $\psi_3(\tau) > 1$ then the individuals entering unemployment at τ on average have lower values of their unobserved characteristics (*i.e.* lower exit probabilities) than the individuals entering at the calendar time base. For instance, this parameter could capture the effect of (relatively) highly qualified graduates, usually entering the labor market in the third quarter. To express the exit probabilities $\theta(t|\tau)$ appearing in the r.h.s. of equation (3) in terms of $\theta(t|\tau,v)$, we have to integrate v out of the latter. It can be shown that the following relation holds (see ABBRING, VAN DEN BERG and VAN OURS [2002]),

$$\theta(t|\tau) = \psi_1(t)\psi_2(\tau)\psi_3(\tau-t)\frac{E_v[v\prod_{i=1}^{t}(1-\psi_1(t-i)\psi_2(\tau-i)\psi_3(\tau-t)v)]}{E_v[\prod_{i=1}^{t}(1-\psi_1(t-i)\psi_2(t-i)\psi_3(\tau-t)v)]} \tag{5}$$

in which $E_v(.)$ denotes the expectation with respect to the distribution G. Substitution of equation (5) in equation (3) establishes the link between the observed exit probabilities and the model determinants.

Our model is closed by the specification of an equation for the inflow size (the incidence equation). We measure the size of the inflow by the number of people in the first duration class $U(0|\tau)$. This number is smaller than the true inflow, because people who enter and leave within a quarter are excluded.[1] We specify

$$U(0|\tau) = \psi_4(\tau) \tag{6}$$

with the function ψ_4 positive and uniformly bounded from above. Substitution of (6) into equation (2) links the observed $\widetilde{U}(0|\tau)$ and the unknown function $\psi_4(\tau)$.

In the model described above, the structural determinants are the functions $\psi_1, \psi_2, \psi_3, \psi_4$ and G. As shown by VAN DEN BERG and VAN OURS [1996], the assumptions above ensure nonparametric identifiability of the model without effects of calendar time at the moment of inflow. In particular, they ensure that duration dependence and unobserved heterogeneity can be distinguished empirically without the need to specify parametric functional forms on the shape of ψ_1 or G. From equation (5) it is clear that the functions $\psi_1(\tau)$ and $\psi_2(\tau)$ are identified from the multiplicative effect on $\theta(t|\tau)$ of respectively t and τ. By expanding the product terms in equation (5) it follows that $\theta(t|\tau)$ depends on $G(v)$ by way of the first $t+1$ moments of v, denoted by μ_i, and that these are identified from interaction effects between t and τ (*i.e.*, between $\psi_1(\tau)$ and $\psi_2(\tau)$) in $\widetilde{\theta}(t|\tau)$. If the calendar time effect on ψ_3 is repetitive, as in case of seasonal effects, then ψ_3 is identified, see ABBRING, VAN DEN BERG and VAN OURS [2002]. In the sequel, we assume that ψ_3 only includes seasonal effects. The function ψ_4 is trivially identified from the $\widetilde{U}(0|\tau)$ data.

2.3 Parameterization

We adopt the nonparametric estimation method by ABBRING, VAN DEN BERG and VAN OURS [2002]. First,

$$\psi_1(t) = \exp\left\{\sum_{i=0}^{n_t-1} \psi_{1i} I_{1,i}(t)\right\}$$

in which $I_{i,t} = 1$ if $t = i$ and 0 otherwise, and n_t is the number of duration classes considered. The unobserved heterogeneity distribution is estimated through the "parameters" representing its normalized moments $\mu_1, \gamma_2, \gamma_3, \ldots, \gamma_{n_t}$;

$$\gamma_i := \frac{\mu_i}{\mu_1^i}$$

We adopt products of flexible high-order polynomials (capturing business cycle effects) and dummy variables (capturing seasonal effects) for the structural functions ψ_2 and ψ_4. In notation to be explained below,

$$\psi_j(\tau) = \omega_j(\tau)\,\psi_{j,c}(\tau), \quad j = 2,4,$$

1. In the literature both this measure and the true inflow have been used (*e.g.* LAYARD, NICKELL and JACKMAN [1991]). From additional analysis it is clear that the dynamic features of both series are similar.

whereas $\psi_3(\tau)$ is specified to equal $\omega_3(\tau)$. The seasonal effects in ψ_2, ψ_3 and ψ_4 are specified as

$$(7) \qquad \omega_j(\tau) = \exp\left\{\sum_{s=1}^{4} \omega_{sj} I_s(\tau)\right\}$$

where I_s is an indicator function for season s, $s = 1,...,S$. The cyclical and trend effects in ψ_2 and ψ_4 are represented by polynomials of indexed order that are mutually orthogonal on the data interval for τ. Let the functions $p_1(\tau), p_2(\tau), p_3(\tau),...$ denote these Chebyshev polynomials. Then

$$\psi_{j,c}(\tau) = \sum_{i=0}^{k} \alpha_{ij} p_i(\tau), \quad j = 2,4.$$

Note that we can compare our estimates to the way in which conventional business cycle indicators behave over time. We normalize the duration model by taking $\alpha_{02} = 1$, $\omega_{21} = \omega_{31} = 0$ (so the first season is the base season), and $\psi_1(0) = 1$ (so $\psi_{10} = 0$). We normalize the incidence model by taking $\alpha_{04} = 1$ and $\omega_{41} = 0$. Finally, we include a multiplicative term exp(c) in ψ_4, where c is a parameter to be estimated.

Before finishing this section we point out a procedure to test the MPH assumption (see VAN DEN BERG and VAN OURS [1996]). Consider the estimates of $\gamma_2,..,\gamma_{n_t}$. If the model is correct, then $\gamma_2,..,\gamma_{n_t}$ are mutually consistent as normalized moments of a distribution with positive bounded support (from zero until the upper bound depending on the functions ψ_1 and ψ_2). This can be tested for. For example, if $\gamma_2 < 1$ or $\gamma_3 < \gamma_2^2$ then there is no distribution with positive support that is able to generate such moments (see SHOHAT and TAMARKIN [1970]; for example $\gamma_2 < 1$ would imply $Var(v) < 0$). Similar constraints must hold for the higher order moments. These tests are useful as specification tests, as they can be shown to be informative on the validity of the proportionality assumption (equation (4); see ABBRING, VAN DEN BERG and VAN OURS [2002]).

3 The data

We use French administrative data on numbers of unemployed individuals in three age groups: youths (aged below 25), adults (aged 25-49) and elderly people (aged 50 and over), for both genders. These were collected by the French public employment offices (A.N.P.E.), and subsequently collected on a nation-wide scale by the Department of Labor. They cover individuals who are actively looking for full-time permanent jobs, and who are immediately available. The data are collected each quarter, and they allow for calculation of exit probabilities out of the first five quarterly duration classes, over the period 1982.IV-1994.IV. The latter time interval cannot be lengthened, because from 1995.I onwards the definitions of the administrative data changed substantially, causing an irreparable break in the series. Each quarter, a number of individuals move from one age group to another. We do not have data on these numbers, but their magnitude should be very small in comparison to the size of the inflow and outflow.[2] Note that in our analysis the basis of our data concerns stocks of unemployed. We use information about incomplete durations at particular moments in time to calculate exit probabilities for groups of workers.[3]

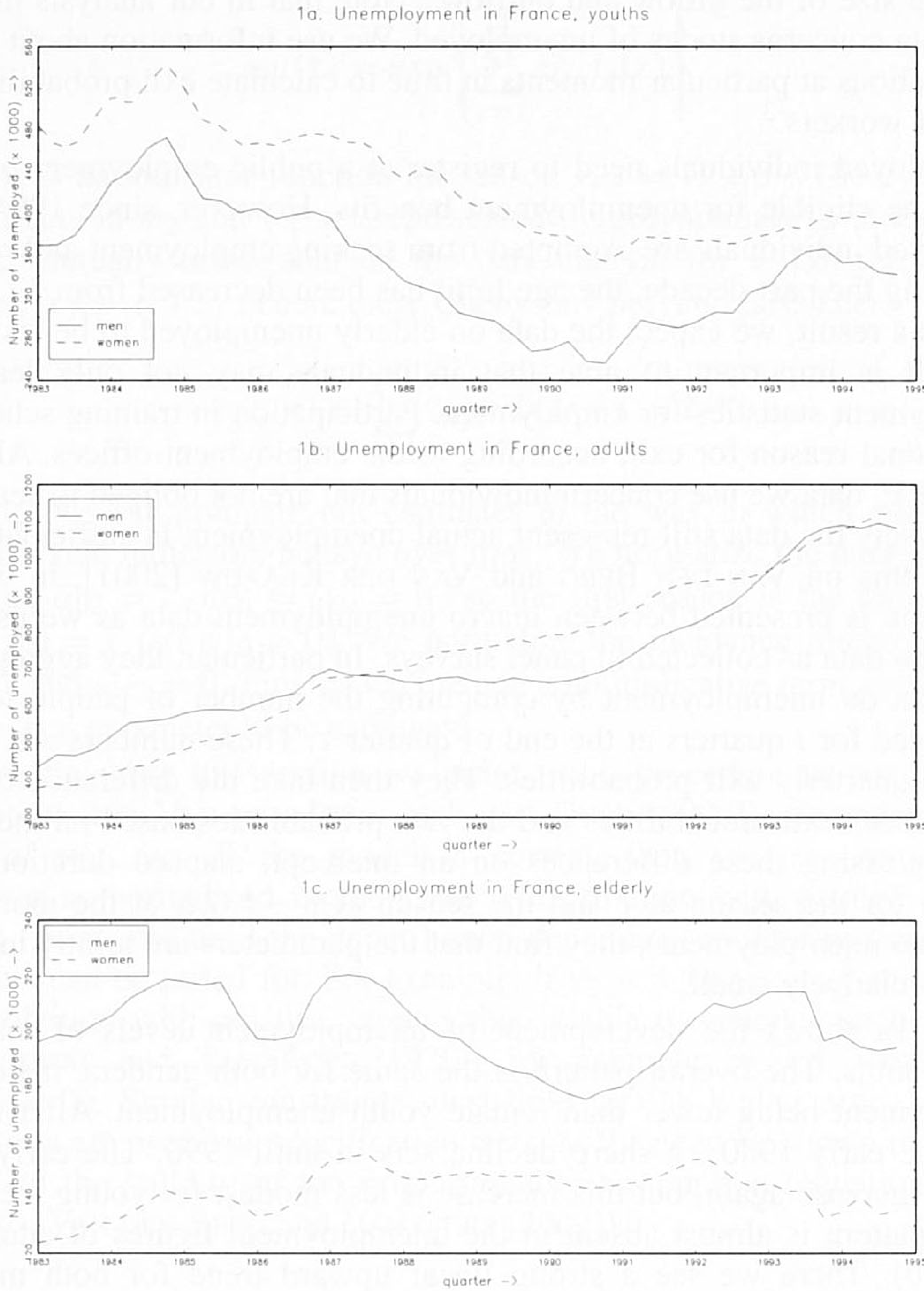
Unemployed individuals need to register at a public employment office in order to be eligible for unemployment benefits. However, since 1984, older unemployed individuals are exempted from seeking employment and registering. During the past decade, the age limit has been decreased from 57.5 to 55 years. As a result, we expect the data on elderly unemployed to be less informative. It is important to note that individuals may not only leave the unemployment statistics for employment. Participation in training schemes is an additional reason for exit, according to the employment offices. Although the A.N.P.E. data we use concern individuals that are not obliged to search for a job actively the data still represent actual unemployment in sufficient detail. We base this on VAN DEN BERG and VAN DER KLAAUW [2001], in which a comparison is presented between macro unemployment data as we use them with micro data as collected in panel surveys. In particular, they aggregate the micro data on unemployment by computing the number of people who are unemployed for t quarters at the end of quarter τ. These numbers are used to calculate quarterly exit probabilities. They then take the difference between these "micro" exit probabilities and the exit probabilities based on the macro data. Regressing these differences on an intercept, elapsed duration t and dummies for the season at τ and the season at $\tau - t$ (*i.e.* at the moment of inflow into unemployment), they find that the parameters are jointly insignificant and relatively small.

Figure 1a shows the development of unemployment levels of male and female youths. The overall pattern is the same for both genders, male youth unemployment being lower than female youth unemployment. After a sharp rise in the early 1980s, a sharp decline sets in until 1990. The early 1990s show an increase again, but this increase is less modest for young men. This cyclical pattern is almost absent in the unemployment figures of adults (see Figure 1b). There we see a strong linear upward trend for both men and women. The levels of unemployment are more or less the same for adult men and women. The level of unemployment of the elderly is nearly constant over time, unemployment levels being higher for older men than for older women (see Figure 1c).

2. Note that the movements of individuals between age groups because of ageing is symmetric. There are losses on the high end of the age distribution of a specific interval but additions on the low end of the interval. Therefore, ageing does not introduce systematic errors in our calculated exit probabilities.

3. This allows us to work with observed exit probabilities but implies that at the edges of the duration intervals *individual completed* durations of unemployment can be very different. An individual that is at the low end of a duration interval at one moment in time and leaves unemployment just before the next time of measurement has a substantial longer unemployment than an individual that is at the high end of a duration interval but leaves unemployment right after the time of measurement. Since within a duration interval individuals are equally spread these differences cancel out and do not affect the average exit probabilities for groups of workers.

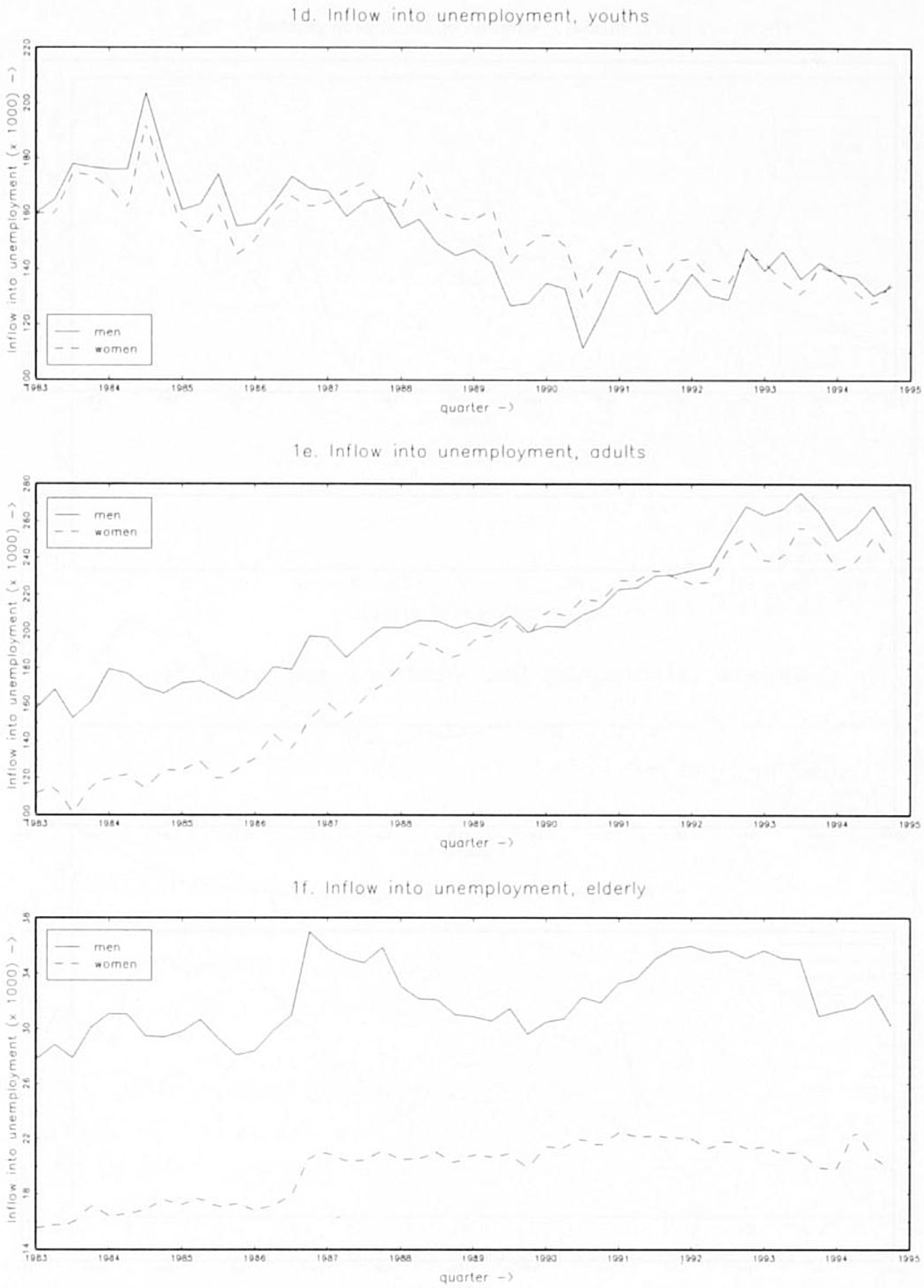
FIGURE 1a-b-c



The graphs in Figures 1d-1f on the inflow size as a function of time resemble those for the unemployment levels. The inflow size for youths shows a downward trend, while the inflow size for adults is strongly upward trended. The inflow size for elderly is more or less constant. The trend for youths is caused by the declining participation rates for youths. This can be seen from Figures 1g-1i, where the inflow *rate* is graphed. The inflow rate is defined as the inflow size divided by the size[4] of employment, for each age/gender

4. Our inflow data consist of a combination of flows from a job due to dismissals and inflow from non-participants due to school-leavers and re-entering (mostly female) workers. To compare inflow data we use labor force survey information from Eurostat to quantify the number of employed. These are based on a different definition of labor market states than the administrative data (VAN DEN BERG and VAN DER KLAAUW [2001]), but unfortunately we do not have employment size data based on the latter definition. The employment data are yearly, but as the number of employed is much larger than the inflow size, seasonal fluctuations in the employment size should not have a substantial effect on the inflow rate.

FIGURE 1d-e-f

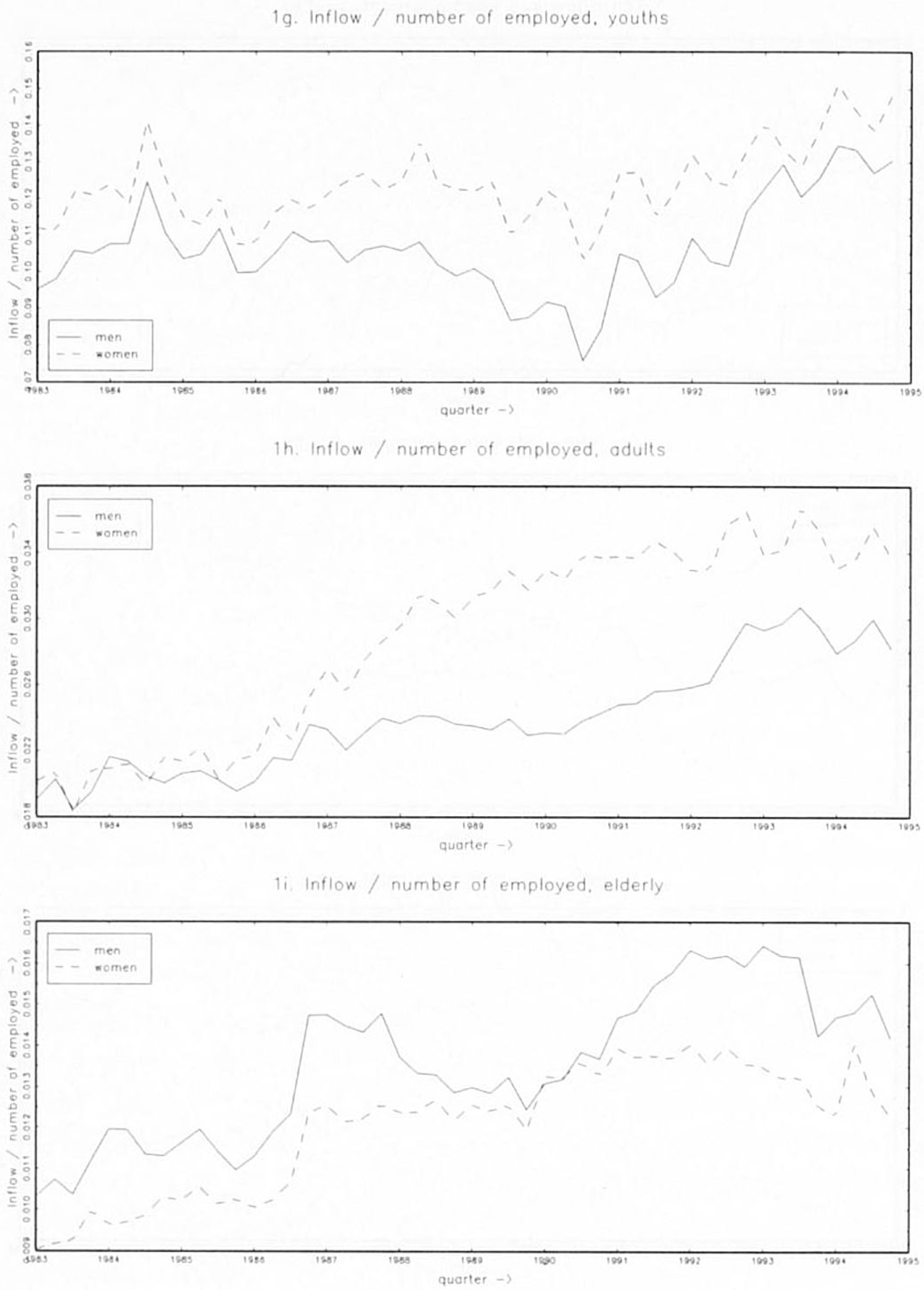


group.[5] From the figures it is clear that the inflow rate for youths is not downward trended. The inflow rate equals the probability of inflow into unemployment for a randomly-chosen employed participant. Therefore, this variable is more relevant for our purposes than the inflow size. In the next section we therefore focus on the inflow rates. In particular, $\psi_4(\tau)$ is estimated from inflow rate data.

The upward trend in the inflow size for adult women is also due to a certain extent to the increased participation rate of adult women (compare Figures 1e and 1h; note however from Figure 1h that the inflow rates for male and female adults have both increased over time). The upward trended inflow size of adults and the downward trended inflow size of youths cause the share of youths in the

5. The declining participation rate for youths is a typical French phenomenon; it reflects the extension of school attendance over this period (CSERC [1996]). The decline may be the result of a decision of youths to stay out of the labour market and enrol in further education *because of* the high risk of unemployment. It is not clear whether this is desirable or not.

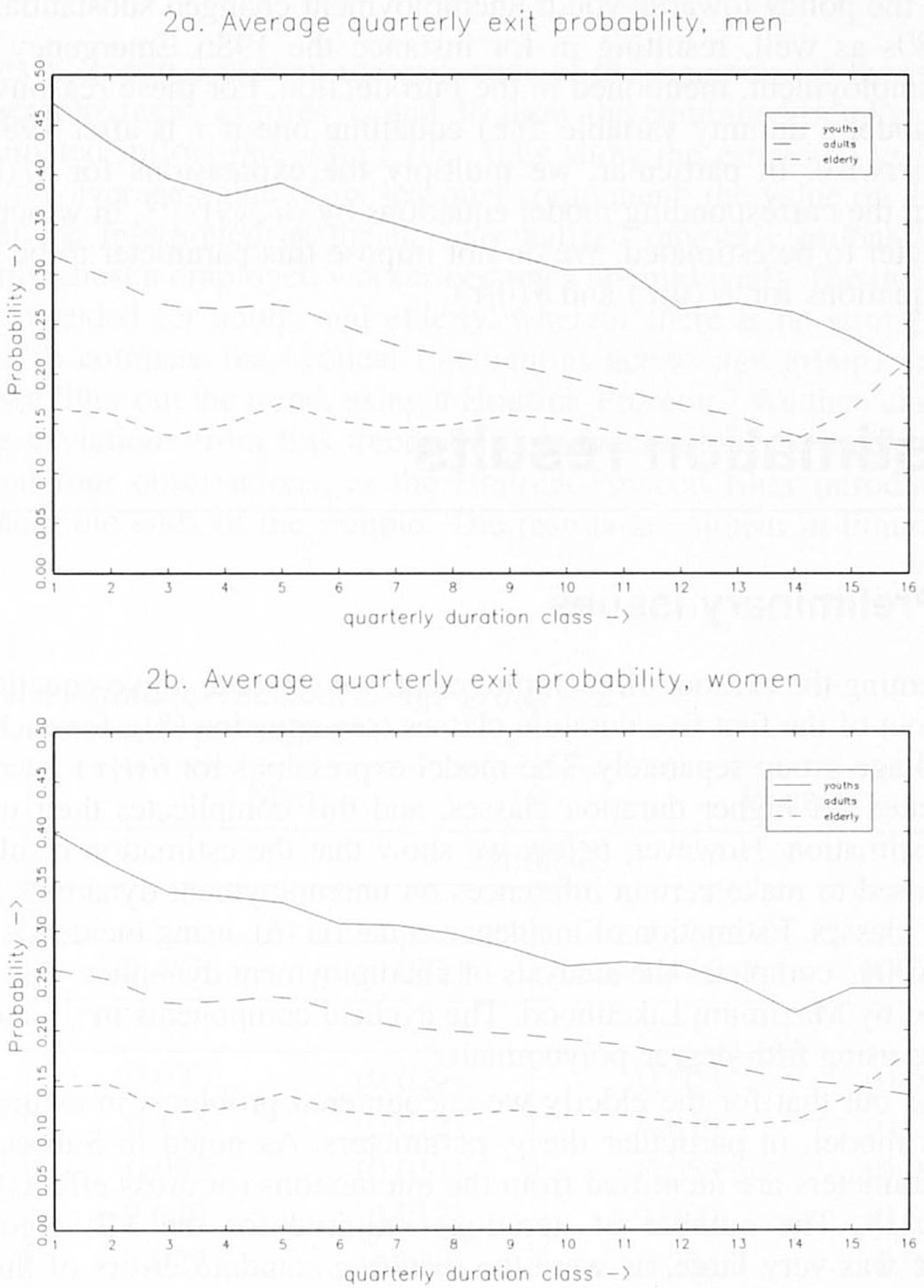
FIGURE 1g-h-i



inflow size to diminish over time. In 1983 the inflow size share of male (female) youths amounted to 52 (56) percent. By 1994, this share had shrunk to 29 (33) percent. The inflow size share of elderly during this period was more or less constant over time, being 7 (6) percent for men (women). In sum, the composition of the inflow size has changed in terms of age. Note that if one would ignore the change in composition, and merge the data of all age groups together for a single empirical analysis, then the results would be biased.

Compared to other age groups, the inflow size for youths is high. For youths, $\widetilde{U}(0|\tau)$ constitutes on average about 40 percent of total unemployment at a date τ, whereas this is about 25 percent for adults and 15 percent for elderly workers. These numbers indicate a dynamic youth labor market. This is also conveyed by the empirical exit probabilities in the data. Figure 2 shows the relationship between empirical exit probabilities out of unemployment and unemployment duration, averaged over calendar time. Obviously, youths have the highest exit probabilities. The fact that inflow and outflow rates for

FIGURE 2



youths are high is well documented (see the references in Section 1). High youth inflow rates may be due to the fact that many young workers are still searching for a good match. High youth outflow rates may be due to the fact that youths are flexible and have on average lower benefits. In France, both may also be due to a specific type of youth job contracts with little or no job protection. We return to this in the next section.

For youths and adults, the exit probability declines (non-monotonously) over the duration, while for the elderly it is more or less constant. There are small differences in the level of the exit probabilities for men and women in the first duration classes. For higher duration classes the exit probabilities are approximately the same across gender. The decline of the unemployment exit probability over the duration of unemployment can be due to unobserved heterogeneity, negative duration dependence, or a combination of both. The non-monotonicity on the other hand may be caused by the unemployment benefit system and a duration-dependent flow into public employment programs.

In 1986, the procedure according to which the data are collected was changed. As a result, the time series on $\widetilde{U}(t|\tau)$ exhibit ruptures at 1986.IV. Further, the policy towards youth unemployment changed substantially in the mid-1980s as well, resulting in for instance the 1986 Emergency Plan for Youth Employment, mentioned in the introduction. For these reasons, we add to the model a dummy variable $d(\tau)$ equalling one if τ is after 1986.IV and zero otherwise. In particular, we multiply the expressions for $U(0|\tau)$ and $\theta(0|\tau)$ in the corresponding model equations by $(d_{\geqslant'87})^{d(\tau)}$, in which $d_{\geqslant'87}$ is a parameter to be estimated. We do not impose this parameter to be the same in the equations for $U(0|\tau)$ and $\theta(0|\tau)$.

4 Estimation results

4.1 Preliminary issues

Concerning the exit out of unemployment, we estimate a five-equation model for exit out of the first five duration classes (see equation (5)), for each gender-type and age group separately. The model expressions for $\theta(t|\tau)$ become very complicated for higher duration classes, and this complicates their use in the model estimation. However, below we show that the estimation results can in turn be used to make certain inferences on unemployment dynamics in higher duration classes. Estimation of incidence equation (6), using incidence observations $\widetilde{U}(0|t)$, completes the analysis of unemployment dynamics. The model is estimated by Maximum Likelihood. The cyclical components in ψ_2 and ψ_4 are modelled using fifth-degree polynomials.[6]

It turns out that for the elderly we encountered problems in estimating the duration model, in particular the γ_i parameters. As noted in Subsection 2.2, these parameters are identified from the interactions (or cross effects) of t and τ in $\theta(t|\tau)$. The number of iterations required for the ML algorithm to converge was very large, as were the resulting standard errors of the γ_i estimates. (This does not depend on the number of duration classes (*i.e.* on the number of equations used in the estimation).) As a result, we could not reject the null hypothesis that there is no unobserved heterogeneity among the elderly. This may be explained by the way the data on elderly are collected. As noted in Section 3, unemployed individuals older than 55 (previously 57.5) do not have to register in order to be eligible for unemployment benefits. Therefore, the administrative data only contain information on a subset of people who do not want to retire and expect that they will easier find a job by registering. We decided to estimate for the elderly a modified version of the duration model described in Subsection 2.2, not allowing for unobserved heterogeneity. Equation (4) then reduces to

$$\theta(t|\tau,v) = \psi_1(t)\cdot \psi_2(\tau)$$

where the functions ψ_1 and ψ_2 are parameterized as described in Subsection 2.3.

6. According to statistical tests and graphical eyeball checks, the fit of the model is not improved by including higher-order polynomial terms.

4.2 Business cycles and the age-specific incidence of unemployment

Tables 1, 2, and 3 present the estimates of the equation for the inflow rate into unemployment. Figures 3a and 3b show the combined trend and cycle in the estimated inflow rate $\psi_4(\tau)$ (*i.e.*, they show the estimated $\psi_4(\tau)$ evaluated at the average value of its seasonal component; the value on the vertical axis can be interpreted as the de-seasonalized quarterly probability that a randomly chosen employed worker becomes unemployed). The inflow rate is upward trended for adults and elderly, whereas there is no strong trend for youths. To compare the cyclical fluctuations across age groups and gender types, we filter out the trend, using a Hodrick-Prescott.[7] We then calculate the relative deviations from this trend. In these calculations we neglect the first and final four observations, as the Hodrick-Prescott filter introduces phase shifts near the ends of the sample. The results are shown in Figures 3c and 3d.[8]

TABLE 1
Parameter estimates incidence. Age group < 25.
(Standard errors in parentheses)

	Men		Women	
	Estimates			
constant				
c	−2.487	(0.027)	−2.486	(0.028)
cycle				
α_{14}	0.033	(0.027)	0.003	(0.028)
α_{24}	0.115	(0.012)	0.079	(0.013)
α_{34}	0.092	(0.011)	0.053	(0.012)
α_{44}	−0.049	(0.012)	−0.020	(0.012)
α_{54}	−0.027	(0.010)	0.004	(0.010)
season				
ω_{24}	−0.112	(0.018)	0.058	(0.018)
ω_{34}	0.442	(0.018)	0.694	(0.018)
ω_{44}	0.364	(0.018)	0.339	(0.018)
measurement error				
σ	0.044	(0.004)	0.044	(0.004)
$d_{\geqslant '87}$	1.124	(0.043)	1.176	(0.046)

7. This smoothing method selects the trend path that minimizes the sum of the squared deviations, subject to the constraint that the sum of the squared second differences not be too large. This constraint determines the smoothness. We have set the smoothness parameter to the value 1600, as recommended in the literature, see PRESCOTT [1996].

8. The estimated relative fluctuations in the inflow *size* (not reported here) are virtually the same as in the inflow rate, as should be expected. Note that the combination of estimated trends and cycles resemble very much the raw data presented in Figures 1d-1f.

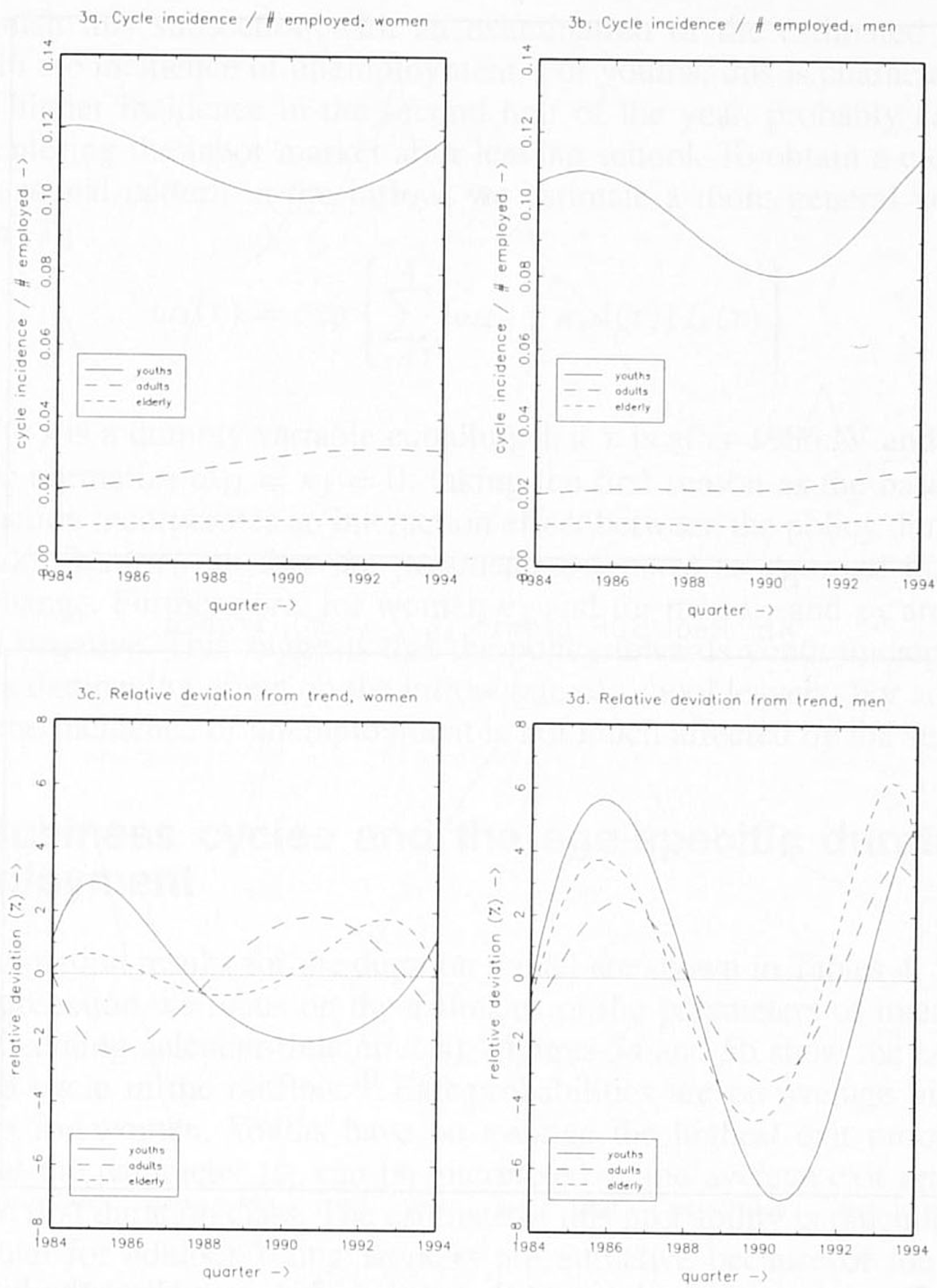
TABLE 2
Parameter estimates incidence. Age group 25-49.
(Standard errors in parentheses)

	Men		Women	
	Estimates			
constant				
c	−3.789	(0.027)	−3.654	(0.021)
cycle				
α_{14}	0.159	(0.021)	0.249	(0.016)
α_{24}	0.033	(0.010)	−0.050	(0.008)
α_{34}	0.005	(0.009)	−0.043	(0.008)
α_{44}	−0.032	(0.009)	0.013	(0.008)
α_{54}	−0.028	(0.008)	0.006	(0.006)
season				
ω_{24}	−0.151	(0.015)	−0.097	(0.012)
ω_{34}	0.008	(0.015)	0.119	(0.012)
ω_{44}	0.127	(0.015)	0.064	(0.012)
measurement error				
σ	0.035	(0.004)	0.029	(0.003)
$d_{\geqslant'87}$	1.096	(0.034)	1.094	(0.028)

TABLE 3
Parameter estimates incidence. Age group 50+.
(Standard errors in parentheses)

	Men		Women	
	Estimates			
constant				
c	−4.372	(0.034)	−4.474	(0.025)
cycle				
α_{14}	0.081	(0.030)	0.124	(0.021)
α_{24}	−0.017	(0.014)	−0.064	(0.011)
α_{34}	−0.003	(0.013)	−0.020	(0.010)
α_{44}	−0.066	(0.014)	−0.017	(0.010)
α_{54}	−0.033	(0.011)	−0.001	(0.008)
season				
ω_{24}	−0.144	(0.021)	−0.105	(0.015)
ω_{34}	−0.119	(0.021)	−0.052	(0.015)
ω_{44}	0.022	(0.021)	0.017	(0.015)
measurement error				
σ	0.051	(0.005)	0.037	(0.004)
$d_{\geqslant'87}$	1.184	(0.054)	1.098	(0.036)

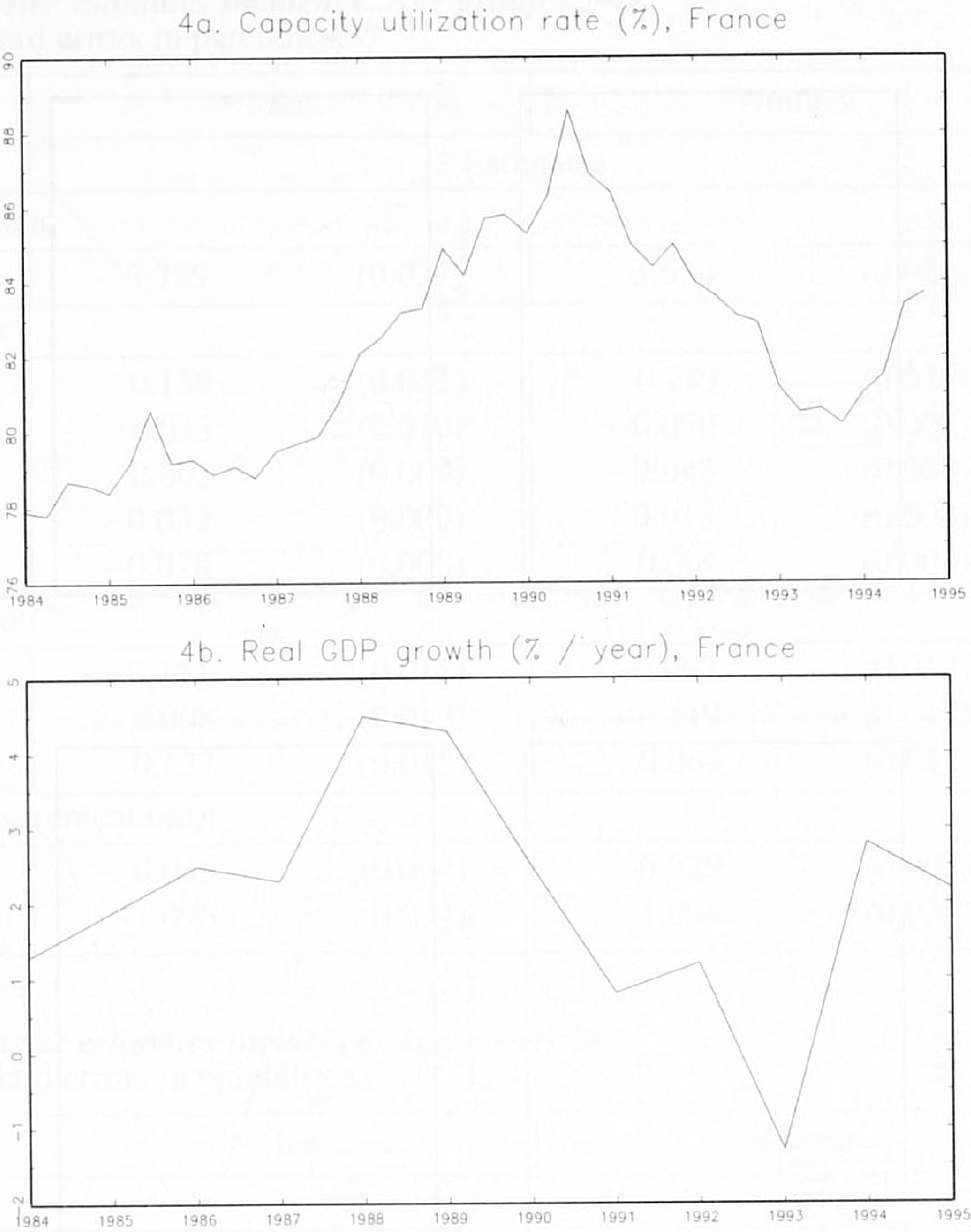
FIGURE 3



The capacity utilization ratio and Real GDP growth are conventional business cycle indicators. Figure 4 shows the development of these indicators for France over the period 1984.I-1994.IV. By comparing the capacity utilization ratio and Real GDP growth to the cyclical fluctuations in the incidence for men, it follows that, for all age groups, male incidence is counter-cyclical, while female incidence is hardly cyclical at all. The latter can be explained by a discouraged worker effect. Women who are not entitled to unemployment benefits may decide not to register at the ANPE during a recession, feeling that it is useless. They may therefore tend to stay non-participant. The strong cyclicality of male incidence can be explained by the fact that men are strongly represented in sectors that are sensitive to cyclical shocks (OECD [1996]), like manufacturing.[9]

9. From the labour force statistics published by the OECD [1995] it follows for instance that in 1991 28.2 % of working males were employed in manufacturing, compared to only 15.4 % of working women.

FIGURE 4



The inflow is most volatile for male youths. This, as well as the high level of the inflow for youths, can be explained by institutional features of the French labor market (see COHEN, LEFRANC and SAINT-PAUL [1997], who observe high separation rates for French young workers in labor force survey data). In particular, one can distinguish between two types of employment contracts: short-term contracts of one year, renewable once, with inexpensive separation possibilities (CDDs or "contrats à durée determinée") on the one hand, and long-term contracts in which involuntary job termination is difficult (CDIs or "contrats à durée indeterminée") on the other. The short-term contracts are often used for young workers (see for instance ILO [1998]). Obviously, the workers with such contracts have a high inflow rate into unemployment. This contributes to the high youth inflow rate. COHEN, LEFRANC and SAINT-PAUL [1997] argue that youths thus bear the full burden of the increased flexibility of the French labor market. The option to be able to fire workers at low cost is particularly attractive for firms in a recession, so one may expect the inflow rate into unemployment for the corresponding workers to be particularly high during a recession. This is exactly what we find.

There is no systematic difference between the phases of the cycles for young men and adult men. Since 1988, the cycle for male youths seems to lag one year behind the cycle for adult men.

We finish this subsection with an examination of the estimated seasonal pattern in the incidence of unemployment. For youths, this is characterized by notably higher incidence in the second half of the year, probably caused by youths entering the labor market after leaving school. To obtain a closer look at the seasonal pattern in the inflow, we estimate a more general version of equation (7);

$$\omega_4(\tau) = \exp\left\{\sum_{s=1}^{4} [\omega_{4s} + \kappa_s d(\tau)]\, I_s(\tau)\right\}$$

where $d(\tau)$ is a dummy variable equalling 1 if τ is after 1986.IV and 0 otherwise. We normalize $\omega_{41} = \kappa_1 = 0$, taking the first season as the base season. This equation incorporates an interaction effect between the policy dummy and the season. It turns out that the parameter estimates as reported in Table 1 hardly change. Furthermore, for women κ_3 and for men κ_2 and κ_3 are significant and negative. This suggests that the policy towards youth unemployment has had a dampening effect on the inflow rate of school leavers. For adults and elderly, the incidence of unemployment is not much affected by the season.

4.3 Business cycles and the age-specific duration of unemployment

The estimation results for the duration model are shown in Tables 4, 5, and 6. In this subsection we focus on the estimates of the parameters of interest (*i.e.*, those concerning calendar-time effects). Figures 5a and 5b show the combined trend and cycle in the outflow.[10] Exit probabilities are on average higher for men than for women. Youths have on average the highest exit probabilities. (Note that the parameter μ_1 can be interpreted as the average exit probability out of the first duration class. The estimate of this probability is much larger for youths than for adults.) Young workers are attractive because of the type of contract on which they can be hired. In addition, many young workers leave unemployment to special youth training and workfare programs. It is not clear whether the latter type of exits from unemployment are very attractive. Some of the workfare programs do not seem to provide much valuable work experience (BONNAL, FOUGÈRE and SÉRANDON [1997]). Also, some programs resemble regular employment, with the crucial difference that wages are allowed to be below the mandatory minimum wage for adults (ABOWD *et al.* [1999]). From a study of individual labor market histories, ABOWD *et al.* [1999] conclude that the individual probability of unemployment increases substantially at the moment at which the individual crosses the maximum age for these programs (usually 25 years). In sum, the youth outflow rate level by itself may suggest a rosier picture than warranted by the positions taken after exit out of unemployment and long-run prospects in general.

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10. Precisely, they show the estimated $\psi_2(\tau)$ multiplied by μ_1. This equals the exit probability out of the first duration class, evaluated at the average value of the seasonal effect on the exit probabilities, if the season of inflow is the first season.

TABLE 4

Parameter estimates duration. Age group < 25.

(Standard errors in parentheses)

	Men		Women	
	Estimates			
unobserved heterogeneity				
μ_1	0.445	(0.009)	0.351	(0.009)
γ_2	1.037	(0.029)	1.031	(0.054)
γ_3	1.155	(0.136)	1.066	(0.279)
γ_4	1.452	(0.514)	1.260	(1.282)
γ_5	2.117	(1.778)	2.825	(5.554)
duration dependence				
ψ_{11}	0.021	(0.030)	0.007	(0.037)
ψ_{12}	−0.061	(0.049)	−0.034	(0.069)
ψ_{13}	−0.097	(0.058)	0.030	(0.083)
ψ_{14}	−0.053	(0.063)	0.066	(0.097)
cycle outflow				
α_{12}	−0.062	(0.009)	−0.036	(0.010)
α_{22}	−0.051	(0.007)	−0.044	(0.008)
α_{32}	−0.025	(0.007)	−0.062	(0.009)
α_{42}	0.063	(0.006)	0.041	(0.007)
α_{52}	−0.001	(0.005)	−0.006	(0.007)
season outflow				
ω_{22}	−0.132	(0.030)	−0.035	(0.036)
ω_{32}	−0.085	(0.024)	0.010	(0.030)
ω_{42}	0.041	(0.025)	0.147	(0.032)
season composition inflow				
ω_{23}	−0.012	(0.005)	0.003	(0.006)
ω_{33}	0.018	(0.007)	0.012	(0.010)
ω_{43}	0.034	(0.008)	0.035	(0.011)
measurement error				
σ	0.042	(0.003)	0.037	(0.003)
ρ	0.614	(0.055)	0.649	(0.059)
$d_{\geqslant '87}$	1.123	(0.018)	1.112	(0.021)

Moment-inequality statistics	(Wald w.r.t. 0)	
	Men	Women
$\gamma_2 - 1$	1.283	0.576
$\gamma_3 - \gamma_2^2$	0.920	0.013
$\gamma_2\gamma_4 - \gamma_3^2 - \gamma_4 - \gamma_2^3 + 2\gamma_2\gamma_3$	0.103	0.172
$\gamma_3\gamma_5 - \gamma_4^2 - \gamma_2^2\gamma_5 - \gamma_3^2 + 2\gamma_2\gamma_3\gamma_4$	− 0.228	− 0.218

TABLE 5

Parameter estimates duration. Age group 25-49.

(Standard errors in parentheses)

	Men		Women	
	Estimates			
unobserved heterogeneity				
μ_1	0.321	(0.007)	0.252	(0.007)
γ_2	1.260	(0.059)	1.445	(0.069)
γ_3	2.056	(0.296)	2.902	(0.374)
γ_4	3.883	(1.252)	7.600	(1.754)
γ_5	6.308	(5.311)	22.599	(8.064)
duration dependence				
ψ_{11}	0.124	(0.033)	0.230	(0.032)
ψ_{12}	0.094	(0.052)	0.241	(0.055)
ψ_{13}	0.091	(0.062)	0.352	(0.068)
ψ_{14}	0.173	(0.068)	0.534	(0.077)
cycle outflow				
α_{12}	−0.177	(0.012)	−0.191	(0.016)
α_{22}	−0.001	(0.007)	−0.058	(0.012)
α_{32}	−0.040	(0.008)	−0.126	(0.012)
α_{42}	0.077	(0.006)	0.052	(0.009)
α_{52}	0.033	(0.006)	0.035	(0.009)
season outflow				
ω_{22}	−0.070	(0.029)	−0.055	(0.037)
ω_{32}	−0.081	(0.025)	0.034	(0.030)
ω_{42}	−0.261	(0.031)	−0.279	(0.041)
season composition inflow				
ω_{23}	−0.014	(0.005)	−0.006	(0.007)
ω_{33}	0.019	(0.006)	0.030	(0.007)
ω_{43}	0.054	(0.005)	0.050	(0.007)
measurement error				
σ	0.025	(0.002)	0.025	(0.002)
ρ	0.732	(0.051)	0.761	(0.048)
$d_{\geqslant'87}$	1.137	(0.017)	1.179	(0.026)

Moment inequality statistics	(Wald w.r.t.0)	
	Men	Women
$\gamma_2 - 1$	4.366	6.500
$\gamma_3 - \gamma_2^2$	2.880	3.965
$\gamma_2\gamma_4 - \gamma_3^2 - \gamma_4 - \gamma_2^3 + 2\gamma_2\gamma_3$	−0.703	2.276
$\gamma_3\gamma_5 - \gamma_4^2 - \gamma_2^2\gamma_5 - \gamma_3^2 + 2\gamma_2\gamma_3\gamma_4$	−1.522	−0.119

TABLE 6

Parameter estimates duration. Age group 50+.
(Standard errors in parentheses)

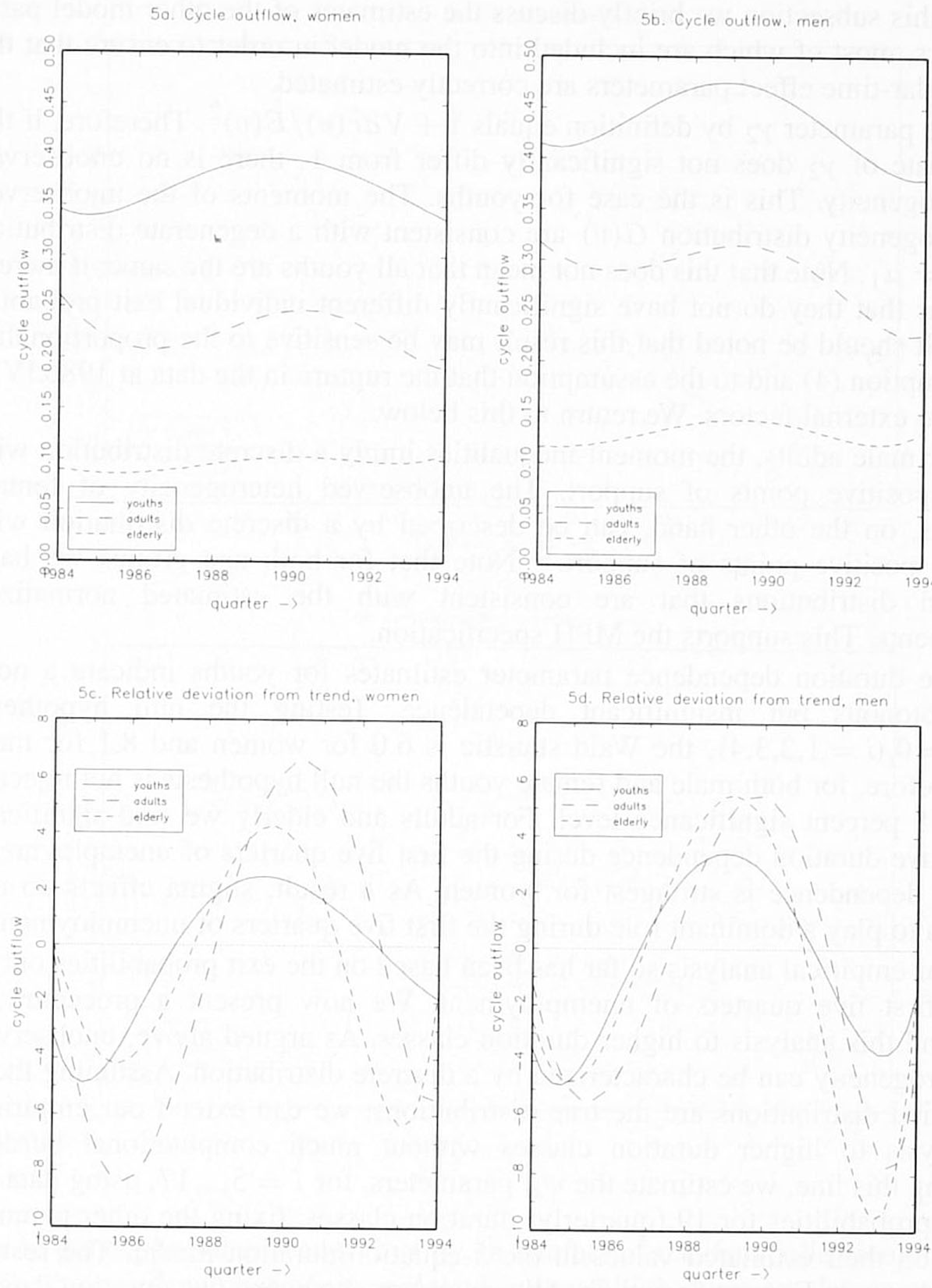
	Men		Women	
	Estimates			
duration dependence				
ψ_{11}	0.240	(0.057)	0.467	(0.080)
ψ_{12}	0.059	(0.060)	0.193	(0.088)
ψ_{13}	0.150	(0.057)	0.254	(0.083)
ψ_{14}	0.274	(0.056)	0.335	(0.082)
cycle outflow				
α_{02}	0.156	(0.011)	0.127	(0.013)
α_{12}	0.013	(0.004)	0.014	(0.004)
α_{22}	0.001	(0.003)	0.008	(0.003)
α_{32}	0.006	(0.003)	0.000	(0.003)
α_{42}	0.016	(0.003)	0.008	(0.003)
α_{52}	0.005	(0.003)	0.005	(0.003)
season outflow				
ω_{22}	−0.249	(0.100)	−0.359	(0.171)
ω_{32}	−0.051	(0.059)	−0.037	(0.070)
ω_{42}	−0.467	(0.107)	−0.829	(0.150)
measurement error				
σ	0.036	(0.003)	0.036	(0.004)
ρ	0.703	(0.062)	0.650	(0.102)
$d_{\geqslant '87}$	1.379	(0.081)	1.631	(0.137)

The outflow rates for adults seem to be rather strongly downward trended. Figures 5c and 5d show the relative deviations from the trend, for each age group. The pattern described by the deviations resembles the pattern described by the conventional business cycle indicators (see Figure 4), so the exit probabilities are pro-cyclically affected. A striking result is that the exit probabilities of young workers are less affected by the cycle than those of adult workers. This is actually in agreement with the importance of youth job contracts. In a recession, hiring young workers is relatively attractive in comparison to hiring adult workers, for the reason that the former can be fired easily. In other words, the main advantage of hiring youths in a recession is not that they can be hired so easily but rather that they can be fired so easily.[11]

The phase of the cycle differs between men and women. For men, the turning points are about a half to one year earlier in time than they are for women. This can be explained by the fact that men are over-represented in

11. Note that the combined trend and cycle resemble much the raw data concerning outflow probabilities (not shown), which indicate that the presence of unobserved heterogeneity does not very much affect the trend and cycle of the "true" exit probabilities.

FIGURE 5



sectors that are sensitive to cyclical shocks from abroad, like manufacturing sectors, which are leading sectors in economic cycles. Women predominantly work in service sectors (OECD [1996]).

The seasonal effect on the outflow works by way of a direct effect on the outflow probabilities, and by way of an indirect effect on the composition of the inflow. The direct seasonal effect on the outflow probabilities of youths is small. Adults and elderly experience a strong negative effect in the fourth quarter, relative to the first quarter. The indirect seasonal effect on the composition of the inflow is similar for youths and adults. (Remember we do not estimate this effect for elderly.) Individuals who become unemployed in the second half of the year have more success in leaving unemployment quickly.

4.4 The other parameter estimates

In this subsection we briefly discuss the estimates of the other model parameters, most of which are included into the model in order to ensure that the calendar-time effect parameters are correctly estimated.

The parameter γ_2 by definition equals $1 + Var(v)/E(v)^2$. Therefore, if the estimate of γ_2 does not significantly differ from 1, there is no unobserved heterogeneity. This is the case for youths. The moments of the unobserved heterogeneity distribution $G(v)$ are consistent with a degenerate distribution in $v = \mu_1$. Note that this does not mean that all youths are the same; it merely means that they do not have significantly different individual exit probabilities. It should be noted that this result may be sensitive to the proportionality assumption (4) and to the assumption that the rupture in the data at 1986.IV is due to external factors. We return to this below.

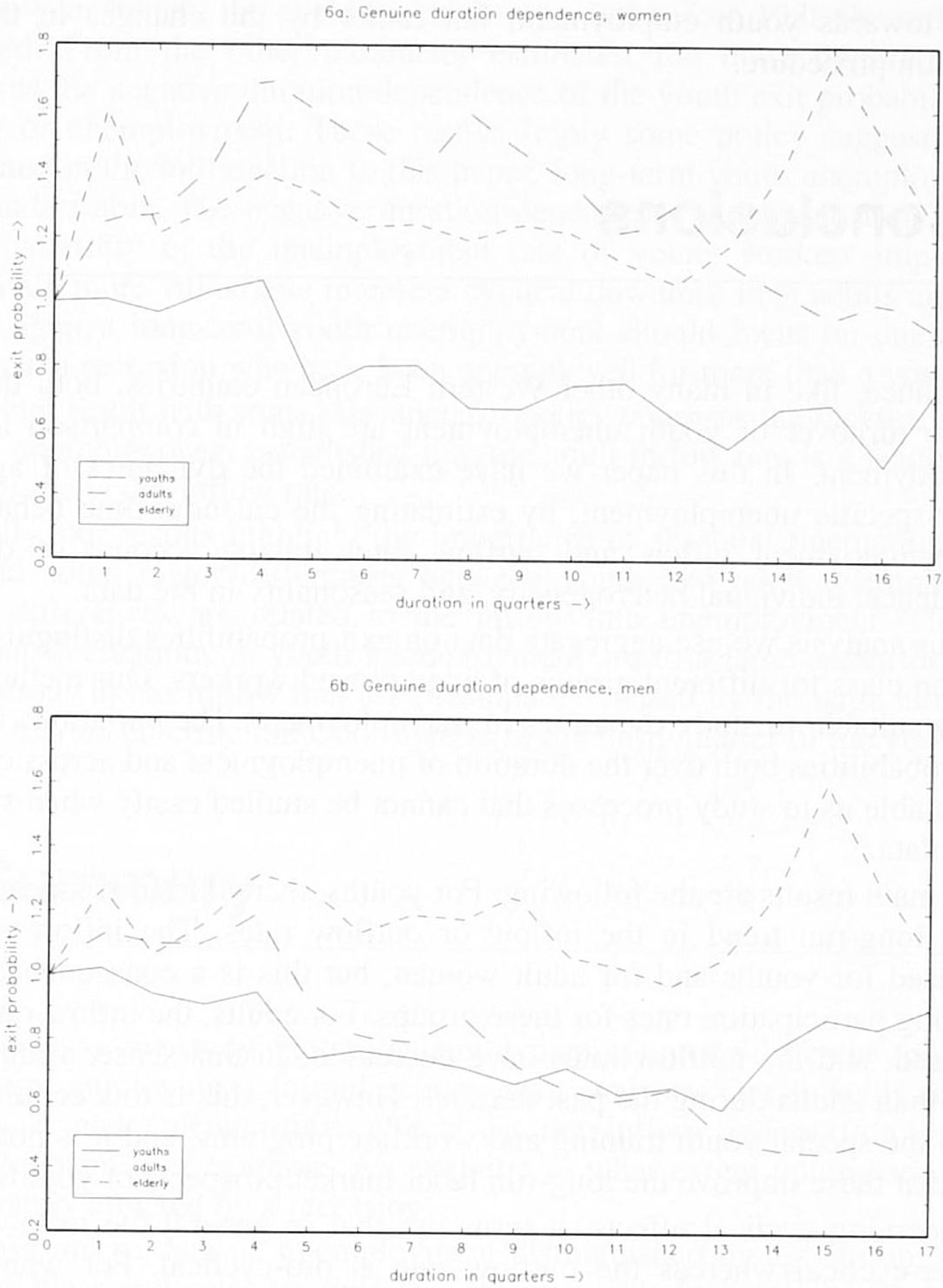
For male adults, the moment-inequalities imply a discrete distribution with two positive points of support. The unobserved heterogeneity of female adults, on the other hand, can be described by a discrete distribution with three positive points of support.[12] Note that for both age groups we have found distributions that are consistent with the estimated normalized moments. This supports the MPH specification.

The duration dependence parameter estimates for youths indicate a non-monotonous but insignificant dependence. Testing the null hypothesis $\psi_{1i} = 0, (i = 1,2,3,4)$, the Wald statistic is 6.0 for women and 8.1 for men. Therefore, for both male and female youths the null hypothesis is not rejected at a 5 percent significance level. For adults and elderly we find significant positive duration dependence during the first five quarters of unemployment. This dependence is strongest for women. As a result, stigma effects do not seem to play a dominant role during the first five quarters of unemployment.

Our empirical analysis so far has been based on the exit probabilities out of the first five quarters of unemployment. We now present a procedure to extend this analysis to higher duration classes. As argued above, unobserved heterogeneity can be characterized by a discrete distribution. Assuming these implied distributions are the true distributions, we can extend our empirical analysis to higher duration classes without much computational burden. Along this line, we estimate the ψ_{1i} parameters, for $i = 5,..,17$, using data on exit probabilities for 19 (quarterly) duration classes, fixing the other parameters on their estimated values in the 5-equation duration model. The results are shown in Figures 6a and 6b. All age groups show negative duration dependence after 4 quarters of unemployment. After 13 quarters of unemployment the individual exit probabilities of youth and elderly increase. This may be

12. This suggests that the variation across female adults is larger than across male adults, and this is confirmed by the higher value of the estimate of γ_2 for female adults. It may be interesting to infer the specification of the implied discrete unobserved heterogeneity distribution. For male adults it turns out that 86 % of the inflow into unemployment has a heterogeneity value equal to 0.80 times the mean μ_1 of the distribution, and 14 % has a heterogeneity value equal to 2.27 times this mean (so $Pr(v = 0.80\mu_1) = 0.86$ and $Pr(v = 2.27\mu_1) = 0.14$). For adult women, $Pr(v = 0.22\mu_1) = 0.24$, $Pr(v = 1.09\mu_1) = 0.70$, $Pr(v = 3.31\mu_1) = 0.05$. Thus, among female adults, there is a small subgroup with a very large exit probability. Among adult men, the group with a very high exit probability is a somewhat larger. The individuals in these groups disappear rapidly from unemployment, as the duration proceeds.

FIGURE 6



due to the expiration of benefits or by an artefact of the data collection procedure (the small number of unemployed in these high duration classes causes the exit probability to be inexactly measured). The latter explanation is supported by the fact that the effect does not show up for adults, who constitute the largest group and as such are relatively abundant in the higher duration classes.

The measurement errors all have a standard deviation close to 0.04, and they are positively correlated across duration classes at one calendar moment. From this we conclude that the model fits the data well, and that misclassification of unemployed individuals into adjacent duration classes is not a major source of errors in the observed unemployment figures. The estimates of $d_{\geqslant '87}$ indicate a significant positive effect for all gender types and age groups. This effect varies between 5 and 15 percent for the incidence equation and between 11 and 18 percent for the equation for $\theta(0|\tau)$. There is not much difference across genders. Also, the effect is not larger for youths than for adults. This suggests that the significant effect of the dummy variable is not caused by policy towards youth employment, but rather by the changes in the data collection procedure.

5 Conclusions

In France, like in many other Western European countries, both the level and the turnover of youth unemployment are high in comparison to adult unemployment. In this paper we have examined the dynamics of age- and gender-specific unemployment, by estimating the calendar-time behavior of the unemployment inflow and outflow rates, taking account of duration dependence, individual heterogeneity, and seasonality in the data.

In our analysis we use aggregate data on exit probabilities distinguished by duration class for different groups of unemployed workers. Our methodology is very suitable to study dynamics in unemployment. The variations in these exit probabilities both over the duration of unemployment and across calendar time enable us to study processes that cannot be studied easily when studying micro data.

Our main results are the following. For youths, there does not appear to be a strong long-run trend in the inflow or outflow rates. The inflow size has decreased for youths and for adult women, but this is a consequence of the declining participation rates for these groups. For adults, the inflow rates have increased, and the outflow rates have decreased. In this sense, youths fared better than adults during the past decades. However, this is to a certain extent due to the special youth training and workfare programs, and it is not always clear that these improve the long-run labor market prospects of youths.

Concerning cyclical effects, it turns out that in general the inflow rate is counter-cyclical whereas the outflow rate is pro-cyclical. For women, the cycles in the inflow rate are not pronounced. This may be due to a discouraged worker effect during recessions, and to a lower incentive to register as unemployed. The strong cyclicality of the male inflow rate can be explained by the fact that men are strongly represented in sectors that are sensitive to cyclical shocks. For men, the cycle in the inflow rate is somewhat larger for youths than for adults. For both men and women, the cycle in the outflow is somewhat smaller for youths. The volatility of the youth unemployment rate can thus be attributed to the volatility of the youth inflow rate, whereas for adults the opposite is closer to the truth.

Many differences in cyclical behavior between (male) youths and (male) adults can be explained by institutional features of the French labor market. Young workers are often employed in jobs with short-term contracts or in training or workfare programs. The former can be argued to contribute to the high youth inflow and outflow rates, the volatility of the youth inflow rate, and the lack of volatility of the youth outflow rate. The latter programs can be argued to contribute to the high youth outflow rates.

There is no systematic difference between the phases of the inflow cycles for young men and adult men. Since 1988, the cycle for male youths seems to lag one year behind the cycle for adult men, but before 1988 the ordering is reversed. From the other parameter estimates, the most important result concerns the negative duration dependence of the youth exit probability after a year of unemployment. These results imply some policy suggestions. As explained in the introduction to this paper, long-term youth unemployment is very undesirable. The negative duration dependence in combination with the larger volatility of the unemployment rate of young workers implies that youths are more vulnerable in case a cyclical downturn than adults are. Thus, policy against long-term youth unemployment should focus on unemployed youths in a recession who have been unemployed for more than a year.

Another result with some relevance for policy concerns the fact that it could not be unambiguously established that the adult inflow rate is a leading indicator of the youth inflow rate.

Finally, our results highlight the importance of seasonal fluctuations. Here we find some major differences between youth and adult unemployment. These differences are related to the inflow into unemployment. The large seasonal fluctuations in youth unemployment are to a large extent driven by fluctuations in the inflow that are presumably caused by the large number of school leavers entering the labor market in the third quarter of the year.

6 Summary

In this paper we study unemployment dynamics among different age groups in France, employing a formal econometric analysis. Our focus is on business-cycle and calendar-time effects on the inflow and outflow rates of unemployment. For example, we examine to what extent youths are disproportionately affected by a recession.

We use macro data on unemployment distinguished by age group, gender, duration class and calendar time and calculate exit probabilities from unemployment. By comparing exit probabilities both across duration intervals and over time we can give a complete overview of the relevant components of unemployment dynamics. We discuss the importance of duration dependence and unobserved heterogeneity for the exit probabilities out of unemployment. And we discuss the relevance of trends, cycles and seasonality for both the inflow to and the outflow from unemployment. In our analysis we use French unemployment data for the period 1982-1994, distinguished between males and females and between three age groups: youths, adults and old.

We find that for youths there does not appear to be a strong long-run trend in the inflow or outflow rates. The inflow size has decreased for youths and for adult women, but this is a consequence of the declining participation rates for these groups. For adults, the inflow rates have increased, and the outflow rates have decreased. In this sense, youths fared better than adults during the past decades. However, this is to a certain extent due to the special youth training and workfare programs, and it is not always clear that these improve the long-run labor market prospects of youths.

In general, the inflow rate into unemployment is counter-cyclical, whereas the outflow rate is pro-cyclical. Yet there are pronounced differences between gender-types and age groups. For instance, female inflow rates are hardly cyclical. This may be explained by discouraged worker effects and lower incentives to register as unemployed. The strong cyclicality of male inflow rates on the other hand can be explained by the strong representation of men in sectors that are sensitive to economic shocks. Comparing age groups, the results show that the cycle in the inflow rate of male youths is larger than that of adult males. Moreover, the cycle in the outflow rate is smaller for both male and female youths, compared to their adult counterparts. The volatility of the youth unemployment rate can thus be attributed to volatility in the youth inflow rate. These differences can be explained by the above mentioned training and workfare programs for youths and the prevalence of short-term contracts for young workers. Training programs lead to high outflow rates, whereas short-term contracts lead to high and volatile inflow rates in combination with less volatile outflow rates.

Apart from the business cycle effects, we find evidence on the importance of seasonal effects on youth unemployment. These effects mainly concern the inflow into unemployment. In particular, school-leavers cause the incidence to be higher in the second half of the year. Moreover, we find that training programs absorb many of these new labor market entrants.

Finally, we find that youth exit probabilities are negatively duration dependent. In combination with the previously mentioned larger volatility of the unemployment rate of young workers this implies that youths are more vulnerable in case a cyclical downturn than adults are. Therefore, policy to prevent long-term youth unemployment should aim at these unemployed youths during a recession. Another result with some relevance for policy concerns the fact that it could not be unambiguously established that the adult inflow rate is a leading indicator of the youth inflow rate. ▼

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