Dynamics and Seasonality in Quarterly Panel Data: An Analysis of Earnings Mobility in Spain

Javier Alvarez
CEMFI

Working Paper No. 9914
November 1999

I thank Manuel Arellano, Samuel Bentolila, Olympia Bover, Enrique Sentana, and seminar audiences at CEMFI, UPF, UCL and University of Alicante. Financial support from CEMFI and Fundación Caja de Madrid is gratefully acknowledged. All remaining errors are my own.
(E-mail address: Javier.Alvarez.de.Pedro@econ.ku.dk).

CEMFI, Casado del Alisal 5, 28014 Madrid, Spain.
Tel: 34 91 4290551, fax: 34 91 4291056, www.cemfi.es.

Abstract

In this paper I present an empirical analysis of the dynamics of individual earnings using Spanish quarterly earnings. I propose a new econometric methodology to control for the seasonality in my dataset. Moreover, I apply this methodology to the study of earnings mobility in Spain, using transition probabilities among earnings quintiles for the period 1985-1996. I find substantial mobility from one year to the next. However, earnings changes are basically among adjacent quintiles. Workers with university education are more mobile than workers with primary and secondary education. On the other hand, I observe greater negative mobility among earnings quintiles and more persistence of low earnings situations over the nineties, and especially for workers with primary education.

1 Introduction

In this paper, I present an empirical analysis of the dynamics of individual earnings using Spanish quarterly data. The analysis is aimed at the study of earnings mobility in Spain, using transition probabilities among earnings classes, which can be calculated given knowledge of earnings dynamics. I propose a new econometric methodology to cope with the problem of seasonality in the data. The quarterly earnings data used in the paper present a very strong seasonal behaviour, but the seasonal pattern varies randomly from one individual to another. I, therefore, consider a stochastic seasonality which varies across individuals (i.e. seasonal individual random effects). Since individual time series are short, I am less concerned with the random variation in the seasonal pattern over time (as is customary in time series analysis) than with cross section random variation. Thus the seasonal pattern will be allowed to vary across individuals but it will be fixed over time for a given individual. Controlling for seasonal variation is important to the analysis because the observed dynamics in earnings compounds seasonal and nonseasonal persistence, and the interest lies in evaluating probabilities of transition net of seasonal variation and other permanent heterogeneity in earnings.

The panel data model with seasonal individual effects gives rise to orthogonality conditions for equation errors in seasonal differences from which GMM estimates can be obtained. Coefficients on time-invariant explanatory variables may or may not be identified depending on whether I assume that the random effects are purely seasonal effects (that are orthogonal to the explanatory variables) or not. In the latter case the seasonal effects will absorb

both the observed and the unobserved time invariant effects (like ability).

Another contribution of this paper is to consider an extended set of orthogonality conditions by relying on mean stationarity. The additional moment restrictions use seasonal differences of lagged earnings as instrumental variables for errors in levels. This gives rise to a seasonal system GMM estimator along the lines of the method proposed by Arellano and Bover (1995) for nonseasonal panels. These additional instruments prove to be crucial in obtaining estimates with sufficient precision in my empirical earnings equations.

The rotating panel covers the period 1985-1996. I present results for the entire period and also for the two subperiods 1985-1990 and 1991-1996. I find substantial earnings mobility from one year to the next although small earnings changes are more likely than large changes. Workers with university education are more mobile than workers with secondary and primary education. On the other hand, I found greater negative mobility over the nineties and especially for workers with primary education. Moreover, low earnings states seem to be more persistent during the nineties and particularly in the case of young workers with primary education.

Evidence for different industrialized countries is provided in some recent papers (Jarvis and Jenkins (1998) for the UK, Buchinsky and Hunt (1997) for the US, or Buchinsky, Fougère and Kramarz (1998a and 1998b) for France and the US). The existing empirical work for the second half of the eighties concludes that earnings mobility was substantial and very similar across different industrialized countries over this period (see the 1997 OECD Employment Outlook for a review of this work).

The organization of the paper is as follows. In section 2, I specify the model and the econometric methodology used to analyze the data. In section 3, I describe the dataset. In sections 4 and 5, I present the main empirical results of the paper. Finally, a discussion about the conclusions of the paper is contained in section 6.

2 The model

The dataset is a rotating panel which provides information about quarterly earnings of employed household members who are interviewed for up to eight consecutive quarters. Information on individual variables like age or education is also reported. The earnings variable shows a clear seasonal pattern which partly reflects the fact that a fraction of Spanish workers regularly receive statutory bonuses equal to one extra installment of the regular monthly pay in July and December.

I now present two different specifications of an empirical earnings function which are the basis for the analysis of earnings dynamics. I start with a basic specification of the earnings function and later I consider an extended version which enriches the dynamics of the model.

2.1 The basic specification

Consider an empirical earnings function given by:

$$w_{it} = x_{1i}'\beta_1 + x_{2it}'\beta_2 + \epsilon_{it}, i = 1, .., N, \ t = 1, .., T_i, \tag{2.1}$$

where w_{it} denotes the log of quarterly real labor earnings of worker i in the th quarter of collaboration. A worker i is observed for T_i quarters, with a maximum T_i of eight. Different individuals are observed for different historical periods which may or may not be overlapping.

On the right hand side of (2.1), I consider two kinds of explanatory variables. Firstly, I have a $(r_{11} \times 1)$ vector of time-invariant variables x_{1i}, like for example education dummies. Moreover, I also consider a $(r_{12} \times 1)$ vector of time-varying variables x_{2it} which could include non individual variables like time dummies or other time-varying individual variables. The error structure is an autocorrelated individual component model of the form:

$$\epsilon_{it} = d_{1t}\lambda_{1i} + d_{2t}\lambda_{2i} + d_{3t}\lambda_{3i} + d_{4t}\lambda_{4i} + v_{it} \tag{2.2}$$

$$v_{it} = \alpha_1 \, v_{it-1} + \alpha_2 \, v_{it-2} + \xi_{it}, \tag{2.3}$$

where the d_{kt} are seasonal dummy variables and the λ_{ki} are seasonal individual effects. Some workers get seasonal earnings and others do not, and the seasonal pattern varies across workers corresponding to the first group. The error structure contains a permanent and a transitory component. The permanent component includes four different random individual effects (one for each quarter). I specify individual stochastic effects to control for the fact that seasonality varies across individuals. Some workers get seasonal earnings and others do not, and the seasonal pattern varies across the former. A model including seasonal dummies in the earnings equation is less flexible because it imposes the same structure for all individuals and it would be too restrictive with this data. Moreover, note that although seasonality is allowed to change across individuals, it is constant over time. This contrasts with the typical time series treatment of seasonality, which pays more

attention to the control of random variation over time. Such problem is less relevant here because individual time series are short. The individual effects may reflect pure seasonality or a mixture of seasonality and other individual effects (like ability or pre-sample labor histories) that would be subsumed in them. As explained below, there are important differences in terms of identification related to this distinction.

The time-varying component of the earnings errors is a homogeneous AR(2) process. Later, this will be relaxed by introducing observed heterogeneity in the autoregressive coefficients. Given the model, the shocks in the autoregressive process will be uncorrelated with lagged earnings, but not with present or future earnings:

$$E(\xi_{it} z_{it}) = 0 \text{ , with } z_{it} = (w_{i1}, .., w_{it-1})'$$

It is also assumed that for all i, t and s the error term ξ_{it} is considered to be uncorrelated with the explanatory variables:

$$E(\xi_{it} x_{1i}) = E(\xi_{it} x_{2is}) = 0$$

The data indicated that at least an AR(2) model was needed to capture the dynamics. This is why a second instead a first order process was chosen. On the other hand, given seasonal effects and the length of the time-series in the dataset, the highest order that I could consider is three.

Related models for non seasonal earnings panel data have been considered for example by Lillard and Willis (1978), Abowd and Card (1989), and Moffit and Gottschalk (1995) amongst others.

One could also specify a dynamic earnings equation with seasonal individual effects, including lagged earnings as explanatory variables. If all the ex-

planatory variables were time-invariant or aggregate time-varying variables, this would just be an alternative representation of the same model. If on the other hand, the model contains time-varying individual variables, the model can be seen as a dynamic earnings equation subject to common factor restrictions (cf. Sargan, 1980). Here, I have a preference for the serial correlation model because a partial adjustment model would be difficult to rationalize in the context of a wage equation.

By substituting the expressions (2.3) and (2.2), the earnings equation can be written as:

$$\begin{aligned} w_{it} &= \alpha_1\, w_{it-1} + \alpha_2\, w_{it-2} + x_{1i}^{'}\beta_1(1-\alpha_1-\alpha_2) + \\ &\quad + x_{2it}^{'}\beta_2 - x_{2it-1}^{'}\beta_1\alpha_1 - x_{2it-2}^{'}\beta_2\alpha_2 + u_{it}, \end{aligned} \tag{2.5}$$

where

$$u_{it} = \sum_{k=1}^{4} \left(d_{kt} - \alpha_1 d_{kt-1} - \alpha_2 d_{kt-2}\right) \lambda_{ki} + \xi_{it}. \tag{2.6}$$

The number of coefficients in the parameter vector (which I denote as θ) in the linear equation (2.5) is equal to $2 + r_{11} + 3r_{12}$, but they are restricted to be functions of the $(r_1 + 2) \times 1$ parameter vector $\gamma = \left(\alpha_1\alpha_2\ \beta_1^{'}\ \beta_2^{'}\right)^{'}$, where $r_1 = r_{11} + r_{12}$. Thus, the serial correlation model can be seen as a second-order dynamic model with common factor (COMFAC) restrictions imposed on certain coefficients.

2.1.1 Identification and Orthogonality Conditions

I now discuss the conditions under which I achieve parameter identification. As a matter of notation, I assume that the first observation of earnings occurs at $t = 1$ so that the earnings equation (2.5) is defined from $t = 3$. First of all,

given (2.5) and taking into account that $\Delta_4 d_{kt} = 0$ and then $\Delta_4 u_{it} = \Delta_4 \xi_{it}$, the following moment conditions hold

$$E(w_{is}\Delta_4 u_{it}) = 0,\ t = 7, T_i,\ s = 1, .., t-5. \tag{2.7}$$

These generalize that proposed by Arellano and Bond (1991) and Holtz-Eakin, Newey and Rosen (1988) for non seasonal models.

Then, the moment conditions (2.7) follow from the assumption of predeterminedness of the earnings variable. As an example, suppose that the equation contains no time-varying variables and I consider an individual i with $T_i = 7$. The moment conditions (2.7) are:

$$\begin{aligned} E[(\Delta_4 w_{i7} - \alpha_1 \Delta_4 w_{i6} - \alpha_2 \Delta_4 w_{i5}) w_{i1}] &= 0 \\ E[(\Delta_4 w_{i7} - \alpha_1 \Delta_4 w_{i6} - \alpha_2 \Delta_4 w_{i5}) w_{i2}] &= 0 \end{aligned}$$

from which α_1 and α_2 would be just identified subject to the standard rank condition. Nevertheless, in practice, the moment conditions (2.7) will often not be very informative due to a problem of weak instruments. For a standard model with one individual effect in (2.2), w_{i3}, w_{i4} and w_{i5} are also valid instruments for equation errors in first differences.

If the individual effects are assumed to be pure seasonal effects or a mixture of seasonal and other individual effects that are uncorrelated with the time-invariant explanatory variables, I also have the following restrictions

$$E(x_{1i} u_{it}) = 0,\ t = 3, .., T_i. \tag{2.8}$$

Moreover if the x_{2it} are uncorrelated with the seasonal effects and are exogenous, for all t and s I have:

$$E(x_{2it}u_{is}) = 0,\ t = 3, .., T_i \tag{2.9}$$

If the x_{2it} are only predetermined then only the moments with $s \geq t$ are valid. The empirical model will include two time-varying variables, age and GDP growth. Then, notice that the GMM estimation will only consider the moment conditions (2.9) with $t = s$. Finally, I consider the following conditions which have been shown to be very informative in practice:

$$E(u_{it}\Delta_4 w_{is}) = 0,\ t = 6, .., T_i, s = 5, .., t-1 \tag{2.10}$$

The moment conditions (2.10) follow from assuming constant correlation of the individual effects and the earnings for observations which are one year apart:

$$E\left(\lambda_{ki} w_{it}\right) = E\left(\lambda_{ki} w_{it-4}\right) \text{ for all } k \text{ and } t. \tag{2.11}$$

These restrictions can be justified on the grounds of stationarity of the earnings process and generalize those proposed by Arellano and Bover (1995) for non seasonal models. In that context, efficiency gains are achieved by using first differences of lagged dependent variables as instrumental variables for errors in levels, especially in situations where T is small or the roots of the autoregresive process are close to one (see Blundell and Bond (1998)).

2.1.2 GMM Estimation

I consider a system GMM estimator of the parameters of the equation (2.5) based on the moment conditions given by the equations (2.7) − (2.11).

A compact expression for all moment conditions is

$$E\begin{bmatrix} Z_{li}^{'}u_i \\ Z_{di}^{'}\Delta_4 u_i \end{bmatrix} = 0, \tag{2.12}$$

where $u_i = (u_{i3}, .., u_{iT_i})^{'}$, Z_{li} is a $(Ti-2)\times 6(r_1+1)$ diagonal matrix whose sth block is given by $(x_{1i}^{'}, x_{2is+2}^{'})$ for $s = 1, 2, 3$, and by $(x_{1i}^{'}, x_{2is+2}^{'}, \Delta_4 w_{i5}, .., \Delta_4 w_{is+1})$ for $s = 4, 5, 6$, and Z_{di} is a $(Ti-6)\times 5$ block-diagonal matrix whose sth block is given by $z_{is+2}^{'}$[1] . The number of orthogonality conditions of the model is $q = 6(r_1 + 1) + 5$.

The GMM estimator of γ (the restricted parameter) based on the corresponding sample moments and with weight matrix A_N is given by

$$\widehat{\gamma_{GMM}} = \arg\min_{\gamma} \left[\sum_{i=1}^{N} u_i^{+'} Z_i\right] A_N \left[\sum_{i=1}^{N} Z_i^{'} u_i^{+}\right], \tag{2.13}$$

where $u_i^{+} = (u_i^{'}\Delta_4 u_i^{'})'$, $Z_i = diag(Z_{di}, Z_{li})$. The one-step GMM estimator of γ ($\widehat{\gamma_{GMM1}}$) is the solution of (2.13) with weighting matrix defined as:

$$A_N = \left(\sum_{i=1}^{N}(Z_{di}^{'}Z_{di}) + \sum_{i=1}^{N}(Z_{li}^{'}Z_{li})\right)^{-1}. \tag{2.14}$$

This provides a consistent but asymptotically inefficient estimator of γ. For a model which involves moment conditions in levels and in seasonal differences, the form of the covariance matrix of the orthogonality conditions depends on the particular assumptions of the model.

A two-step GMM estimator of γ ($\widehat{\gamma_{GMM2}}$) corresponds to a choice of the weighting matrix given by

$$A_N = \left[\sum_{i=1}^{N} Z_i^{'}\widehat{u_i^{+}}\widehat{u_i^{+'}}Z_i\right]^{-1}, \tag{2.15}$$

[1]For individuals with $T_i = 7$, the last row of both matrices which corresponds to the missing equation is deleted and replaced by zeroes.

where $\widehat{u_i^+}$ is a vector of system residuals obtained by substituting $\widehat{\gamma_{GMM1}}$ for the values in the equation errors. From standard GMM theory, the asymptotic covariance matrix of $\widehat{\gamma_{GMM2}}$ is defined by:

$$Var\left(\widehat{\gamma_{GMM2}}\right) = (H^{'} D_0^{'} V_0^{-1} D_0 H)^{-1}, \tag{2.16}$$

where

$$\begin{aligned} H &= \frac{\partial \theta(\gamma)}{\partial \gamma^{'}}, D_0^{'} = E\left[(\Delta_4 \widetilde{x}_i^{'} \ \widetilde{x}_i^{'}) Z_i\right], \\ V_0 &= E\left[Z_i^{'} u_i^{+} u_i^{+'} Z_i\right]. \end{aligned} \tag{2.17}$$

and $\widetilde{x_i}$ is a $(T_i - 2)\times\ (2 + r_{11} + 3r_{12})$ matrix with rows defined by:

$$\left(w_{ij-1}, w_{ij-2}, x_{1i}^{'}, x_{2ij}^{'}, x_{2ij-1}^{'}, x_{2ij-2}^{'}\right), \text{ for } j = 3, .., T_i.$$

A consistent estimator of $Var\left(\widehat{\gamma_{GMM2}}\right)$ is obtained by inserting consistent estimators of H, D_0 and V_0 into (2.17). These estimators are

$$\begin{aligned} \widehat{H} &= \frac{\partial \theta(\widehat{\gamma_{GMM2}})}{\partial \gamma^{'}}, \widehat{D_0}^{'} = \sum_{i=1}^{N} (\Delta_4 \widetilde{x}_i^{'} \ \widetilde{x}_i^{'}) Z_i \ , \\ \hat{V}_0 &= \sum_{i=1}^{N} (Z_i^{'} \widehat{u_i^{+}} \widehat{u_i^{+'}} Z_i). \end{aligned} \tag{2.18}$$

I also consider a Sargan test of over-identifying restrictions which is

$$S = \left[\sum_{i=1}^{N} \widetilde{u_i^{+'}} Z_i\right] \left[\sum_{i=1}^{N} (Z_i^{'} \widetilde{u_i^{+}} \widetilde{u_i^{+'}} Z_i)\right]^{-1} \left[\sum_{i=1}^{N} Z_i^{'} \widetilde{u_i^{+}}\right], \tag{2.19}$$

where $\widetilde{u_i^{+}}$ is the vector of two-step residuals. Under the null of no misspecification, S is asymptotically distributed as chi-square with $q-\ (r_1 + 2)$ degrees of freedom.

2.2 An extended model with heterogeneous dynamics

I turn now to consider an extended specification that will be used in the empirical analysis. The only difference with the basic model is that now α_1 and α_2 are allowed to change with time-invariant observed explanatory variables. The AR(2) process for v_{it} will be:

$$v_{it} = \alpha_{1i}\, v_{it-1} + \alpha_{2i}\, v_{it-2} + \xi_{it}, \tag{2.20}$$

where $\alpha_{1i} = \alpha_1^{'} e_{1i}$, $\alpha_{2i} = \alpha_2^{'} e_{2i}$, and e_{1i} and e_{2i} are $(r_{21} \times 1)$ and $(r_{22} \times 1)$ vectors of time-invariant explanatory variables.

The presence of individual heterogeneity in the parameters of the AR(2) process reflects a different dynamics across individuals according to some individual characteristic, like for example education.

I again consider the same kind of individual and stochastic effects which preserve the same properties of the basic specification.

In line with the previous discussion, I shall now obtain the following extended second-order dynamic model that contains interactions of the earlier variables with those in e_{1i} and e_{2i}:

$$\begin{aligned} w_{it} \;=\; & \alpha_{1i}\, w_{it-1} + \alpha_{2i}\, w_{it-2} + x_{1i}^{'}\beta_1(1-\alpha_{1i}-\alpha_{2i}) + x_{2it}^{'}\beta_2 \\ & - x_{2it-1}^{'}\beta_2\alpha_{1i} - x_{2it-2}^{'}\beta_2\alpha_{2i} + u_{it}^{*}, \end{aligned} \tag{2.21}$$

where

$$u_{it}^{*} = \sum_{k=1}^{4} \left(d_{kt} - \alpha_{1i} d_{kt-1} - \alpha_{2i} d_{kt-2}\right) \lambda_{ki} + \xi_{it}.$$

Now, the number of parameters is equal to $r_1 + r_2 + r_1 r_2$ with $r_2 = r_{21} + r_{22}$.

The coefficients in the extended specification are restricted to be functions of the $(r_1 + r_2) \times 1$ parameter vector $\left(\alpha_1^{'}\alpha_2^{'}\ \beta_1^{'}\ \beta_2^{'}\right)^{'}$.

The orthogonality conditions employed in this case are similar to those considered earlier. In addition to the moment conditions (2.7), I now assume that interactions of earnings with the e_{1i} and e_{2i} variables are also valid instruments. Namely:

$$E[\Delta_4 u^*_{it} w_{is} e_{1i}] = 0,\ t = 7, T_i,\ s = 1, .., t-5 \tag{2.22}$$

and

$$E[\Delta_4 u^*_{it} w_{is} e_{2i}] = 0,\ t = 7, T_i,\ s = 1, .., t-5. \tag{2.23}$$

Similarly, the conditions (2.8) and (2.9) remain valid if:

$$E(\lambda_{ki}|x_{1i}) = E(\lambda_{ki} x_{2it}|x_{1i}) = 0.$$

Then, I assume the mean independence of the effects λ_{ki} given the time-invariant variables x_{1i} instead of non-correlation which is a sufficient condition. The moment conditions (2.10) would be valid if I replaced the assumption of constant correlation between the individual seasonal effects and observations which are one year apart, with the more general assumption given by:

$$E\left(\lambda_{ki} w_{it}|e_{1i}, e_{2i}\right) = E\left(\lambda_{ki} w_{it-4}|e_{1i}, e_{2i}\right),\ \text{for all } k \text{ and } t. \tag{2.24}$$

In addition, based on (2.24), I consider another set of orthogonality conditions defined as:

$$E[u^*_{it} \Delta_4 w_{it-1} e_{1i}] = 0, t = 1, .., T_i \tag{2.25}$$

$$E[u^*_{it} \Delta_4 w_{it-1} e_{2i}] = 0,\ t = 1, .., T_i \tag{2.26}$$

Finally, a system GMM estimator similar to the one discussed above can be defined for the new errors and the extended set of orthogonality conditions.

3 The data

3.1 The characteristics of the database

The data that I use come from the Spanish Continuous Family Expenditure Survey (ECPF). This is a rotating panel carried out by the Instituto Nacional de Estadística (INE). The ECPF is conducted every quarter on all members of around 3200 households. One eighth of the sample is renewed quarterly and hence an individual can be followed for a maximum of eight quarters. The sample unit in the ECPF is the household and the sample period available for this study is 1985(I)-1996(IV). The ECPF provides information about quarterly earnings and expenditures of all household members. The ECPF distinguishes among household heads, partners and the rest of the members.

In order to study changes in the dynamics of earnings, the main feature of the ECPF is that it provides information over a decade. Thus, although I only observe a maximum of eight quarters for each individual, it is possible to evaluate how the earnings dynamics changed by looking at the evolution over the whole period.

With respect to information about earnings, the ECPF offers information about monetary and non monetary income obtained by all household members during the quarter of interview. In addition to earnings information, the ECPF contains information on individual characteristics (for a detailed description of some relevant variables, see the Appendix). A key variable is the education level which is only reported in the case of heads of households. There are seven groups which correspond to the three well-identified education groups (primary education, secondary education and university).

The ECPF does not contain information on either days of work per month or hours of work per day, which made impossible the computation of average hourly wages. As a result, I analyse the behavior of quarterly earnings. In particular, I consider real income from employment obtained by heads of household, men, aged 20 to 60 and in employed full-time (who work more than one third of the normal shift) for all quarters of collaboration. I focus on heads of households due to the fact that they are the only household members for whom their education level is reported. I also exclude women in order to avoid having to deal with female labor supply and non participation. Lastly, I do not consider in my analysis workers being unemployed over the collaboration period.[2]

An interesting problem would be how to incorporate workers with unemployment spells into the analysis of earnings dynamics. Blundell, Reed and Stoker (1998) study the issues involved in the aggregation of wages. One of these issues is the importance of participation in aggregation. They consider a wage equation which incorporates a control for self-selection through a reservation wage equation and an equation for hours. The lack of information about hours makes it difficult to implement this methodology. Moreover, it would be questionable to extract conclusions about mobility from a latent distribution of earnings.

After filtering the original dataset (see the Appendix for a description of the sample), I drew a sample of 47780 observations, which refer to 10251

[2]Over a sample of heads of household, men, aged 20 to 60 and who are in full-time employment (and excluded if they have other source of income) or unemployed during the collaboration period, I find that a 80% of them are employed for the whole collaboration period, a 6% are unemployed for the whole collaboration period and the remaining 14% have transitions among both states.

household heads employed.

The most important characteristics of the observations are contained in Tables A1 and A2. Table A1 shows the frequency of quarterly observations in the group of the employed full-time. The number of observations per individual varies, with 22.5% of the full-time employed being observed for eight quarters.

In Table A2, I break down my sample of employees according to age and schooling level and also considering two subperiods, 1985-90 and 1991-96. Most observations in the sample correspond to individuals with primary education, although this percentage decreases in the second subperiod. On the other hand, the age distribution does not change much over time, with the majority of employed heads of household being aged 31 to 40.

3.2 The evolution of real earnings

I now study the evolution of real earnings in the sample. I deflated nominal monetary earnings by the national consumer price index (base 1996:1). In graph 1 I represent the median of log real quarterly earnings for the period 1985-1996. Notice that the earnings variable seems to show a marked seasonal pattern with peaks in the first and in the third quarters. In order to get an impression of the evolution followed by earnings and its relation with the business cycle, in Table 1 I summarize the average over the year of the annual growth of earnings and GDP (annual growth rate defined as the rate of change of a quarter with respect to the same quarter of the previous year) and of the unemployment rate for the period 1986-1996. As it can be seen, the period 1987-1992 is the one with the fastest growth of real median

earnings, and especially the subperiod 1987-1988. The period 1987-1991 is the one with the fastest economic growth, and it is also a period of decrease in unemployment. On the other hand, real median earnings declined during 1994-1995, a period which meant the end of a recession which began in 1992. Thus, I conclude that real earnings in the sample do not appear to exhibit a clear procyclicality and even more, they seem to be countercyclical during the nineties.

When considering differences among workers according to education, the most remarkable differences appear when comparing the behaviour of the earnings of workers with primary and secondary education relative to those of workers with university education. For workers with primary and secondary education and for all ages, earnings increased over the period 1985-1991 and declined over the period 1992-1996. The earnings of workers with university education increased over the whole period and especially over the second half of the nineties. As a result, the return to university education and secondary education relative to primary education seemed to go down over the second half of the eighties and to go up over the first half of the nineties.

4 Earnings Function Estimates

In this section, I present the results corresponding to the estimation of two alternative specifications of an empirical earnings function. In the first subsection, I consider the basic specification given by equations (2.1), (2.2), and (2.3). In the second subsection, I consider the extended specification with heterogeneity in the autoregressive coefficients given by equations (2.1), (2.2), and (2.20). Both specifications include the following explanatory variables: a

constant, education dummies (secondary and university education dummies), age, age squared and the annual GDP growth rate.

4.1 Estimation of the basic specification

In Table 2 I report estimates of the coefficients on the explanatory variables and on the error dynamics which result from estimating the parameters of the equation (2.5) subject to the common factor restrictions. In particular, the first column (GMM2s) are two-step seasonal system GMM estimates based on the moment conditions (2.12). For comparison, I show three alternative estimates obtained from other methods. OLS1 denotes OLS estimates of the model without including seasonal dummies in the error equation error (2.2) to control for seasonality. By contrast, the third column (OLS2) collects OLS estimates of the model including seasonal dummies in the error structure (2.2) and which are time invariant explanatory variables in (2.5) (coefficients on these variables are denoted by λ_k).[3]

Finally, the last column (GMM1s) presents two-step system GMM estimates based on moment conditions using earnings in levels and in first differences for error equations in first differences and in levels, respectively.[4] Moreover, seasonal dummies are included as explanatory variables and mo-

[3]Notice that the first column also includes the coefficients λ_k which denote the GMM2s estimated means of the seasonal individual effects.

[4]In particular, these estimates are based on moment conditions:

$$E\left[\begin{array}{c} Z_{li}^{'}u_i \\ Z_{di}^{'}\Delta u_i \end{array}\right] = 0,$$

where Z_{li} is now a $(T_i-2)\times 6(r_1+1)$ diagonal matrix whose sth block is given by $(x_{1i}^{'}, x_{2is+2}^{'}\ \Delta w_{is+1})$ for $s=1,..,6$ and Z_{di} is a $(T_i-2)\times 21$ block-diagonal matrix whose Sth block is given by $z_{is+1}^{'}$.

ment conditions using these variables as instruments for errors in levels are also considered. Hence, these estimates correspond to standard system GMM estimates for a model with only one individual effect in (2.2).

Looking at the dynamics, the pattern of OLS autoregressive coefficients corresponds precisely to that implied by the presence of seasonality. The large second-order partial autoregressive coefficient suggests a strong correlation of earnings at t and at $t-2$. The introduction of seasonal dummies implies a small reduction of the second-order coefficient and an increase in the first-order one. I obtain positive estimates of the first and of the third quarter dummies, which is consistent with the seasonal pattern shown above.

The GMM2s autoregressive coefficients clearly decline as a result of controlling for the seasonal persistence. All coefficients are significant and the Sargan test does not reject the validity of the orthogonality conditions implied by the model. The estimated means of the effects have the expected sign and are smaller than the OLS seasonal dummies estimates. The coefficients on age and age squared have the expected sign and the coefficients on secondary and university education dummies show that the return to education increases with the education level. The negative coefficient on the variable GDP seems to suggest that real earnings are countercyclical.[5]

[5] With respect to the cyclicality of the real wages, a wide range of studies using aggregate and micro longitudinal data points out an inconclusive evidence. A good review of the available evidence for the U.S. is provided by Abraham and Haltiwanger (1995) who also presented a set of factors related to the method and the measurement of the variables affecting the cyclicality of the real wages in opposite ways. For Spain, the evidence seems to be of a procyclicality of wages with respect to the unemployment rate. Bentolila and Dolado (1994) using a panel of manufacturing firms for the period 1983-1988 found procyclicality of wages with respect to the national unemployment rate. Bentolila and Jimeno (1998) using sectoral data corresponding to Spanish regions for the period 1980-1988 found procyclicality of earnings (defined as national account data on total compesation per employee) with respect to the national and the regional rate of unemployment. Blundell,

The GMM1s coefficients on the explanatory variables seem to be biased and the Sargan test rejects the validity of the orthogonality conditions. Compared to OLS estimates I find smaller coefficients on the constant and on the education dummies and larger coefficients on the variables age and age squared. The dynamics is completely different, with negative coefficients α_1 and α_2 and with the first coefficient being larger in magnitude than the second one.

Table *A*3 includes the estimation results for four different subperiods corresponding to observations with some degree of overlap. In particular, I estimate the model using observations of individuals who start collaborating before 1987(IV), from 1988(I) to 1990(IV), from 1991(I) to 1993(IV) and after 1993(IV). The main purpose is to detect possible changes affecting coefficients which could suggest changes in dynamics over the whole sample period. Although estimates by subgroups may be affected by measurement error, coefficients are not homogenous over time.

By comparing the autoregressive coefficients α_1 and α_2, I find that the coefficients are much more larger in the cases of estimates involving observations over the second half of the eighties (estimates 1 and 2). This is especially the case of individuals who start collaborating at the beginning of this subperiod (estimates 1). With respect to the parameter estimates on the explanatory variables, I observe larger returns to experience and education for individuals who start collaborating after 1990(IV). The variable GDP has a negative coefficient which is only significant in the case of the second

Reed and Stoker (1998) analyze different sources of bias related to the aggregation process which explains divergences in terms of cyclicality between aggregate and individual wage data.

and the fourth estimates. Thus, I conclude that there are two subperiods for which there is a clear change affecting dynamics, the second half of the eighties and the first half of the nineties.

In Tables 3 and 4 I summarize the two-step seasonal GMM estimates for these two subperiods. All coefficients are significant and the Sargan test does not reject the validity of the orthogonality conditions. The smaller estimates of α_1 and α_2 suggest a smaller correlation of the earnings for homogenous groups of workers over the nineties than over the eighties.. The difference in dynamics is statistically significant. The test of structural change in the dynamics rejects the null hypothesis of homogenous autoregressive coefficients (the value of the statistical test which is distributed as a χ-square with two degrees of freedom is 23.6). On the other hand, for the nineties subperiod, I also find a greater education premium and a smaller coefficient on age.

4.2 Components of variance

Before exploring the results of the estimation of an extended model with heterogeneity in dynamics, I present the components of the variation in log earnings which will be used to calculate transition probabilities in section 5.

In order to obtain these variances, I assume that conditional on a given quarter and on the explanatory variables, the vectors λ_i are identically distributed with zero mean and covariance matrix Σ, where $\lambda_i = (\lambda_{1i}, \lambda_{2i}, \lambda_{3i}, \lambda_{4i})'$.[6] Moreover, conditional on a given quarter and on the explanatory variables, the stochastic effects ξ_{it} are considered to be *iid* with zero mean and vari-

[6] In practice, I consider seasonal individual effects with means different from zero. This only implies a redefinition of the effects consisting of subtracting the mean from the corresponding effect. Then, I also estimate different cross-sectional means for each effect.

ance σ_ξ^2 and independent of the individual effects λ_{ki}. Thus, the marginal variances of ϵ_{it} and v_{it} turn out to be:

$$\sigma_\epsilon^2 = Var(\epsilon_{it}) = E[Var(\epsilon_{it}|d_k, x_i)] = \frac{\sum_{k=1}^4 \sigma_{\lambda_k}^2}{4} + \sigma_v^2 \tag{4.1}$$

$$\sigma_v^2 = Var(v_{it}) = p(\alpha_{1,}\alpha_2)\sigma_\xi^2, \tag{4.2}$$

where d_k is the vector of seasonal dummies $(d_{k1}, d_{k2}, d_{k3}, d_{k4})'$, x_i is the vector $(x_{1i}, x_{2it})'$ and $p(\alpha_{1,}\alpha_2)$ is given by

$$\left(\frac{1-\alpha_2}{1+\alpha_2}\right)\left(\frac{1}{(1-\alpha_2)^2-\alpha_1^2}\right). \tag{4.3}$$

Notice that σ_ϵ^2 is obtained from the average over all quarters of the variances of the effects λ_{ki} and (4.2) is the expression corresponding to the variance of a second-order autoregressive model under stationarity. Therefore, I consider the following estimators:

$$\widehat{\sigma_\epsilon^2} = \frac{\sum_{k=1}^4 \widehat{\sigma_{\lambda_k}^2}}{4} + \widehat{\sigma_v^2} \tag{4.4}$$

$$\widehat{\sigma_v^2} = p(\widehat{\alpha_{1,}}\widehat{\alpha_2})\widehat{\sigma_\xi^2}, \tag{4.5}$$

where

$$\widehat{\sigma_{\lambda_k}^2} = \widehat{\sigma_{\epsilon_k}^2} - \widehat{\sigma_v^2} \tag{4.6}$$

$$\widehat{\sigma_\xi^2} = \frac{\widehat{Var(\Delta_4 u_{it})}}{2} = \sum_{i=1}^N \sum_{t=7}^{T_i} \frac{\Delta_4 \widehat{u_{it}}^2}{2N(T_i-6)} \tag{4.7}$$

$$\widehat{\sigma_{\epsilon_k}^2} = \frac{\sum_{i=1}^N \sum_{t=3}^{T_i} (w_{it} - \widehat{\beta}_1^{'} x_{1i} - \widehat{\beta}_2^{'} x_{2it} - \overline{\lambda_k})^2 d_{kt}}{\sum_{i=1}^N \sum_{t=3}^{T_i} d_{kt}}, \tag{4.8}$$

and

$$\overline{\lambda_k} = \frac{\sum_{i=1}^N \sum_{t=3}^{T_i} (w_{it} - \widehat{\beta}_1^{'} x_{1i} - \widehat{\beta}_2^{'} x_{2it}) d_{kt}}{\sum_{i=1}^N \sum_{t=3}^{T_i} d_{kt}}. \tag{4.9}$$

Thus, these estimates are not a direct output from the GMM estimation. For example, the variance of ξ_{it} is obtained from the variance of $\Delta_4 u_{it}$ given that $\Delta_4 u_{it} = \Delta_4 \xi_{it}$[7] . Moreover, a preliminary estimate of the cross-sectional mean of the individual effect λ_{ik} is required to evaluate (4.8) for each quarter k.

4.3 Estimation of an extended model with heterogeneity

The basic specification implies that differences in dynamics across individuals only come from differences in individual means. Nevertheless, it is logical to think of including individual heterogeneity in dynamics through interactions between the autoregressive coefficients and the explanatory variables. A preliminary analysis revealed that the main source of heterogeneity is the education level. Then, I calculate two-step seasonal system GMM estimates of the equation (2.21) with coefficients α_{1i} and α_{2i} depending on the education dummies. The explanatory variables are the same as in the case of the basic specification.

In Tables 5 and 6, I show the GMM estimates of this extended model when considering the same two subperiods as in Tables 3 and 4. In both cases, the Sargan test does not reject the validity of the orthogonality conditions. Notice that coefficients on all explanatory variables are similar in magnitude to those shown in Tables 3 and 4, and they are significant. On

[7] Another alternative estimate of σ_ξ^2 may be obtained from the variance of $\Delta_4 \epsilon_{it}$, given the fact that $\Delta_4 \epsilon_{it} = \Delta_4 v_{it}$ and that $var(\Delta_4 v_{it}) = 2p(\alpha_1, \alpha_2)\sigma_\xi^2 \left(1 - \frac{\alpha_1^4 + 3\alpha_1^2\alpha_2 - \alpha_1^2\alpha_2^2 + \alpha_2^2 - \alpha_2^3}{1-\alpha_2}\right)$.

the other hand, by looking at Table 5, I find that coefficients on one and two lags of the earnings are larger than in the basic specification. Moreover, coefficients on all terms of interactions between lags of earnings and education dummies are negative though only the interaction of one lag of earnings and the dummy of university education is significant. Turning to Table 6, as compared to the basic specification, I have a larger coefficient on one lag of earnings and a smaller coefficient on the second lag of earnings, which is not significant. The coefficients on interactions of lags of earnings and the dummy of university education are significant and of opposite sign. With respect to the terms of interactions with the dummy of secondary education, only the interaction with the second lag of earnings is marginally significant and positive. The introduction of heterogeneity in the coefficients α_1 and α_2 induces a different dynamics for individuals with different education in the direction of a smaller correlation of earnings for workers with university education. In addition, though there are no significant differences in dynamics between workers with primary and secondary education, estimates seem to suggest a smaller persistence of earnings for workers with primary education than for those with secondary education over the nineties.

5 Transition probabilities

I now derive transition probabilities based on estimates of the basic specification. Taking into account these transition probabilities, I present some considerations about mobility. Although the estimation of the model has already shown the existence of changes in dynamics over the sample period, the analysis of mobility in this section also allows me to observe whether

those changes have occurred at different parts of the distribution. In order to obtain transition probabilities, I assume that $\lambda_i|d_k,x_i \sim N(0,\Sigma)$ and $\xi_{it}|d_k,x_i \sim N(0,\sigma_\xi^2)$. Both effects are also assumed to be mutually independent conditional on a given quarter and on the explanatory variables. The normality assumption is not necessary but it is convenient analytically.

5.1 The concept of transition probabilities

Individual transition probabilities The individual transition probabilities are the probabilities of given workers having earnings in a certain earnings interval in a year, conditional to have had earnings in another interval one year before. These probabilities also condition on a given quarter, and on values of the explanatory variables and of the individual effects. For a quarter k, these probabilities are defined as:

$$p_{kt+4|t} = \frac{p_{kt,t+4}}{p_{kt}}. \tag{5.1}$$

The denominator in this expression (p_{kt}) is the probability of a given worker having earnings in an earnings interval conditional on a given quarter and on values of the explanatory variables and of the individual effects, which is given by:

$$P(w_1^* \leq w_{it} \leq w_2^*|d_k,x_i,\lambda_i) = P(b_{1it} \leq (v_{it}/\sigma_v) \leq b_{2it}) = \int_{b_{1it}}^{b_{2it}} \phi(z_{it})dz_{it}, \tag{5.2}$$

where $b_{\tau it} = \frac{w_\tau^* - x_{1i}'\beta_1 - x_{2it}'\beta_2 - \sum_{k=1}^4 d_{kt}\lambda_{ki}}{\sigma_v}$ for $\tau = 1,2$, w_1^* and w_2^* are predetermined earnings levels (for example quintiles of the earnings distribution for a given year), and ϕ is the standard normal density function.

On the other hand, the numerator in (5.1) is the joint probability of climbing within the earnings distribution over two consecutive years, conditional

on a given quarter, and on values of the explanatory variables and of the individual effects which is defined as:

$$\begin{aligned} P(w_1^* &\leq w_{it} \leq w_2^*, w_3^* \leq w_{it+4} \leq w_4^* | d_k, x_i, \lambda_i) = \\ P(b_{1it} &\leq (v_{it}/\sigma_v) \leq b_{2it}, b_{3it+4} \leq (v_{it+4}/\sigma_v) \leq b_{4it+4}) = \\ &\int_{b_{1it}}^{b_{2it}} \int_{b_{3it+4}}^{b_{4it+4}} \phi_2(z_{it}, z_{it+4}) dz_{it} dz_{it+4}, \end{aligned} \tag{5.3}$$

where

$$b_{\tau it+4} = \frac{w_\tau^* - x_{1i}^{'}\beta_1 - x_{2it+4}^{'}\beta_2 - \sum_{k=1}^{4} d_{kt+4}\lambda_{ki}}{\sigma_v}, \tau = 3, 4,$$

and ϕ_2 is the standard bivariate normal density function with correlation coefficient

$$\frac{cov(v_{it}, v_{it+4})}{\sigma_v^2} = \left(\frac{\alpha_1^4 + 3\alpha_1^2\alpha_2 - \alpha_1^2\alpha_2^2 - \alpha_2^3 + \alpha_2^2}{1 - \alpha_2} \right).$$

Based on these quarterly probabilities, I am concerned with average transition probabilities over quarters:

$$p_{t+4|t} = \sum_{k=1}^{4} \frac{p_{kt+4|t}}{4}. \tag{5.4}$$

Aggregate transition probabilities The aggregate transition probabilities are the probabilities of random workers having earnings in a certain earnings interval in a year, conditional to have had earnings in another interval one year before. Unlike the individual transition probabilities, these probabilities condition on a given quarter and on certain values of the explanatory variables. For quarter k this probability is defined as:

$$P_{kt+4|t} = \frac{P_{kt,t+4}}{P_{kt}}. \tag{5.5}$$

The denominator in this expression is now defined as the probability of a random worker having earnings in an earnings interval, given a quarter and certain values of the explanatory variables:

$$P(w_1^* \leq w_{it} \leq w_2^* | d_k, x_i) = P(a_{1it} \leq (\epsilon_{it}/\sigma_{\epsilon_k}) \leq a_{2it}) = \int_{a_{1it}}^{a_{2it}} \phi(z_{it}) dz_{it}, \quad (5.6)$$

where $a_{\tau it} = \frac{w_\tau^* - x_{1i}^{'}\beta_1 - x_{2it}^{'}\beta_2}{\sigma_{\epsilon_k}}$ for $\tau = 1, 2$.

On the other hand, the numerator in (5.5) is the joint probability of a random worker being in a sequence of intervals of earnings for two consecutive years and conditional on a given quarter and on certain values of the explanatory variables:

$$\begin{aligned} P_{kt,t+4} &= P(w_1^* \leq w_{it} \leq w_2^*, w_3^* \leq w_{it+4} \leq w_4^* | d_k, x_i) = \quad (5.7) \\ P(a_{1it} &\leq (\epsilon_{it}/\sigma_{\epsilon_k}) \leq a_{2it}, a_{3it+4} \leq (\epsilon_{it+4}/\sigma_{\epsilon_k}) \leq a_{4it+4}) = \\ &\int_{a_{1it}}^{a_{2it}} \int_{a_{3it+4}}^{a_{4it+4}} \phi_2(z_{it}, z_{it+4}) dz_{it} dz_{it+4}, \end{aligned}$$

where

$$a_{\tau it+4} = \frac{w_\tau^* - x_{1i}^{'}\beta_1 - x_{2it+4}^{'}\beta_2}{\sigma_{\epsilon_k}}, \tau = 3, 4,$$

and ϕ_2 is the standard bivariate normal density function with correlation coefficient

$$\frac{\sigma_{\lambda_k}^2 + cov(v_{it}, v_{it+4})}{\sigma_{\epsilon_k}^2}.$$

Based on the corresponding quarterly probabilities, I also calculate average probabilities over quarters like above. It is clear that aggregate transition probabilities result from integrating individual transition probabilities over the distribution of individual effects.

Notice that in the absence of correlation, joint individual probabilities are equal to the product of individual probabilities but this is not the case

of joint aggregate probabilities due to the presence of correlation induced by individual heterogeneity.. Another characteristic of the model is that it preserves some properties of markovian processes like for example the fact that the conditional probability of being under an earnings level at $t+4$ given the worker was under that the corresponding level at t is greater than if he was not. Nevertheless, transition probabilities are not strictly markovian due to their dependence on the whole past history of states and not only on the previous state.

5.2 Empirical transition probabilities

I now calculate different transition probabilities by evaluating the expressions shown above at the parameter estimates. I start by considering the aggregate transition probabilities among earning quintiles (relative mobility) which are obtained from the distribution of annual earnings for the whole sample. I first derive the aggregate probability of a random worker having earnings in an earnings quintile for a given quarter of the year 1986 (1996), conditional to have had earnings in another quintile for the same quarter of the year 1985 (1995) (expression (5.5)). The expression is evaluated at the parameter estimates shown in Tables $3-4$ (estimates for the second half of the eighties and for the first half of the nineties) and at the corresponding estimates of $\sigma^2_{\epsilon_k}$. Although I take as reference periods the beginning and the end of the sample, the probabilities calculated do not differ very much from the average transition probabilities for the second half of the eighties and for the first half of the nineties

In Table 7 I show the yearly average of the quarterly probabilities for

the subperiods 1985-1986 and 1995-1996, and for 35 years-old workers with primary, secondary and university education.

Panel *A* shows that for random workers with primary education, situations of low earnings were more persistent for the second subperiod than for the first subperiod. 64 percent of workers of the poorest quintile in 1985 were in the poorest quintile in 1986 compared to 71 percent for the second subperiod. There was substantial mobility but basically among adjacent earnings quintiles.. Of workers leaving the poorest quintile in 1985, 27 percent moved to the second poorest quintile while only 8 percent moved to the middle quintile. Mobility at the middle of the distribution was greater than at the bottom or at the top. This reflects the fact that by definition people at the bottom and at the top cannot move down or up, respectively.

On the other hand, although there are no big differences, I find greater negative mobility of workers over the second subperiod and especially at the middle of the distribution. 30 percent of workers of the middle quintile in 1985 moved down in 1986, compared to 34 percent for the second subperiod.

Panel *B* collects the results for the case of random workers with secondary education. Compared to workers with primary education, I find greater positive mobility of workers of the poorest quintile and especially over the second subperiod. 51 and 57 percent of workers of the poorest quintile were in the same quintile for each subperiod, but most of them moved to the second poorest quintile and only a small percentage moved to superior quintiles. Unlike workers with primary education, workers with secondary education at the middle and at the top of the distribution had larger probabilities of climbing up than of climbing down. Looking at the differences over time

among workers with secondary education, I observe greater negative mobility for the second subperiod and especially for workers at the middle and at the top of the distribution. In particular, 22 percent of workers of the middle quintile of the earnings distribution in 1985 moved down in 1986, compared to 25 percent for the subperiod 1995-1996.

Finally, Panel C summarizes the results for the case of workers with university education. Compared to workers with primary and secondary education, low earnings situations were less persistent and it was also more likely to observe large transitions. 21 percent of workers of the second poorest quintile in 1985 moved to the second richest quintile in 1986, compared to 14 percent of workers with secondary education, or to 9 percent of workers with primary education. Looking at differences over time among workers with university education, I find less positive mobility over the second subperiod. 53 percent of workers with university education and with earnings at the middle of the distribution in 1985 moved up in 1986, compared to 50 percent for the second subperiod.

I now turn to transition probabilities among earnings quintiles for other age groups. In Table $A4$ I show the case of workers at ages 25 and 50 with primary education. The pattern of transition probabilities for workers with secondary or university education is similar, so that I do not include any table collecting probabilities for them. Low earnings situations were more persistent for 25 years-old workers with primary education than for 35 years-old workers. 75 and 83 percent of 25 years-old workers were in the poorest quintile for the two subperiods considered, compared to 64 and 71 percent of 35 years-old workers. Moreover, young workers at the middle of the earnings

distribution exhibited a greater negative mobility than 35 years-old workers at the same region, and especially over the second subperiod. On the other hand, in the case of 50 years-old workers with primary education, low earnings situations were less persistent and those workers had a larger probability of climbing up the earnings distribution.

I now turn to consider the distribution of individual probabilities that underlies the aggregate probabilities that have been analysed to this point. First of all, I compute the individual transition probabilities of a given worker at age 35 having earnings in a determined quintile in 1986 (1996) conditional on having had earnings in another quintile in 1985 (1995) and for a given quarter (expression (5.1)). For each quarter, the expression is evaluated at different values of λ_{ik} given by zero, $\pm 0.5\widehat{\sigma_{\lambda_k}}$ and $\pm\widehat{\sigma_{\lambda_k}}$, respectively. Table 8 shows the average over quarters of these probabilities (expression (5.5)) for the subperiods 1985-1986 and 1995-1996, and for workers with primary, secondary and university education.

Panel *A* shows the transition probabilities of workers with primary education of the poorest and the middle quintile in 1985 (1995). It is clear that there are big differences in probabilities among observationally equivalent workers (workers who share identical values of the explanatory variables) but with different individual effects. For example, 57 percent workers with λ equal to one standard deviation below zero in 1985 were in the same quintile in 1986, compared to 12 percent workers with λ equal to zero. Positive mobility increases with λ and it is substantial for all values of λ over the first subperiod and for values larger than 0.5 standard deviations below zero over the second one. Compared to the aggregate transition probabilities (Table

8, Panel A) with the exception of workers one standard deviation below zero for the second subperiod, low earnings situations were less persistent for all workers considered than for a random worker. Then, while 64 and 71 percent of workers chosen at random were in the poorest quintile over the two years of each subperiod, this happened in the case of 12 and 23 percent of workers with λ equal to zero.

In the case of workers at the middle of the distribution, I find that the probability of a worker with primary education being in the middle quintile is not a monotonic function of λ. This probability initially increases with λ to reach a peak at zero and 0.5 standard deviations above zero for each subperiod. Notice that only workers with λ equal to one standard deviation above zero have a larger probability of climbing up the earnings distribution than random workers of the middle quintile.. On the other hand, I observe a greater negative mobility of workers over the second subperiod, though differences decrease as λ increases.

Panel *B* summarizes the same transition probabilities for workers with secondary education. Workers at the bottom of the distribution had a larger probability of climbing up than workers with primary education and the same individual effects. For example, 18 percent of workers with secondary education and an individual effect equal to one standard deviations below zero in 1985 were in the middle quintile in 1986, compared to 51 percent of workers with primary education and the same individual effect. All workers considered had a smaller probability of being in the middle quintile than random workers. With respect to workers of the middle quintile, there is less negative mobility than in the case of workers with primary education and

identical individual effects.

Panel C collects the transition probabilities for workers with university education at the middle and at the top of the distribution in 1985 (1995). Workers with university education at the middle of the distribution have a larger probability of moving up than identical workers with secondary education. 49 percent of workers with university education and an individual effect equal to one standard deviations below zero in 1985 moved to the second richest quintile in 1986, while only 14 percent of workers with secondary education made it. Workers with λ above one half standard deviation below zero are more mobile than random workers of the middle quintile. Finally, workers with university education and individual effects below zero have a larger probability of climbing down the earnings distribution than random workers.

As a result of the analysis of individual transition probabilities, I conclude that transition probabilities exhibit a remarkable cross-sectional variation and that positive mobility is greater for workers higher up the distribution of individual effects. This distribution over quarters can be interpreted as a distribution of ability. Hence, among workers who are observationally equivalent, the greatest the ability, the greatest the probability of climbing up the distribution. Another conclusion emerging of the comparison between aggregate and individual probabilities is that small values of λ are more likely over the first subperiod than over the second one. This fact may be reflecting a change of the distribution of ability over time, in the sense of giving more weight to high values of λ over the nineties.

6 Conclusions

In this paper, I have carried out an empirical analysis of the dynamics of individual earnings using Spanish quarterly panel data. I consider an earnings function which incorporates individual effects and serially correlated errors. The data show a strong seasonal pattern subject to cross-sectional randomness, which is due to some workers receiving seasonal bonus payments. Thus, it is important to control for seasonal persistence in an appropriate way, so that the error dynamics is not confounded with seasonal autocorrelation. I propose a new econometric methodology which proved to be useful in implementing this control. It is based on the introduction of seasonal individual effects which are constant over time but vary unrestrictedly across individuals. This structure is well adapted to the main features of the seasonality in the data set I use. Namely, short time series with cross-sectional stochastic variation in the seasonal pattern.

I estimate the model using a system GMM method based on moment conditions in levels and in seasonal differences. Indeed, the introduction of a set of moment conditions in levels based on a stationarity assumption proves crucial for being able to estimate the model's parameters with sufficient precision.

Since the quarterly time series of earnings for any given individual in the sample are short (never exceeding two years), the type of earnings mobility that can be realistically analyzed with these data are transition probabilities over a two-year horizon at most. Nevertheless, another important feature of the data is that they expand a ten year period from the mid 80's to the mid 90's. This fact allows me to observe potential changes in the pattern of

mobility across different subperiods. Thus, having obtained parameter estimates of the empirical earnings function, I calculate transition probabilities among earnings classes for different subperiods and across heterogenous and homogenous workers (aggregate and individual probabilities).

I reached the following conclusions about earnings mobility. First, I found substantial mobility from one year to the next, but mainly for adjacent quintiles of the earnings distribution. By education, workers with university education were more mobile than workers with primary and secondary education. Looking at differences over time, there is evidence of greater negative mobility among earnings deciles (relative mobility) over the nineties than over the eighties, and specially for workers with primary education. Low earnings states were more persistent over the nineties, especially for young workers with primary education.

A substantial part of earnings persistence is due to individual heterogeneity so that the comparative analysis in terms of individual probabilities reveals important differences in the dynamics among groups of workers differing in their individual effects. Workers at the middle and at the top of the distribution of individual effects have larger probabilities of climbing up than workers at the bottom.

In future work, I would like to relax the normality assumption employed in the calculations of the transition probabilities reported in the paper. This is potentially important since in related work on static models (cf. Horowitz and Markatou (1996) or Geweke and Keane (1997)) it has been found that the assumption of normality of the log-earnings errors may lead to different qualitative conclusions when computing transition probabilities by compari-

son with more robust techniques. Moreover, another posible extension would be to consider more general dynamics in earnings. For example, by allowing dynamics in the variance and not only in the mean of the transitory component.

References

[1] Abowd, J.M. and D. Card (1989), "On the Covariance Structure of Earnings and Hours Changes", *Econometrica*, 57, 411-445.

[2] Abraham, K.G. and J.C. Haltiwanger (1995), "Real Wages and the Business Cycle", *Journal of Economic Literature*, 33, 1215-1264.

[3] Arellano, M. and S.R. Bond (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and Application to Employment Equations", *Review of Economic Studies* 58, 277-297.

[4] Arellano, M. and O. Bover (1995), "Another Look at the Instrumental-Variable Estimation of Error-Components Models", *Journal of Econometrics*, 68, 29-51.

[5] Bentolila, S. and J. Dolado (1994), "Labor Flexibility and Wages: Lessons from Spain", *Economic Policy*, 18, 55-99.

[6] Bentolila, S. and J.F. Jimeno (1998), "Regional Unemployment Persistence (Spain, 1976-1994)", *Labour Economics*, 5, 25-51.

[7] Blundell, R. and S. Bond (1998), "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models", *Journal of Econometrics*, 87, 115-143.

[8] Blundell, R., H. Reed and T. Stoker (1998), "The Evolution of Aggregate Wages: Heterogeneity, Selection and Distribution", mimeo*, IFS*, July.

[9] Buchinsky, M., D. Fougère, and F. Kramarz (1998a), "Wage Mobility in France: 1967-1987", *Revue Economique*, 3, 879-890.

[10] Buchinsky, M., Fougère, D. and F. Kramarz (1998b), "Interfirm Mobility and Wages in France and in the U.S.", Unpublished Manuscript.

[11] Buchinsky, M. and J. Hunt (1997), "Wage Mobility in the United States", NBER Working Paper 5455.

[12] Geweke, J. and M. Keane (1997), "An Empirical Analysis of Income Dynamics Among Men in the PSID:1968-1989", Unpublished Manuscript.

[13] Gottschalk, P. and R.A. Moffit (1995), "Trends in the Covariance Structure of Earnings in the U.S.: 1969-1987", Unpublished Manuscript.

[14] Holtz-Eakin, D., W. Newey and H. Rosen (1988), "Estimating Vector Autoregressions with Panel Data", *Econometrica* 56, 1371-1395.

[15] Horowitz, J.H. and M. Markatou (1996), "Semiparametric Estimation for Regression Models for Panel Data", *Review of Economic Studies*, 63, 145-168.

[16] Jarvis, S. and S.P. Jenkins (1998), "How Much Income Mobility is There in Britain?", *The Economic Journal*, 108, 428-443.

[17] Lillard, L.A. and R.J. Willis (1978), "Dynamic Aspects of Earnings Mobility", *Econometrica*, 46, 985-1012.

[18] OECD (1997), "Earnings Mobility: Taking a Longer Run View", *Employment Outlook*, 27-61.

[19] Sargan, J.D. (1980), "Some Tests of Dynamic Specification for a Single Equation", *Econometrica*, 48, 879-897.

Appendix

Data set. Panel of data from the Spanish Continuous Family Expenditure Survey from 1985(I) to 1996(IV), provided by the Instituto Nacional de Estadística. The ECPF includes information about family expenditures and earnings of 3200 households approximately.

Individual variables. The ECPF asks individuals about variables related to individual earnings and certain individual characteristics. The main variables to be considered are:

* Monetary income in the interview quarter. Monetary income is the sum across all household members of income (net of taxes) obtained from different sources (income from employment, income from self-employment, capital income, unemployment benefit and income from private and occupational pensions plus other transfers) during the previous quarter to the interview week.

* Education. This variable is only reported for heads of household and classifies them in seven groups: illiterates, without studies, primary schooling, secondary schooling (first level), secondary schooling (second level), university and post-graduate studies.

* Labor situation in the interview week. This variable classifies heads of household and their partners in six groups: employed part-time (working less than one third of the legal shift), employed full-time (working at least one third of the legal shift), unemployed, retired, housewife and others.

* Activity group in the interview week. This variable classifies household heads and their partners in seven groups: entrepreneurs with employees, entrepreneurs without employees (farming), workers in farming, entrepreneurs

without workers (not in farming), directors and managers, civil servants and workers in other sectors different from farming and agriculture.

* Source of income. This variables classifies all household members in six groups according to the source of their income: income from employment, income from self-employment, capital income, unemployment benefit, pensions, and transfers.

Sample. I build a sample of male heads of household aged 20 to 60 years-old. I consider individuals employed full-time all quarters and whose basic source of income is income from employment. Then, I exclude those employed full-time all quarters who declare to have obtained income from unemployment, self-employment or pensions in addition to income from employment. According to the variable activity group I also exclude employed full-time all quarters who declare to be entrepreneurs or farm-workers.

Table A1
Frequency of observations. Employed all quarters

Frequency	Number of individuals	Percentage
1 quarter	1821	17.6
2 quarters	1280	12.4
3 quarters	1006	9.7
4 quarters	1024	9.9
5 quarters	1030	9.9
6 quarters	806	7.8
7 quarters	773	7.5
8 quarters	2611	25.2
total	10351	100

Table A2
Frequency of observations by age and education

	Subperiod $1985-1990$		Subperiod $1991-1996$	
	Number of observations	%	Number of observations	%
Education				
Primary	13956	57.5	10230	45.0
Secondary	7285	30.0	9196	40.5
University	3014	12.5	3299	14.5
Age	Number of observations	%	Number of observations	%
$20-30$	3487	14.4	2749	12.1
$31-40$	8152	33.6	7861	34.6
$41-50$	7352	30.3	7361	32.4
$51-60$	5264	21.7	4754	20.9

Table A3
GMM estimates by subperiod
A. Subperiod 1

Coefficient	GMM estimates	t-ratio
constant	11.1368	44.98
secondary educ.	0.2311	8.25
university educ.	0.5518	12.74
GDP	−0.0011	−0.17
age	0.0819	7.09
age squared	−0.0009	−6.71
α_1	0.2786	7.10
α_2	0.3599	9.55
Sargan Test = 51.07, df = 39		

Note.- N^o. of observations: 5428, n^o of individuals: 720, individuals who start collaborating before 1987(IV).

B. Subperiod 2

Coefficient	GMM estimates	t-ratio
constant	11.6099	65.85
secondary educ.	0.1952	9.11
university educ.	0.4731	15.68
GDP	−0.0126	−2.64
age	0.06392	7.88
age squared	−0.0007	−7.46
α_1	0.2941	7.71
α_2	0.2528	6.73
Sargan Test = 35.2, df = 39		

Note.- N^o of observations: 8330, n^o of individuals: 1061, individuals who start collaborating from 1988(I) to 1990(IV).

C. Subperiod 3

Coefficient	GMM estimates	t-ratio
constant	11.4708	56.90
secondary educ.	0.2044	8.63
university educ.	0.5053	14.25
GDP	−0.0073	−2.26
age	0.0677	7.09
age squared	−0.0007	−6.43
α_1	0.2177	6.09
α_2	0.2054	4.84
Sargan Test = 44.61, df = 39		

Note.- N^o of observations: 7897, n^o of individuals: 1005,
individuals who start collaborating from 1991(I) to 1993(IV).

D. Subperiod 4

Coefficient	GMM estimates	t-ratio
constant	11.4799	47.56
secondary educ.	0.2709	10.47
university educ.	0.5719	17.56
GDP	−0.0062	−0.79
age	0.0602	5.40
age squared	−0.0006	−4.58
α_1	0.2703	10.47
α_2	0.1551	17.56
Sargan Test = 20.00, df = 39		

Note.- N^o of observations: 3844, n^o of individuals: 498,
individuals who start collaborating from 1994(I) to 1996(IV).

Table A4
Aggregate transition probabilities among earnings quintiles
A.Workers at age 25 with primary education

Quintile in 1985	**Quintile in 1986**				
	1	2	3	4	5
1	0.754	0.192	0.048	0.006	0.000
2	0.293	0.394	0.247	0.062	0.004
3	0.084	0.287	0.386	0.209	0.034
4	0.015	0.112	0.323	0.394	0.156
5	0.001	0.015	0.109	0.357	0.518

Quintile in 1995	**Quintile in 1996**				
	1	2	3	4	5
1	0.828	0.134	0.034	0.004	0.000
2	0.339	0.371	0.229	0.058	0.003
3	0.120	0.301	0.367	0.190	0.022
4	0.027	0.141	0.342	0.380	0.110
5	0.002	0.024	0.141	0.415	0.418

B.Workers at age 50 with primary education

Quintile in 1985	**Quintile in 1986**				
	1	2	3	4	5
1	0.624	0.276	0.088	0.012	0.000
2	0.228	0.385	0.291	0.088	0.008
3	0.060	0.244	0.392	0.256	0.048
4	0.009	0.080	0.279	0.420	0.212
5	0.000	0.008	0.069	0.284	0.639

Quintile in 1995	**Quintile in 1996**				
	1	2	3	4	5
1	0.663	0.241	0.083	0.012	0.001
2	0.249	0.365	0.286	0.093	0.007
3	0.077	0.249	0.382	0.253	0.039
4	0.014	0.095	0.293	0.428	0.170
5	0.001	0.011	0.085	0.339	0.564

Note.- Quintile 1 contains the poorest, quintile 10 contains the richest, annual earnings quintiles calculated from the sample of fully employed at the corresponding year.

Graph1. Median log earnings

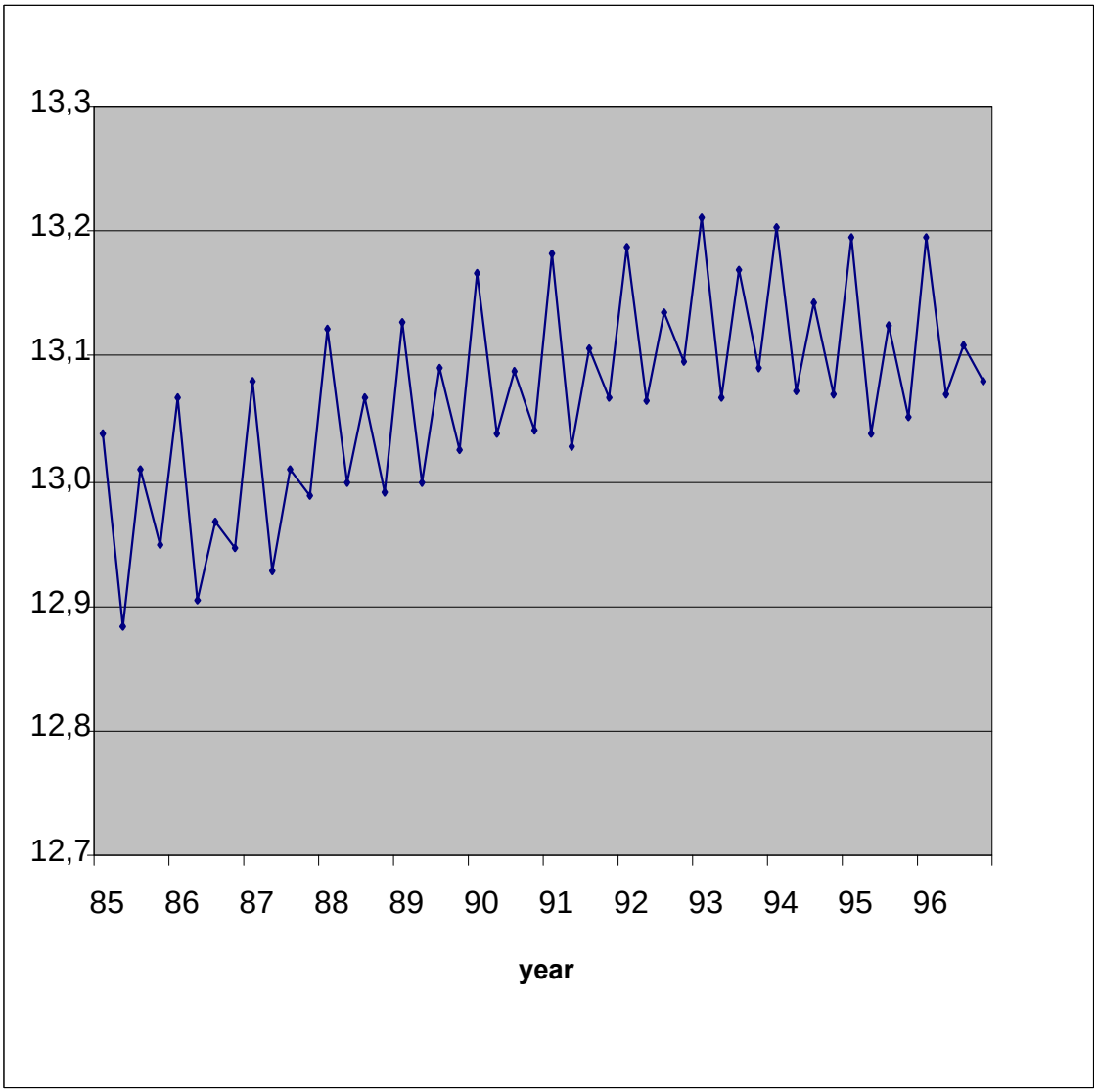


Table 1
Cyclical variables and earnings

	earnings growth	GDP growth	unemployment rate
1986	0.68	3.19	21.23
1987	3.04	5.63	20.54
1988	4.97	5.17	19.48
1989	1.48	4.74	17.28
1990	1.70	3.74	16.25
1991	1.18	2.27	16.34
1992	2.29	0.69	18.40
1993	1.47	−1.16	22.72
1994	−1.03	2.14	24.16
1995	−1.10	2.73	22.93
1996	1.63	2.26	22.21

Note.- This table summarizes the average over the year of the earnings growth rate, the GDP growth rate and the unemployment rate. The earnings and the GDP growth rates are defined as the rate of change of a quarter with respect to the same quarter of the previous year.

Table 2
Earnings equation estimates, 1985-1996

Coefficient	GMM2s	OLS1	OLS2	GMM1s
constant	11.4551	11.9845	12.8861	7.7420
	(104.32)	(72.54)	(56.02)	(130.4)
secondary educ.	0.2214	0.2254	0.2354	0.1489
	(17.52)	(10.83)	(11.26)	(25.43)
university educ.	0.5285	0.5597	0.5698	0.3472
	(28.27)	(19.77)	(20.04)	(33.55)
GDP	−0.0085	−0.0031	−0.0018	−0.0058
	(−3.66)	(−2.15)	(−1.28)	(−4.57)
age	0.0677	0.0440	0.0416	0.0450
	(13.16)	(6.00)	(5.68)	(19.19)
age squared	−0.0007	−0.0004	−0.0004	−0.0005
	(−12.05)	(−5.52)	(−5.16)	(−17.11)
α_1	0.2534	0.3092	0.3520	−0.4806
	(10.05)	(63.99)	(70.21)	(−56.53)
α_2	0.2556	0.5662	0.5276	−0.0741
	(9.50)	(118.11)	(106.27)	(−11.80)
λ_1	0.0703*	−	0.1070	0.0506
			(34.67)	(25.39)
λ_2	−0.0056	−	−0.0172	0.0068
			(−9.01)	(3.05)
λ_3	0.0084	−	0.0516	0.0074
			(23.34)	(3.86)
λ_4	−0.0399	−	−	−
Sargan test	49.00	−	−	701.62
(df)	(39)			(69)

* The seasonal coefficients of the first column represent the GMM2s estimated means of the seasonal individual effects. For the other columns, the coefficients denote seasonal dummies.

Note.-GMM2s are two-step seasonal system GMM estimates. OLS2 and OLS1 are OLS estimates with and without seasonal dummies. GMM1s denote two-step system GMM estimates based on moment conditions for errors in levels and in first differences. t-ratios in parentheses.

Table 3
GMM estimates for the 1980's

Coefficient	GMM estimates	t-ratio
constant	11.4579	70.51
secondary	0.2150	11.38
university	0.5189	18.37
GDP	−0.0091	−2.36
age	0.0697	9.30
age square	−0.0007	−8.82
α_1	0.2999	9.72
α_2	0.3331	11.09
Sargan Test = 47.3, d.f = 39		

Note.- GMM estimates are seasonal system GMM estimates. N^o of observations: 13758, n^o of individuals: 1781. Individuals who start collaborating before 1990(IV).

Table 4
GMM estimates for the 1990's

Coefficient	GMM estimates	t-ratio
constant	11.4926	71.53
secondary	0.2236	11.99
university	0.5295	19.88
GDP	−0.0089	−2.67
age	0.0647	8.53
age square	−0.0007	−7.57
α_1	0.2340	7.45
α_2	0.1435	3.78
Sargan Test = 34.43, d.f = 39		

Note.- GMM are seasonal system GMM estimates. N^o of observations: 11741, n^o of individuals: 1503. Individuals who start collaborating after 1990(IV).

Table 5
GMM estimates with heterogeneity in coefficients for the 1980's

Coefficient	GMM estimates	t-ratio
constant	11.4553	70.58
secondary educ.	0.2089	3.61
university educ.	0.5208	6.42
GDP	−0.0060	−1.58
age	0.0692	9.27
age squared	−0.0007	−8.78
α_{10}	0.3311	8.50
α_{20}	0.3748	10.04
$\alpha_{11}*$ secondary educ.	−0.0257	−0.39
$\alpha_{11}*$ university educ.	−0.1788	−2.45
$\alpha_{21}*$ secondary educ.	−0.0829	−1.17
$\alpha_{21}*$ university educ.	−0.0762	−1.17
Sargan Test = 40.76, d.f = 57		

Table 6
GMM estimates with heterogeneity in coefficients for the 1990's

Coefficient	GMM estimates	t-ratio
constant	11.4896	63.40
secondary educ.	0.2212	4.41
university educ.	0.5278	20.90
GDP	−0.0081	−2.44
age	0.0652	8.47
age squared	−0.0007	−7.66
α_{10}	0.3131	7.04
α_{20}	0.0463	0.74
$\alpha_{11}*$ secondary educ.	−0.0574	−0.85
$\alpha_{11}*$ university educ.	−0.2965	−4.91
$\alpha_{21}*$ secondary educ.	0.1571	1.82
$\alpha_{22}*$ university educ.	0.2684	2.94
Sargan Test = 33.50, d.f = 57		

Table 7
Aggregate transition probabilities among earnings quintiles
A.Workers at age 35 with primary education

Quintile in 1985	**Quintile in 1986**				
	1	2	3	4	5
1	0.637	0.267	0.085	0.011	0.000
2	0.225	0.384	0.294	0.090	0.007
3	0.059	0.241	0.392	0.259	0.049
4	0.008	0.079	0.278	0.420	0.215
5	0.000	0.008	0.072	0.294	0.626
Quintile in 1995	**Quintile in 1996**				
	1	2	3	4	5
1	0.707	0.214	0.069	0.011	0.000
2	0.264	0.367	0.276	0.088	0.005
3	0.083	0.258	0.381	0.243	0.035
4	0.016	0.102	0.303	0.421	0.158
5	0.001	0.013	0.097	0.362	0.527

B.Workers at age 35 with secondary education

Quintile in 1985	**Quintile in 1986**				
	1	2	3	4	5
1	0.513	0.330	0.134	0.022	0.001
2	0.159	0.354	0.341	0.132	0.014
3	0.035	0.186	0.381	0.319	0.079
4	0.004	0.050	0.222	0.430	0.294
5	0.000	0.003	0.040	0.214	0.743
Quintile in 1995	**Quintile in 1996**				
	1	2	3	4	5
1	0.573	0.286	0.119	0.021	0.001
2	0.188	0.345	0.326	0.130	0.011
3	0.051	0.204	0.378	0.309	0.058
4	0.008	0.067	0.248	0.448	0.229
5	0.000	0.006	0.057	0.283	0.654

C.Workers at age 35 with university education

Quintile in 1985	**Quintile in 1986**				
	1	2	3	4	5
1	0.351	0.379	0.216	0.050	0.004
2	0.089	0.288	0.384	0.208	0.031
3	0.016	0.118	0.334	0.391	0.141
4	0.001	0.023	0.145	0.402	0.429
5	0.000	0.001	0.013	0.106	0.880
Quintile in 1995	**Quintile in 1996**				
	1	2	3	4	5
1	0.398	0.347	0.203	0.050	0.002
2	0.110	0.287	0.371	0.206	0.026
3	0.024	0.136	0.342	0.388	0.110
4	0.003	0.033	0.171	0.442	0.351
5	0.000	0.002	0.022	0.162	0.814

Note.- Quintile 1 contains the poorest, quintile 10 contains the richest, annual earnings quintiles calculated from the sample of full employed at the corresponding year.

Table 8
Individual transition probabilities among earnings quintiles
A.Workers at age 35 with primary education
Transition probabilities, Quintile in 1985=1, Quintile in 1995=1

	Quintile in 1986					**Quintile in 1996**				
Effect	1	2	3	4	5	1	2	3	4	5
$\lambda = -\widehat{\sigma_\lambda}$	0.567	0.350	0.077	0.005	0.001	0.858	0.131	0.010	0.001	0.000
$\lambda = -0.5\widehat{\sigma_\lambda}$	0.303	0.460	0.210	0.027	0.000	0.565	0.355	0.076	0.004	0.000
$\lambda = 0$	0.118	0.405	0.377	0.096	0.004	0.231	0.464	0.267	0.037	0.001
$\lambda = 0.5\widehat{\sigma_\lambda}$	0.033	0.243	0.461	0.241	0.022	0.052	0.301	0.462	0.178	0.007
$\lambda = \widehat{\sigma_\lambda}$	0.006	0.100	0.388	0.420	0.086	0.006	0.098	0.401	0.436	0.059

Transition probabilities, Quintile in 1985=3, Quintile in 1995=3

	Quintile in 1986					**Quintile in 1996**				
Effect	1	2	3	4	5	1	2	3	4	5
$\lambda = -\widehat{\sigma_\lambda}$	0.331	0.457	0.190	0.022	0.000	0.822	0.163	0.015	0.000	0.000
$\lambda = -0.5\widehat{\sigma_\lambda}$	0.138	0.423	0.354	0.082	0.003	0.514	0.386	0.095	0.005	0.000
$\lambda = 0$	0.040	0.268	0.457	0.216	0.019	0.197	0.457	0.299	0.047	0.000
$\lambda = 0.5\widehat{\sigma_\lambda}$	0.008	0.116	0.406	0.397	0.073	0.041	0.271	0.471	0.207	0.100
$\lambda = \widehat{\sigma_\lambda}$	0.001	0.034	0.247	0.507	0.211	0.004	0.081	0.375	0.466	0.074

B.Workers at age 35 with secondary education
Transition probabilities, Quintile in 1985=1, Quintile in 1995=1

	Quintile in 1986					**Quintile** in **1996**				
Effect	1	2	3	4	5	1	2	3	4	5
$\lambda = -\widehat{\sigma_\lambda}$	0.180	0.450	0.302	0.056	0.002	0.369	0.451	0.166	0.014	0.000
$\lambda = -0.5\widehat{\sigma_\lambda}$	0.061	0.321	0.440	0.166	0.012	0.109	0.399	0.395	0.095	0.002
$\lambda = 0$	0.014	0.157	0.439	0.341	0.049	0.016	0.175	0.467	0.317	0.025
$\lambda = 0.5\widehat{\sigma_\lambda}$	0.002	0.052	0.303	0.488	0.155	0.000	0.015	0.160	0.498	0.327
$\lambda = \widehat{\sigma_\lambda}$	0.000	0.012	0.145	0.490	0.353	0.000	0.004	0.083	0.492	0.421

Transition probabilities, Quintile in 1985=3, Quintile in 1995=3

	Quintile in 1986					**Quintile** in **1996**				
Effect	1	2	3	4	5	1	2	3	4	5
$\lambda = -\widehat{\sigma_\lambda}$	0.074	0.346	0.426	0.145	0.009	0.324	0.463	0.194	0.019	0.000
$\lambda = -0.5\widehat{\sigma_\lambda}$	0.018	0.179	0.449	0.314	0.041	0.088	0.374	0.419	0.115	0.004
$\lambda = 0$	0.003	0.062	0.324	0.474	0.137	0.012	0.150	0.454	0.352	0.032
$\lambda = 0.5\widehat{\sigma_\lambda}$	0.000	0.015	0.160	0.498	0.327	0.001	0.030	0.247	0.556	0.166
$\lambda = \widehat{\sigma_\lambda}$	0.039	0.002	0.054	0.365	0.579	0.000	0.003	0.068	0.464	0.465

C.Workers at age 35 with university education

Transition probabilities, Quintile in 1985=3, Quintile in 1995=3

	Quintile in 1986					**Quintile** in **1996**				
Effect	1	2	3	4	5	1	2	3	4	5
$\lambda = -\widehat{\sigma_\lambda}$	0.002	0.050	0.294	0.490	0.164	0.009	0.127	0.438	0.386	0.040
$\lambda = -0.5\widehat{\sigma_\lambda}$	0.000	0.011	0.136	0.483	0.370	0.000	0.022	0.218	0.565	0.195
$\lambda = 0$	0.000	0.002	0.043	0.332	0.623	0.000	0.002	0.054	0.435	0.509
$\lambda = 0.5\widehat{\sigma_\lambda}$	0.000	0.000	0.009	0.159	0.832	0.000	0.000	0.006	0.176	0.818
$\lambda = \widehat{\sigma_\lambda}$	0.000	0.000	0.001	0.053	0.946	0.000	0.000	0.000	0.037	0.963

Transition probabilities, Quintile in 1985=5, Quintile in 1995=5

	Quintile 1986					**Quintile 1996**				
Effect	1	2	3	4	5	1	2	3	4	5
$\lambda = -\widehat{\sigma_\lambda}$	0.000	0.012	0.145	0.486	0.357	0.006	0.104	0.414	0.424	0.052
$\lambda = -0.5\widehat{\sigma_\lambda}$	0.000	0.002	0.044	0.332	0.622	0.000	0.017	0.186	0.566	0.231
$\lambda = 0$	0.000	0.000	0.008	0.146	0.846	0.000	0.001	0.041	0.395	0.563
$\lambda = 0.5\widehat{\sigma_\lambda}$	0.000	0.000	0.001	0.038	0.961	0.000	0.000	0.004	0.141	0.855
$\lambda = \widehat{\sigma_\lambda}$	0.000	0.000	0.000	0.006	0.994	0.000	0.000	0.000	0.024	0.976

Note.- Transition probabilities among workers of the poorest, the middle and the richest quintiles in 1985 and 1995. Average of quarterly probabilities evaluated at values of the individual effects equal to 0, $\pm 0.5\widehat{\sigma_{\lambda_k}}$ and $\pm\widehat{\sigma_{\lambda_k}}$, for each quarter k.