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EARNINGS DYNAMICS AND INEQUALITY IN EU, 1994-2001

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ABSTRACT

This paper uses ECHP for 14 EU countries to explore the dynamic structure of individual earnings and the extent to which changes in cross-sectional earnings inequality reflect transitory or permanent components of individual lifecycle earnings variation. Increases in inequality reflect increases in permanent differentials in four countries and increases in both components in two. Decreases in inequality reflect decreases in transitory differentials in four countries, in permanent differentials in two and in both components in rest. In general, increases in inequality are accompanied by decreases in mobility, whereas only in three countries the increase in mobility is determined by the decrease in inequality.

JEL Classification: C23, D31, J31, J60

Keywords: panel data, wage distribution, inequality, mobility

1. INTRODUCTION

Interest in the extent of individual earnings dynamics has increased greatly in recent years and was fuelled mainly by the rise in earnings inequality experienced by many developed countries during the 1980s and 1990s, which triggered a strong debate with respect to the driving factors and the implications of this increase.

This paper analyses the dynamic structure of individual earnings in order to explain what is happening behind the changes in the distribution of labour market income across 14 EU countries over the period 1994-2001 using ECHP. More precisely, the aim is to examine the extent to which changes in cross-sectional earnings inequality reflect transitory or permanent components of individual lifecycle earnings variation. So far, at the EU level, no study attempted to analyse and to understand in a comparative manner earnings dynamics and the contributions of changes in permanent and transitory components of earnings variation to the evolution of cross-sectional earnings inequality.

Understanding wage dynamics is vitally important from a welfare perspective, particularly given the large variation in the evolution of cross-sectional wage inequality across Europe over the period 1994-2001. It is highly relevant to understand what the source of this variation is. Did the increase in cross-sectional wage inequality observed in some countries result from greater transitory fluctuations in earnings and individuals facing a higher degree of earnings mobility? Or is this rise reflecting increasing permanent differences between individuals with mobility remaining constant or even falling? What about countries that recorded a decrease in cross-sectional earnings inequalities, what lessons can we learn from them? Is this decrease the effect of an increase in mobility which helped individuals improve their income position in the distribution of permanent income? Are there common trends in earnings inequality and mobility across different countries? Understanding the contributions of the changes in permanent and transitory components of earnings variation to increased cross-sectional earnings inequality is very useful in the evaluation of alternative hypotheses for wage structure changes and for determining the potential welfare consequences of rising inequality. (Katz and Autor 1999)

These questions are highly relevant in the context of the changes that took place in the EU labour market policy framework after 1995 under the incidence of the 1994 OECD Jobs Strategy and the 2000 Lisbon Agenda, which recommended policies to increase wage flexibility, lower non-wage labour costs and allow relative wages to better reflect individual differences in productivity and local labour market conditions. (OECD 2004; Dew-Becker and Gordon 2008) This appears to have worsened the apparent trade-off between a strong employment performance and a more equal distribution of earnings, consistent with relative labour demand having shifted towards high-skilled workers. OECD (2004)

As pointed out by OECD (2004) and Dew-Becker and Gordon (2008), the most notable change after 1995 in Europe has been increased country heterogeneity. We will investigate how this heterogeneity translates itself in the level and components of the cross-sectional earnings inequality and earnings mobility. Equally weighted minimum distance methods are used to estimate the covariance structure of earnings, decompose earnings into a permanent and a transitory component and conclude about their evolution.

The structure of this paper is as follows. Section two presents an overview of the literature review. Section three introduces the theoretical background for wage differentials. Section four provides a description of the data. Section five introduces the econometric specification and estimation method. Section six describes the dynamic structure of individual log earnings for 14 EU countries. Section seven fits the error components models to the covariance structure for each country, decomposing the change in inequality into that accounted for by the change in the permanent and transitory components. Lastly, section eight offers some conclusions.

2. LITERATURE REVIEW

The existing literature on earnings dynamics is predominantly based on US data. Atkinson, Bourguignon et al. (1992) provide a comprehensive survey of the literature on earnings dynamics until 1992. Earlier work focused on fitting statistical models to the earnings process. E.g. Lillard and Willis (1978), Lillard and Weiss (1979), MaCurdy (1982), Abowd and Card (1989) fitted models to the autocovariance structure of earnings and hours, but they did not account for the changes in the autocovariance structure of earnings over time.

Later work, Moffitt and Gottschalk (1995; 1998; 2002) used PSID to estimate the permanent and transitory components of male earnings and how it evolved over time. In Moffitt and Gottschalk (1998), the earnings process was fit by a permanent component, modelled as a random walk in age and a highly persistent serially correlated transitory component, with weights on these components for each year. They found that the increase in the cross-sectional inequality of individual earnings and wage rates in the U.S. between 1969-1991 has been roughly equally composed of increases in the variances of the permanent and transitory components of earnings, with little change in earnings mobility rates. Since most of the theoretical explanations for the increase in inequality have been aimed at explaining increases in the variance of the permanent component of earnings (e.g. increases in the price of skills), they found their result surprising and unexpected. Therefore, in their most recent study, Moffitt and Gottschalk (2008) estimated the trend in the transitory variance of male earnings using PSID from 1970 to 2004. They found that the transitory variance increased substantially in the 1980's and remained at the same level until 2004, for both less and more educated workers. Moreover, the transitory variance appears to have a strong cyclical component: its increase accounts for between 30% and 65% of the rise in the overall inequality, depending on the period.

Using the PSID, Baker (1997) compared two competing specifications for the permanent component of earnings: the "profile heterogeneity or the random growth model" and the "random walk model". In spite of the increased popularity of the latter, Baker (1997) proved that the profile heterogeneity model provides a better representation of the data.

Baker and Solon (2003) decomposed the growth in earnings inequality into its persistent and transitory components using longitudinal income tax records from Canada. The earnings process was fit by a permanent component, modelled as a mixed process composed of a random growth and a random walk in age and a highly persistent serially correlated transitory component, with weights on these components for each year. They found that growth in earnings inequality reflects both an increase in the long-run inequality and an increase in earnings instability.

Up until recently, little work has been carried out in Europe on the dynamic nature of individual earnings. Dickens (2000) analysed the pattern of individual male wages over time in UK using the New Earnings Survey (NES) panel data set for the period 1975-1995. This study divided the data into year birth cohorts and analysed the auto-covariance structure of hourly and weekly earnings for each cohort. In the tradition of Moffitt and Gottschalk (1998), the earnings process was fit by a permanent component, modelled as a random walk in age and a highly persistent serially correlated transitory component, with weights on these components for each year. The results showed that about half of the rise of the overall cross-sectional inequality can be explained by the rise in the permanent variance and the rest by the rise in the persistent transitory component.

Ramos (2003) analysed the dynamic structure of earnings in UK using the British Household Panel Study for the period 1991-1999. The earnings specification followed a similar specification with Baker and Solon (2003). Using information on monthly earnings of male full-time employees, this study decomposed the covariance structure of earnings into its permanent and transitory components and concluded that the increase in inequality over the 1990's was due to increased in earnings volatility. Moreover, the relative earnings persistent was found to decline over the lifecycle, which implies a lower mobility for younger cohorts. These findings are at odds with previous literature on earnings dynamics both for UK and the OECD. Unlike previous literature, this study considered also for the effect of observed characteristics and found that human capital and job related characteristics account for nearly all persistent earnings differences and that the transitory component is highly persistent.

Kalwij and Alessie (2003) examined the variance-covariance structure of log-wages over time and over the lifecycle of British men from 1975 to 2001, controlling for cohort effects. Their model follows closely the specification used by Abowd and Card (1989), Dickens (2000) and Baker and Solon (2003) accounting also for cohort effects. They showed that the increase in the cross-sectional inequality was caused mainly by the increase in the transitory component of earnings and to a lesser extent by an increase in the permanent wage inequality. Thus the increase in cross-sectional inequality was accompanied by an increase in earnings mobility.

Cappellari (2003) used the Italian National Social Security Institute for the period 1979-1995 and decomposed the male earnings autocovariance structure into its long-term and transitory components using a model specification similar with Moffitt and Gottschalk (1995) and Backer (1997). The model included a permanent component, modelled as a random growth in age and a highly persistent serially correlated transitory component, with weights on these components for each year and cohort. The findings showed that growth was determined by the long-term earnings component. Other evidence on the contribution of permanent and transitory earnings components to cross-sectional inequality has become available in recent year in Sweden (Gustavson, 2004).

3. THEORETICAL MODEL OF THE DETERMINANTS OF WAGE DIFFERENTIALS

3.1. Determinants of earnings inequality

As pointed out by Katz and Autor (1999), the existing literature contains many explanations for the rise in earnings inequality experienced by many developed countries during the 1980s and 1990s. One approach for explaining changes in wage differential is to decompose overall wage inequality into permanent inequality and transitory inequality.

Following the terminology introduced by Friedman and Kuznets (1954), individual earnings are composed of a permanent and a transitory component. The permanent component of earnings reflects personal characteristics, education, training and other systematic elements. The transitory component captures the chance and other factors influencing earnings in a particular period and is expected to average out over time. Following the structure of individual earnings, overall inequality at any point in time is composed from inequality in the transitory component and inequality in the permanent component of earnings. The evolution of the overall earnings inequality is determined by the cumulative changes in the two inequality components.

The rise in the inequality in the permanent component of earnings may be consistent with increasing returns to education, on-the-job training and other persistent abilities that are among the main determinants of the permanent component of earnings, meaning enhanced relative earnings position of the highly skilled individuals. (Mincer 1957; Mincer 1958; Mincer 1962; Mincer 1974; Hause 1980).

The increase in the inequality of the transitory component of earnings may be attributed to the weakening of the labour market institutions (e.g. unions, government wage regulation, and internal labour markets), increased labour market instability, increased competitiveness, a rise in the temporary workforce which increase earnings exposure to shocks. A period of skill-biased technological change with the spread of new technologies can on the one hand increase the demand for skills, and on the other hand it can increase earnings instability. (Katz and Autor 1999). Rodrik (1997) argued that also globalization and international capital mobility can increase wage instability. Overall, the increase in the return to persistent skills is expected to have a much larger impact on long-run earnings inequality than an increase in the transitory component of earnings. (Katz and Autor 1999; Moffitt and Gottschalk 2002)

3.1.1. Alternative model specifications for the permanent and transitory components

Next we introduce several models of earnings dynamics that have been dominating the literature on permanent and transitory earnings inequality over the past 30 years. To begin with, we introduce the simplest specification, which in spite of its simplicity provides a very intuitive insight into the decomposition of earnings into their permanent and transitory components. Based on this specification earnings are being decomposed as follows:

$$Y_{it} = \mu_i + v_{it}, \quad \mu_i \sim iid(0, \sigma_\mu^2), \quad v_{it} \sim iid(0, \sigma_v^2), \quad t = 1, \dots, T_i, \; i = 1, \dots, N \tag{1}$$

where μ_i represents the permanent time-invariant individual specific component and v_{it} represents the transitory component, which is independent distributed both over individuals and time. This model imposes very rigid restrictions on the covariance structure of earnings:

$$Cov(Y_{it}, Y_{is}) = \begin{cases} \sigma_\mu^2 + \sigma_v^2, & t = s \\ \sigma_\mu^2, & t \neq s \end{cases}$$

Because μ_i is assumed to incorporate the effect of lifetime persistent individual specific characteristics such as ability, the variance of the permanent component σ_μ^2 represents the persistent dispersion of earnings or the inequality in the permanent component of earnings. The transitory shocks are captured by the transitory variance σ_v^2 and are assumed to persist only one year.

This model facilitates the understanding of the inequality decomposition into its permanent and transitory components. The variance of earnings at a certain point in time, as a measure of earnings dispersion, is composed both from a permanent and transitory dispersion ($\sigma_\mu^2 + \sigma_v^2$). The covariances, on the other hand, are determined solely by the permanent component (σ_μ^2). Therefore, the assessment of the relative importance of the two components in the overall earnings dispersion is straightforward: the ratio $\sigma_\mu^2 / \sigma_y^2$ captures the relative importance of the permanent component, whereas the ratio σ_v^2 / σ_y^2 captures the relative importance of the transitory component.

Notwithstanding its attractive features, the empirical evidence rejected the rigid restrictions imposed by model (1). One of the main drawbacks of model (1) is that it does not allow for changes in earnings inequality over time. (Lillard and Willis 1978; Lillard and Weiss 1979; MaCurdy 1982; Abowd and Card 1989) Other studies (Katz 1994; Moffitt and Gottschalk 1995) took the model complexity further by allowing the covariance structure of earnings to vary over time. To account for these time effects, these models considered also time specific loading factors or shifters on both components, which allow the parameters of the process to change with calendar time.

$$Y_{it} = \lambda_{1t}\mu_{it} + \lambda_{2t}v_{it} \tag{2}$$

$\lambda_{kt}, k = 1,2$ are time-varying factor loadings on the permanent and transitory components of earnings. The variance of Y_{it} implied by this model takes the form:

$$Var(Y_{it}) = \lambda_{1t}^{2}\sigma_{\mu}^{2} + \lambda_{2t}^{2}\sigma_{v}^{2} \tag{3}$$

An increase in either time loading factors generates an increase in the cross-sectional earnings inequality. The nature of the change in inequality depends on which of the loading factors changes. On the one hand, a persistent rise in λ_{1t} increases the permanent or long-run inequality (inequality in earnings measured over a long period of time, such as lifetime earnings). As λ_{1t} can be interpreted as time-varying return to skills or skill price, its increase suggests that the relative labour market advantage of high skill workers is enhanced. In this situation, the autocovariances grow in greater proportion that than the variance, causing the autocorrelation to increase. As a consequence, the increase in overall cross-sectional inequality is accompanied by a decrease in mobility. On the other hand, an increase in λ_{2t} without a change in λ_{1t} increases cross-sectional earnings inequality by increasing the transitory inequality, but without any impact on long-run or permanent inequality. In this situation the rise in the variances is not accompanied by a rise in the autocovariances, hence autocorrelations decrease and the increase in the overall inequality is accompanied by an increase in mobility. (Baker and Solon 2003) As pointed out by Katz and Autor (1999), λ_{1t} maintains the rank of the individuals in the earnings distribution, but causes a persistent increase in the spread of the distribution and an increase in λ_{2t} changes the rank of the individual in the short-run. In other words an increase in the time parameters associated with the permanent component of earnings indicates a growing earnings inequality with no impact on the relative position of individuals in the distribution of permanent earnings, whereas an increase in the transitory time parameters indicates an increase in earnings mobility.

Although model (2) incorporates changes over time in the permanent and temporary components of earnings inequality, it disregards other important features of earnings dynamics. Firstly, it disregards the cohort effects. As argued by Katz and Autor (1999), the increased wage inequality may arise from increased dispersion of unobserved labour quality within recent entry cohorts, resulting from unequal school quality. Some studies brought evidence against the hypothesis that the return to education is the same for different cohorts. These changes could be attributed either to the cohort effects or to the larger impact of the labour market shocks on younger than on older cohorts of workers. In the same line of thought, Freeman (1975) put forward the "active labour market" hypothesis, which postulates that changes in the labour market conditions, such as changes in the supply and demand for skills, affect mainly new entrants in the labour market. To account for these cohort effects, these models considered also cohort specific loading factors or shifters on both components, which allow the parameters of the process to change with cohort.

$$Y_{it} = \gamma_{1c}\lambda_{1t}\mu_{it} + \gamma_{2c}\lambda_{2t}v_{it} \tag{4}$$

where γ_{jc}, $j = 1,2$ are cohort specific loading factors.

Secondly, regarding the permanent component, some studies brought evidence in favour of the "random growth rate model" or the "profile heterogeneity model": (Hause 1977; Lillard and Weiss 1979; MaCurdy 1982; Baker 1997; Cappellari 2003)

$$\mu_{it} = \mu_i + \varphi_i age_{it}, \quad \mu_i \sim iid(0,\sigma_\mu^2), \quad \varphi_i \sim iid(0,\sigma_\varphi^2), \quad E(\mu_i,\varphi_i) = \sigma_{\mu\varphi} \tag{5}$$

According to this model, which is consistent with labour market theories such as human capital, and matching models, each individual has a unique age-earning profile with an individual specific intercept (initial earnings μ_i) and slope (earnings growth φ_i) that may be systematically related. The variances σ_μ^2 and σ_φ^2 capture individual heterogeneity with respect to time-invariant characteristics and age-earnings profiles. The covariance between μ_i and $\varphi_i, \sigma_{\mu\varphi}$, represents a key element in the development of earnings differentials over the active life. A positive covariance between μ_i and φ_i implies a rising inequality in the permanent component of earnings over the life cycle. This is consistent with the school-matching models where the more tenure one individual accumulates, the more is revealed about his ability. Thus highly educated people are expected to experience a faster growth in their earnings as the quality of the match is revealed to their employers. A negative covariance implies that the two sources of heterogeneity offset each other, which is consistent with the on-the-job training hypothesis (Mincer 1974; Hause 1980). A negative covariance is expected to generate mobility within the distribution of the permanent component of earnings. (Cappellari 2003)

This structure is equivalent to a random coefficient model where the intercept and the coefficient on age in model (5) are randomly distributed across individuals. Therefore, because earnings evolve along an individual specific age profile, a good prediction of future earnings requires additional information besides the current earnings.

An alternative/additional specification for the permanent component of earnings is the "random walk model" or the "unit root model", which is used in the literature to accommodate earnings shocks that might have permanent effects: (MaCurdy 1982; Abowd and Card 1989; Moffitt and Gottschalk 1995; Dickens 2000).

$$u_{ia} = u_{i,a-1} + \pi_{ia}, \quad \pi_{ia} \sim iid(0,\sigma_{\pi}^2), \quad E(u_{i,a-1},\pi_{ia}) = 0 \tag{6}$$

Equation (6) specifies the random walk process, where the current value depends on the one from the previous age and an innovation term π_{ia}, which represent white-noise non-mean-reverting shocks to permanent earnings. In other words, π_{ia} accommodates any permanent re-ranking of individuals in the earnings distribution. As argued by Baker (1997), the intuition for this model is not obvious, but the high persistency of the unit root model might result from low rates of depreciation on human capital investments or labour market conditions through implicit contacts. In this model, current earnings are a sufficient statistic for future earnings.

Thirdly, regarding the transitory component of earnings, previous research has brought evidence that transitory earnings might be serially correlated. Therefore, a more general autocorrelation structure is called for, that relaxes the restriction on v_{it}'s from the canonical model. For the construction of such a structure, longitudinal studies on earnings dynamics turned to error processes from the literature on time series analysis. Based on MaCurdy (1982), the structure of the transitory component, v_{it}, is assumed to follow an ARMA(p,q) process:

$$\sum_{j=0}^{p} \rho_j v_{it-j} = \sum_{j=0}^{q} \theta_j \varepsilon_{it-j}, \quad \varepsilon_{it} \sim iid(0, \sigma_{\varepsilon}^2), \quad v_{i0} \sim (0, \sigma_{0,c}^2), \tag{7}$$

ε_{it} is assumed to be white noise with mean 0 and variance σ_{ε}^2. The variance $\sigma_{0,c}^2$ measures the volatility of shocks at the start of the sample period and σ_{ε}^2 the volatility of shocks in subsequent years. ρ_j is the autoregressive parameter with $\rho_0 = 1$, which measures the persistence of shocks. θ_j is the moving average parameter with $\theta_0 = 1$, which accommodates sharp drops of the lag-j autocovariance compared with the other autocovariances. In this model, the autoregressive and moving average parameters are assumed to be constant over time.

3.2. Earnings Mobility

Another aspect relevant to the evolution of earnings differentials is earnings mobility, defined by Katz and Autor (1999) as the rate at which individuals shift positions in the earnings distribution. Earnings mobility is closely related to the importance of the permanent and transitory components in earnings variation. A large contribution of the permanent component implies that individual earnings are highly correlated over time and individuals do not change their income position to a large extent experiencing low rates of earnings mobility. Therefore, the changes in earnings mobility are determined by the extent to which changes in cross-sectional inequality are driven by changes in the permanent or transitory variance.

A rise only in the permanent inequality is associated with a decline in mobility rates, whereas a rise only in the transitory variance is associated with an increase in mobility. Equal proportional increases in both components will leave mobility unchanged in spite of increasing overall cross-sectional inequality. It becomes obvious that the question regarding the link between earnings mobility and earnings inequality does not have a straight forward answer. As underlined by Dickens(1999), "changes in earnings mobility could either work to offset or to increase changes in cross-sectional dispersion", with very different implications for permanent earnings inequality. Indeed, mobility is beneficial when it helps low paid individuals to improve their income position in the long-term income distribution.

In the same line of thought, an increase in cross-sectional earnings inequality is considered a distributional problem only if it affects negatively the economic position of people situated in the bottom of the earnings distribution. If earnings increase for people situated both at the bottom and top of the distribution, and the increase is higher at the top than at the bottom, then inequality increases. However, in this situation people at the bottom of the distribution are better off. If mean earnings increase and there are no other changes in the distribution, then less people fall under a fixed poverty line, hence more people are better off. However, if also the variance increases, then it is difficult to predict the exact outcome. Hence, the income position of the low-wage individuals is affected by the combined effects of economic growth, change in inequality and mobility. (Gottschalk 1997)

4. DATA

The study is conducted using the European Community Household Panel (ECHP)[1] over the period 1994-2001 for 14 EU countries. Not all countries are present for all waves. Luxembourg and Austria are observed between 1995 and 2001 and Finland between 1996 and 2001. Following the tradition of previous studies, the analysis focuses only on men.

A special problem with panel data is that of attrition over time, as individuals are lost at successive dates causing the panel to decline in size and raising the problem of representativeness. Several papers analysed the extent and the determinants of panel attrition in ECHP. Behr, Bellgardt and Rendtel (2005) found that the extent and the determinants of panel attrition vary between countries and across waves within one country, but these differences do not bias the analysis of income or the ranking of the national results. Ayala, Navrro and Sastre (2006) assessed the effects of panel attrition on income mobility comparisons for some EU countries. The results show that ECHP attrition is characterized by a certain degree of selectivity, but only affecting some variables and some countries. Moreover, income mobility indicators show certain sensitivity to the weighting system.

In this paper, the weighting system applied to correct for the attrition bias is the one recommended by Eurostat, namely using the "base weights" of the last wave observed for each

[1] The European Community Household Panel provided by Eurostat via the Department of Applied Economics at the Université Libre de Bruxelles.

individual, bounded between 0.25 and 10. The dataset is scaled up to a multiplicative constant[2] of the base weights of the last year observed for each individual.

For the empirical analysis, individuals are categorized into four birth cohorts, which are followed through time. Ideally, one should use birth cohorts formed from people born in a particular year. The limited number of observations forces us to group more birth years in one cohort. The first birth cohort contains people born between 1940-1950, the second one people born between 1951-1960, the third cohort people born between 1961-1970 and lastly people born between 1971-1981. This grouping allows the analysis of the earnings covariance structure for individuals of the same age, followed at different points in time.

For this study we use real log hourly wage adjusted for CPI of male workers aged 20 to 57, born between 1940 and 1981. Only observations with hourly wage lower than 50 Euros and higher than 1 Euro were considered in the analysis. The resulting sample for each country is an unbalanced panel. The choice of using unbalanced panels for estimating the covariance structure of earnings is motivated by the need to mitigate the potential overestimation of earnings persistence that would arise from balanced panels where the estimation is based only on people that have positive earnings for the entire sample period. Details on the number of observations, inflows and outflows of the sample by cohort over time for each country, mean yearly hourly earnings are provided in Table 1 and Table 2. For more descriptive statistics refer to Sologon and O'Donoghue (2009). Mean hourly earnings appear to increase in all countries except for Austria where it records a slight decrease. In general, as illustrated by Table 2 the highest attrition rates from one year to the next are recorded in Ireland, Italy, Greece, Spain and Portugal, where, on average, less than 60% of those who were in the sample in the previous year reported positive earnings in the current year.

5. ECONOMETRIC SPECIFICATION AND ESTIMATION METHOD OF COVARIANCE STRUCTURES

The aim of this section is to fit a parsimonious model to the autocovariance structure of earnings for all cohorts and for all countries. This model can be use to analyse the changes in the

[2] The multiplicative constant equals e.g. p*(Population above 16/Sample Population). The ratio p varies across countries so that sensible samples are obtained. It ranges between 0.001-0.01.

permanent and transitory components of earnings over the sample period and their impact on the overall level of earnings inequality.

This section is structured as follows. The first one explains the econometric specification for the earnings model. The second and third part introduce the specification of the covariance structure of earnings residuals and the equally weighted minimum distance method used to fit the model to the covariance structure for each cohort. The forth part presents the tests used to choose between competing models. Lastly, we introduce the measurement for mobility.

5.1. Econometric Earnings Specification

In order to differentiate lifecycle dynamics from secular changes in earnings inequality, the earnings differentials are analysed within the four cohorts defined in the previous section. The first step is to de-trend earnings for each cohort. The empirical specification of earnings follows the structure:

$$Y_{ict} = \overline{Y_{ct}} + r_{ict}, \quad t = 1,...,T_i,\ i = 1,...,N_c \qquad (8)$$

where Y_{ict} is the natural logarithm of real hourly earnings of the i-th individual, from the $\boldsymbol{c}$-th cohort in the t-th year, $\overline{Y_{ct}}$ is the year-cohort specific mean and r_{ict} is an error term which represents the individual-specific deviation from the year-cohort specific mean. The demeaned earnings r_{ict} are assumed to be independently distributed across individuals, but autocorrelated over time. Earnings differentials within each cohort can be characterised by modelling the covariance structure of individual earnings $VarCov(Y_{ict}) = E(r_{ict}, r_{ict-s}),\ s = 0,...,T_c - t_{0c}$.[3]

This study approaches the problem of choosing a longitudinal process for the demeaned earnings, r_{ict} following the methodology used by MaCurdy(1981) and MaCurdy (1982), meaning in a similar manner with time series. The inspection of the covariance structure of earnings, which is presented in the following section, suggests the following features of the data:

(i) the elements of the autocovariance structure decrease with the lag at a decreasing rate and

(ii) they converge gradually at a positive level;

[3] T_c and t_{0c} represent the total number of years and the first year observed for each cohort.

(iii) the lag-1 autocovariance drops to a larger extent compared with higher order autocovariances, which decline more gradually;

(iv) the autocovariances and mean earnings vary over the sample period, so they cannot be assumed to be stationary over sample period;

(v) the autocovariances vary with age controlling for the period effect, hence they cannot be assumed to be stationary over the life cycle;

(vi) the variance covariance structure appears to be cohort specific.

Each of these features are incorporated in our model. Feature (i) suggests the presence of an AR(1) process, but the presence of feature (iii) calls for a more complex ARMA (1, 1) or ARMA(1, 2) process. Feature (ii) can be captured by the presence of the permanent component. Feature (vi) is captured by incorporating period specific parameters, meaning that the permanent individual component and the transitory component of earnings are allowed to vary with time. The life cycle non-stationarity of the autocovariance structure of earnings mentioned in feature (v) can be captured by modelling the permanent individual component as random walk and/or random growth in age. Cohort heterogeneity is incorporate by parameters that allow the permanent and transitory components to vary between cohorts.

The idea is to start with a broad class of models for r_{ict} and employ preliminary data analysis procedures to choose among competing specifications. In this way one avoids choosing a model specification that is broadly inconsistent with the data. The following general specification encompasses all the relevant aspects of earnings dynamics considered above.

$$\begin{aligned} &Y_{ict} - \overline{Y_{ct}} = r_{ict} = \gamma_{1c}\lambda_{1t}[\mu_i + \varphi_i age_{it} + u_{iat}] + \gamma_{2c}\lambda_{2t}v_{it} \\ &\mu_i \sim iid(0,\sigma^2_{\mu}), \quad \varphi_i \sim iid(0,\sigma^2_{\varphi}), \quad E(\mu_i,\varphi_i) = \sigma_{\mu\varphi} \end{aligned} \tag{9}$$

$$u_{iat} = u_{i,a-1,t-1} + \pi_{ia}, \quad \pi_{ia} \sim iid(0,\sigma^2_{\pi}), \quad E(u_{i,a-1,t-1},\pi_{iat}) = 0 \tag{10}$$

$$v_{it} = \rho v_{it-1} + \varepsilon_{it} + \theta\varepsilon_{it-1}, \quad \varepsilon_{it} \sim (0,\sigma^2_{\varepsilon}), \quad v_{i0} \sim (0,\sigma^2_{0,c}) \tag{11}$$

Based on equation (9), earnings can be decomposed into a permanent component $\gamma_{1c}\lambda_{1t}[\mu_i + \varphi_i age_{it} + u_{iat}]$ and a transitory component $\gamma_{2c}\lambda_{2t}v_{it}$. The component $\mu_i + \varphi_i age_{it}$ models an individual profile heterogeneity as a function of age, called also a random growth (see (Baker 1997), (Moffitt and Gottschalk 1995)), where μ_i and φ_i are time invariant individual intercept and slopes with variance σ_μ^2 and σ_φ^2. Besides the random vector of intercepts and slopes (μ_i, φ_i), the parameterization of individual earnings dynamics includes also a random walk process (Equation (10)). (Moffit and Gottschalk (1995), Baker and Solon (2003)) The variance of the first period shock (assumed to be at age 20, which is also the lowest age observed in our dataset) is estimated together with the σ_μ^2 and is considered part of the unobserved heterogeneity.

Equation (11) specifies the transitory component of earnings which evolves as an ARMA(1,1) process, where the serial correlation ρ parameter captures the decreasing rate of decay of the covariances with the lag, the moving-average parameter θ captures the sharp drop of the lag-1 autocovariance compared with the other autocovariances, and ε_{it} are white-noise mean-reverting transitory shocks. The variance $\sigma_{0,c}^2$ measures the volatility of shocks at the start of the sample period, σ_ε^2 the volatility of shocks in subsequent years and ρ the persistence of shocks. Measurement error in this model is captured by this transitory component.

The non-stationary pattern of earnings is accommodated using time specific loading factors, both on the permanent and transitory component of earnings, $\lambda_{kt,\ k=1,2;\ t=0,7}$, normalized to 1 in the first wave for identification[4]. Cohort heterogeneity is accommodated by allowing both the permanent and the transitory component to vary with the cohort. $\gamma_{jc},\ j=1,2$ are cohort loading factor, normalized to 1 for the cohort born in 1940-1949 for identification.

5.2.Specification of the Covariance Structure of Earnings

When working with ARMA(p,q) processes in the context of panel data, MaCurdy (1981), MaCurdy (1982) and Anderson and Hsiao (1982) underlined the need for a treatment of initial conditions[5]. As illustrated in equations (13) and (14), the autoregressive process induces a recursive structure in the moments: the variance-covariance in year *t* depends on the transitory

[4] 1994 refers to t=0

[5] See Macurdy(1982, page 92/93)

variance-covariance in year *t-1*. If one tracks the recursion back to the first sample year for each cohort, this raises the question of what is the transitory variance for each cohort in that year. In the earlier stage of the literature on earnings dynamics, it was common to restrict the initial transitory variance to be the same for all cohorts. In line, with the most recent literature on earnings dynamics, our model acknowledges that earnings volatility varies across cohorts because they illustrate different stages of the lifecycle and have experienced different period effects, therefore such a strong assumption is untenable.

Following MaCurdy (1981), MaCurdy (1982), we treat the initial transitory variances of the 4 cohorts as 4 additional parameters to be estimated. The complete specification of the covariance structure of earnings is included in Annex 10.1. The covariance structure for the first sample period takes the form:

$$Var(Y_{ic0}) = E(r_{ic0}r_{ic0}) = \sigma_{\mu}^2 + \sigma_{\varphi}^2 E(age_{i0}^2) + 2\operatorname{cov}(\mu_i\varphi_i)E(age_{i0}) + (a-20)\sigma_{\pi}^2 + Var(v_{i0}) \;\; if\; t=0 \quad (12)$$

The covariance structure for subsequent years can be expressed as follows:

$$\begin{aligned} Var(Y_{ict}) = E(r_{ict}r_{ict}) = \gamma_{1c}^2\lambda_{1t}^2[\sigma_{\mu}^2 + \sigma_{\varphi}^2 E(age_{it}^2) + 2\operatorname{cov}(\mu_i\varphi_i)E(age_{it}) + \sigma_{\pi}^2(a-20)] + \\ + \gamma_{2c}^2\lambda_{2t}^2[\rho^2 Var(v_{it-1}) + \sigma_{\varepsilon}^2(1+2\rho\theta+\theta^2)] \;\; if\; t>0 \end{aligned} \quad (13)$$

$$\begin{aligned} & Cov(Y_{ict}Y_{ict-s}) = E(r_{ict}r_{ict-s}) \\ & = \gamma_{1c}^2\lambda_{1t}^2\{\sigma_{\mu}^2 + \sigma_{\varphi}^2 E(age_{it})E(age_{it-s}) + \operatorname{cov}(\mu_i\varphi_i)[E(age_{it}) + E(age_{it-s})] + \sigma_{\pi}^2(a-s-20)\} + \\ & + \gamma_{2c}^2\lambda_{2t}\lambda_{2t-s}[\rho Cov(v_{it-1}, v_{it-s})] \;\; if\; t>0 \;\;\&\;\; s>1 \end{aligned} \quad (14)$$

$$\begin{aligned} & Cov(Y_{ict}Y_{ict-1}) = E(r_{ict}r_{ict-1}) = \\ & = \gamma_{1c}^2\lambda_{1t}^2\{\sigma_{\mu}^2 + \sigma_{\varphi}^2 E(age_{it})E(age_{it-1}) + \operatorname{cov}(\mu_i\varphi_i)[E(age_{it}) + E(age_{it-1})] + \sigma_{\pi}^2(a-1-20)\} \\ & + \gamma_{2c}^2\lambda_{2t}\lambda_{2t-1}\{\rho Var(v_{it-1}) + \theta\sigma_{\varepsilon}^2)\} \;\; if\; t>0 \;\;\&\;\; s=1 \end{aligned} \quad (15)$$

The degree of immobility is measured by the ratio between the permanent and transitory variance.

5.3. Estimation of Covariance Structures

Covariance structures are models that specify a structure for the covariance matrix of the regression error. They can be used to model structures for error dynamics and measurement error. The goal is to estimate the parameters of the covariance structure of earnings for all cohorts. This can be used to analyse the changes in the permanent and transitory components of earnings over the sample period.

The parameters of the models are fit to the covariance structure for each cohort using equally weighted minimum distance methods of estimation. The methodology used is the same as that utilized by Cappellari (2003), Baker and Solon (2003), Ramos (2003), Kalwij and Alessie (2003), Dickens (2000), Baker (1997), Abowd and Card (1989), Cervini and Ramos (2006) adapted to unbalanced panels.

For each cohort ***c*** and individual ***i*,** define a vector which identifies the presence for each individual in the respective cohort and year:

$$\mathbf{d_{ic}} = \begin{pmatrix} d_{ict_1} \\ \cdot \\ \cdot \\ \cdot \\ d_{ict_c} \end{pmatrix}$$

where d_{ict} is an indicator variable that is equal to 1 if the individual from cohort c is present in year t of the panel and t_c is the total length of the panel for each cohort. Similarly, the vector containing the cohort earnings residuals can be represented as follows:

$$\mathbf{R_{ic}} = \begin{pmatrix} r_{ict_1} \\ \cdot \\ \cdot \\ \cdot \\ r_{ict_c} \end{pmatrix}$$

where r_{ict} are the earnings residuals for individual i belonging to cohort c, in year t in mean deviation form for each cohort and year. The elements of the $\mathbf{R_{ic}}$ corresponding to missing years are set to 0. The variance-covariance matrix of the earnings is computed separately for each cohort, $\mathbf{C_c}$. The elements of the variance-covariance matrix for cohort c, $\mathbf{C_c}$**,** which is of dimension $(t_c \times t_c)$ are computed follows:

$$m_c[k,l] = \frac{\sum_{i=1}^{n_c} r_{ick} r_{icl}}{\sum_{i=1}^{n_c} d_{ick} d_{icl}} \qquad (16)$$

where n_c is the total number of individuals in cohort c, $k,l=\{1,...,t_c\}$. Conformably with m_c, m_{ci} represent the distinct elements of the individual cross-product matrix $\mathbf{R_{ic}R_{ic}^{'}}$. Then

$$m_c[k,l]=\frac{\sum_{i=1}^{n_c} m_{ci}[k,l]}{\sum_{i=1}^{n_c} d_{ick}d_{icl}}.$$

The matrix C_c is symmetric with $(\frac{t_c(t_c+1)}{2}\times 1)$ distinct elements. Let $\mathbf{Vech(C_c)}$ be a column vector of dimension $(\frac{t_c(t_c+1)}{2}\times 1)$ which stacks all the elements of the variance covariance matrix $\mathbf{C_c}$ for cohort c. The aggregate vector of moments for all cohorts is denoted by: $\mathbf{m=(Vech(C_1)^T,...,Vech(C_4)^T)^T}$,

which is a column vector of dimension $(\sum_{c=1}^{4}\frac{t_c(t_c+1)}{2}\times 1)$. In this paper, each cohort is observed between 1994 and 2001, therefore $t_c=8$. Since the individuals were grouped in four cohorts, $\mathbf{m}$ is a column vector of dimension (144×1).

To estimate the error components of the structural model illustrated by equations (9), (10) and (11), the elements of $\mathbf{m}$ are fit to a parameter vector $\boldsymbol{\theta}$, so that $\mathbf{m}=f(\boldsymbol{\theta})$, $f(\boldsymbol{\theta})$ takes the form of equations (13), (14), (15) and (12). Minimum distance estimation requires minimising the weighted sum of the squared distance between the actual covariances ($\mathbf{m}$) and a function of the parameter vector ($f(\boldsymbol{\theta})$) which encapsulates the covariance structure implied by the error component model. Therefore, minimum distance estimation involves the following quadratic form: $D(\boldsymbol{\theta})=[\mathbf{m}-f(\boldsymbol{\theta})]\mathbf{W}[\mathbf{m}-f(\boldsymbol{\theta})]'$, where $\mathbf{W}$ is a positive definite weighting matrix. Minimum distance estimator chooses $\hat{\boldsymbol{\theta}}$ to minimise the distance function $D(\hat{\boldsymbol{\theta}})$.

Based on Chamberlain (1984), the asymptotic optimal choice of $\mathbf{W}$ is the inverse of a matrix that consistently estimates the covariance matrix of $\mathbf{m}$, which leads to the optimum minimum distance estimator (OMD). However, Clark (1996) and Altonji and Segal (1994) provided Monte Carlo evidence that OMD is biased in small samples because of the correlation between the measurement error in the second moments and forth moments. Instead, they proposed using the identity matrix as a weighting matrix. This approach, often called "equally weighted minimum distance estimation" (EWMD), involves using the standard nonlinear least squares to fit $f(\boldsymbol{\theta})$ to $\mathbf{m}$. The same procedure is followed in this paper.

For estimating the asymptotic standard errors of the parameter estimates, we apply the delta method. Following Chamberlain (1984), the asymptotic variance-covariance matrix of the estimated parameters is obtained from the following formula:

$$\mathbf{AsyVar(\boldsymbol{\theta}) = (G'WG)^{-1}G'WVWG(G'WG)^{-1}} \quad (17)$$

where $\mathbf{G}$ is the Jacobian of the transformation $f(\boldsymbol{\theta})$ evaluated at $\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}$. $\mathbf{G}$ has dimension $(t_m \times p)$ and rank p, where t_m is the sum across cohorts of $(\frac{t_c(t_c+1)}{2}\times 1)$ and p is the number of parameters. $\mathbf{W}$ is the identity matrix and $\mathbf{V}$ the matrix of fourth sample moments.

Chamberlain (1984) showed that under some fairly general regularity assumptions, the independence of $\mathbf{R_{ic}}$ implies that the sample mean of m_{ci} has an asymptotic normal distribution $m_c \sim N(m_c^*, \mathbf{V}_c^*)$, where m_c^* is the expectation of m_{ci}**,** meaning the true covariance matrix of earnings, and $\mathbf{V}_c^*$ is the variance-covariance matrix, which can be estimated consistently by computing the sample moment matrix of the $\mathbf{Vech(C_c)}$ vector**,** $\mathbf{V_c}$**.** The elements of the variance covariance $\mathbf{V_c}$ can be written as follows**:**

$$Cov(m_c[k,l], m_c[p,q]) = \frac{\sum_{i=1}^{n_c} d_{ick}d_{icl}d_{icp}d_{icq}}{\sum_{i=1}^{n_c} d_{ick}d_{icl}\sum_{i=1}^{n_c} d_{icp}d_{icq}}(m_c[k,l,p,q]-m_c[k,l]m_c[p,q]),$$

$$\text{where } m_c[k,l,p,q] = \frac{\sum_{i=1}^{n_c} r_{ick}r_{icl}r_{icp}r_{icq}}{\sum_{i=1}^{n_c} d_{ick}d_{icl}d_{icp}d_{icq}}$$

The variance-covariance matrix of $\mathbf{m}$ was denoted by $\mathbf{V}$, where $\mathbf{V}$ is the block diagonal matrix which is constructed from all the $\mathbf{V_c}$ matrices**.**

5.4. Strategy for model specification

The chi-squared goodness of fit statistic is computed following Newey(1985):

$$\chi = [\mathbf{m} - f(\hat{\boldsymbol{\theta}})]\mathbf{R}^{-1}[\mathbf{m} - f(\hat{\boldsymbol{\theta}})]'$$

where χ follows a chi-squared distribution with degrees of freedom equal to $\sum_{c=1}^{4}\frac{t_c(t_c+1)}{2}-p=144-p$, $\mathbf{R^{-1}=(WVW')^{-1}}$ **and** $\mathbf{W=I-G(G'AG)^{-1}G'A}$. The majority of the existing studies estimating the covariance structure of earnings used this general form of specification test to assess the goodness of fit of the model. However, in most cases, all models have been rejected. Baker and Solon (2003), Baker (1997), Leamer (1983) criticized these type of tests for several reasons. First, Baker and Solon (2003) and Leamer (1983) underlined that "diagnostic tests such as goodness-of-fit tests, without explicit alternative hypothesis, are useless, since if the sample size is large enough, any maintained hypothesis will be rejected. Such tests therefore degenerate into elaborate rituals for measuring the effective sample size." Second, as pointed by Baker and Solon (2003), an additional problem is that these specification tests have inflated size in small samples and the inflation is positively related with the number of overidentifying restrictions. For example, Baker (1997) revealed through a Monte Carlo study, that for a test with fewer than 150 overidentifying restrictions, the critical values are 40%-50% greater than the critical values based on the asymptotic theory. Therefore, we decided to report this statistic as a reference, but not to use it to assess the goodness of fit of our model. Instead we employed the SSR as a measure of fit.

To test between nested models, we could use Preposition 3' in Chamberlain (1984) or the LR test. Based on Preposition 3' in Chamberlain (1984), assuming that the general model has p parameters, to test between two nested models, one in which k_1 parameters are restricted to 0 (χ_{p-k_1}) and one in which k_2[6] parameters are restricted to 0 (χ_{p-k_2}), Chamberlain (1984) showed that the incremental chi square statistic $\chi=\chi_{p-k_1}-\chi_{p-k_2}$ follows a chi-squared distribution with k_1-k_2 degrees of freedom. The LR test takes the following form: $LR=N\log\frac{SSE_R}{SSE_U}$. Under the null hypothesis, LR is follows a chi-square distribution with d.o.f equal to the number of restrictions k_1-k_2. To test between non-nested model, we use BIC and AIC criterion.

$$AIC=\frac{SSE\cdot e^{2k/144}}{144-k}\quad or\quad BIC=\frac{SSE\cdot 144^{k/144}}{144-k}$$

[6] $k_1 > k_2$

The smaller the value of BIC and AIC are the better the fit is. The difference between the two is that BIC incorporates a higher penalty for additional parameters than AIC and is recommended as the first choice.

6. THE DYNAMIC AUTOCOVARIANCE STRUCTURE OF HOURLY EARNINGS

To begin with, it is informative to have a description of the dynamic structure of individual log hourly earnings for all 14 countries under analysis. The autocovariance structure of earnings is computed for each cohort separately, as well as overall, using formula (16) introduced in the previous section. The overall autocovariance structure of earnings is displayed in Figure 1, whereas the structure by cohort is included in Figure 2. The model used to fit the autocovariance structure of earnings for all cohorts must be consistent with the trends observed in the dynamic autocovariance structure.

The overall autocovariance structure of earnings displays both similar and diverging patterns across countries. In the beginning of the sample period, the overall inequality appears to be the highest in Portugal, followed by Ireland, Spain, France, Luxembourg, UK, Greece, Germany, Austria, Italy, Belgium, Netherlands, Finland and Denmark. In 2001, Portugal still records the highest inequality, followed by Luxembourg, France, Greece, Spain, UK, Italy, Germany, Ireland, Netherlands, Finland, Belgium, Austria and Denmark.

The general picture is that the variance of log hourly earnings appears to decrease over the sample period in Germany, Denmark, Belgium, France, UK, Ireland, Spain and Austria, to increase in Netherlands, Luxembourg, Greece, Portugal and Finland. The purpose of this paper is to decompose the variance for each country into the permanent and transitory variance, and conclude which of these components were the main factors triggering the evolution of overall inequality over time.

The common pattern across all countries is that all lags autocovariances show in general similar pattern as the variance. They are positive and quite large in magnitude relative to the variances. The distance between autocovariances at consecutive lags falls at a decreasing rate. The biggest fall is registered by the lag-1 autocovariance, after which the covariances appear to converge gradually at a positive level. Variances reflect both the permanent and the transitory components of earnings, whereas higher order covariances reflect the permanent component of earnings.

Therefore, the evolution of the covariances, at all orders, suggests the presence of a permanent individual component of wages and a transitory component which is serially correlated. Moreover, the sharp decline of the first lag autocovariance is consistent with the presence of a moving average process of first order.

Both mean earnings and all lags autocovariances vary over time, which provide a first sign suggesting the presence of nonstationarity in the dynamic structure of earnings.

In all countries, the autocovariances display different patterns across cohorts, supporting the hypothesis of cohort heterogeneity with respect to individual earnings dynamics. The general picture is that, in all countries, the variance for all cohorts appears to follow the evolution of the overall variance, but the evolution is not monotonic and the rate of change differs among cohorts. In general, in countries that record a decrease in the variance, the older the cohort, the steeper the decrease. For those that record an increase in the variance over time, the older the cohort, the steeper the increase is. Moreover, the younger the cohort is the lower the autocovariances are. Hence, given that higher order autocovariances capture the permanent component of earnings, it is reasonable to expect that in all countries, for younger cohorts, the transitory variance plays a larger role in the earnings formation than the permanent component compared with older cohorts.

As illustrated in Figure 2, for all cohorts, all lags autocovariances show in general similar pattern as the variance, in line with the overall pattern. The evolution of the covariances, at all orders, suggests the presence of a permanent individual component of wages and a transitory component which is serially correlated. Moreover, the sharp decline of the first lag autocovariance is consistent with the presence of a moving average process of first order. Similar with the overall trend, there is evidence of nonstationarity in the dynamic structure of earnings by cohort.

To look at these lifecycle effects more clearly, it is necessary to remove the time effect that is present in these within cohort autocovariances. For the figures illustrating lifecycle autocovariances refer to Sologon and O'Donoghue (2009). In all countries, all lags autocovariances of log real gross hourly earnings show a similar pattern as the variance. They are positive and evolve parallel with the variance, at different rates over the life cycle. They rise sharply over the life cycle until the late 30s and early 40s, after which they have a rather stable evolution up until late 50s, when more noise can be observed in the variance-covariance structure. The diminishing rate of increase of all lags autocovariances, which characterizes the life cycle from the age of 20 until the late 50s, is consistent with the presence of a permanent component of earnings that rises with age at a diminishing rate. (Dickens, 2000) Moreover, the autocovariances display a noisy evolution over the lifecycle which increases with age, which might suggest also the presence of a random walk in age.

Comparing across years, the life cycle profile of the auto-covariances of log gross hourly earnings appears to become steeper over time in France, Luxembourg, Ireland, Italy, Greece, Portugal and Finland. The slope of the life cycle profile can be interpreted as the returns to the permanent component of earnings, therefore steeper slopes in later years imply increasing returns to the permanent component of earnings over time.

To sum up, the description of the dynamic structure of individual earnings for men suggests five main features of the data, which were incorporated in our model, as mentioned previously:

- First, the covariance elements are not the same at all lags. They decrease with the lag at a decreasing rate and converge gradually at a positive level, suggesting the presence of a transitory element, which is serially correlated, and of a permanent individual component of earnings. The most popular specification for the serially correlated term is the AR(1) process. However, the fact that the lag-1 autocovariance drops to a larger extent compared with the other autocovariances and that the autocovariances at high orders decline very slowly suggest that earnings cannot be modelled simply as a first-order autoregressive process. Therefore a more complex ARMA (p, q) process might be a better choice, where p represents the order of the autoregressive process and q the order of the moving average process.

- Second, as the autocovariances and mean earnings vary over the sample period, they cannot be assumed to be stationary over sample period. The stationarity assumption was tested and rejected using the methodology introduced by MaCurdy (1982). One way to capture this feature is to incorporate period specific parameters, meaning that the permanent individual component and the transitory component of earnings are allowed to vary with time.

- Third, as autocovariances vary with age controlling for the period effect, they cannot be assumed to be stationary over the life cycle. This non-stationarity can be captured by modelling the permanent individual component as random walk and/or random growth in age.

- Lastly, the variance covariance structure appears to be cohort specific, which can be incorporated by parameters that allow the permanent and transitory components to vary between cohorts.

7. Results of Covariance Structure Estimation

7.1. Error component model estimation results

The general specification of the error component model outlined in section 5.2, which encompasses all relevant aspects of earnings dynamics considered above, is fit to the elements of the covariance matrix of each country, for all cohorts pooled together[7]. For choosing the best model for each country we followed a general to specific strategy, by imposing additional restrictions on the general model. The estimation of the general model which incorporates both the random growth and the random walk specifications in the permanent component had some identification problems in all countries. The ARMA process was found only in three countries and homogenous initial conditions only in four. In all countries, the models incorporating both time and cohort shifters performed the best.

We present the parameter estimates only for the models that fit data the best for each country. The estimation results are illustrated in Table 3. Similar to Dickens (2000), all variances are restricted to be positive by estimating the variance equal to the exponent of the parameter. The reported variance estimates represent the exponent of the parameter and the reported standard errors correspond to the parameter estimates.

The formulation of the permanent and transitory components of earnings differs between countries.

[7] i.e. 144 auto-covariances for countries observed over 8 waves, 122 for those with 7 waves and 84 for those with 6 waves.

Permanent component

In Germany, Netherlands, UK, Ireland, Italy, Greece, Spain and Finland, the permanent component follows a random growth model with time and cohort specific loading factors. The estimated coefficients for the permanent component of earnings show that time-invariant heterogeneity and age-earning profile heterogeneity plays a significant role in the formation of long-term earnings differentials in all these countries. Individual specific heterogeneity plays the highest role in Germany, followed by Spain, Netherlands, Greece, UK, Ireland and Italy, which suggests that in Germany there is a higher dispersion in the time-invariant individual specific attributes that determine wage differentials.

The estimated random slope variance implies that hourly earnings growth for an individual located one standard deviation above the mean in the distribution of φ is the largest in Germany, where it is with 4.89%[8] faster than the cohort mean, followed by Greece, Ireland, Spain, Netherlands, UK and Finland with rates between 1% and 1.41% and Italy with 0.89%. All these countries have a negative covariance between the time invariant individual specific effect and the individual specific slope of the age-earning profile, which implies that the initial and lifecycle heterogeneity are negatively associated. This negative association corresponds to the trade-off between earnings early in the career and subsequent earnings growth and is consistent with the on-the-job training hypothesis (Mincer, 1974). Therefore, this suggests the presence of mobility within the distribution of permanent earnings over the sample period. These findings reinforce the results from previous studies.

Therefore for these countries the evolution of the permanent component without the time loading factors could be either increasing or decreasing. The time-specific loading factors for the permanent component are highly significant with values close to 1 in all countries. The trends of the returns to the permanent component vary to a large extent across countries. One common feature is that they reflect, as was emphasized before, trends in the high-order autocovariances in the data. These estimates show that overall, controlling for age and cohort effects, the returns to skills decreased over the sample period in Netherlands, UK, Ireland, Italy, Greece, Spain and

[8] $4.89 = 100 \cdot \sqrt{\sigma_{\varphi}^{2}}$

increased in Germany and Finland. The trends over one year intervals differ between countries, some records a smooth evolution, others noisier. For example, Netherlands experienced decreases in returns almost every second year. In UK, the returns increased in 1997 and 2001 and decreased in the rest. Ireland recorded a decrease until 1996, a boost in 1997 and a clear decline thereafter. In Italy, 1998 and 1999 appear to be years with increases in return to skills, in Greece every second year, in Spain 1996 and 1998. Germany experienced increasing returns to human capital until 2000, and Finland in 1997 and 2001. Therefore, in these years, the relative position of the highly skilled individuals was enhanced.

In Denmark the permanent component follows a random walk in age. The variance of the innovation in the random walk is significantly larger than zero. As the variance of a variable that follows a random walk is the sum of the variances of the innovation term, this finding implies that permanent inequality increases over lifetime. In Denmark, the variance at the age of 20 is higher than the variance at subsequent ages, suggesting the presence of larger permanent shocks at younger ages, which is consistent with matching models, in which the information revealed about a worker's ability increases with time. The final trend in the permanent variance depends on the period specific loading factors, which reveal that overall, the relative position of the highly skilled individuals decreased over the sample period in Denmark. The yearly evolution revealed a smooth decrease until 2000, followed by a small increase in 2001.

In Belgium, France, Luxembourg, Portugal and Austria the persistent dispersion of earnings follows the canonical model, where the permanent component is time-invariant. The highest variance in the time invariant characteristics is recorded in Portugal, followed by France, Luxembourg, Austria and Belgium. In this case, the time-specific loading factors determine the final trend of the permanent differentials: they decreased in Belgium and Austria, and increased in France, Luxembourg and Portugal. With respect to the yearly evolution, France records an increase in the returns to skills until 1997 and again in 2001, Luxembourg until 2000, Belgium in 1995 and 2001, Austria during most of the period, except 1998-1999, and Portugal in 1996 and 1998.

The estimates of the cohort-specific shifters for the permanent earnings are highly significant in all countries. However, the trends suggested by these estimates differ between countries. The permanent component of earnings appears to increase over the life cycle in Germany, France, Luxembourg, Portugal and Austria. In Denmark, Netherlands, Belgium and Spain the permanent component of earnings has an inverted-U shape evolution over the life cycle. These trends confirm the expectation that permanent earnings differentials play a much larger role in the formation of overall earnings differentials of older cohorts compared with younger ones, which experience higher earnings volatility due to temporary contracts. We expect the opposite to hold in the case of cohort-specific shifters for transitory earnings.

The permanent component of earnings appears to decrease over the life cycle in UK, Ireland, Italy, Greece and Finland. One possible explanation is that younger cohorts have more heterogeneous skills. Another explanation is that younger cohorts might experience larger permanent shocks even if they do not have a larger dispersion of skills. This could be the case if the labour market has become tougher over time, such as in the case of the Italian labour market, which is characterised by high rates of youth unemployment.

Temporary component

The formulation of the temporary component of earnings differs between countries. It follows an AR(1) process with time and cohorts loading factors in all countries, except for Italy, Greece and Spain, where it follows an ARMA(1,1). Except for Spain, Portugal and Austria, where all cohorts share the same initial conditions, the other countries are characterized by heteroskedastic initial conditions. The estimated coefficients for the transitory component of earnings are all significant, suggesting that the initial variance(s), the AR(1) process, respectively the ARMA(1,1) process and the time and cohort loading factors contribute significantly to earnings volatility in all countries.

The variance of initial conditions, which represents the accumulation of shocks up to the starting year of the panel, is smaller than that of subsequent shocks in all countries. However, the pattern of the heteroskedstic initial conditions differs between countries. In Denmark, Luxembourg, UK, Ireland, Italy, Portugal and Finland it follows the inverted-U shape: the variance of initial conditions increases over the lifecycle and decreases at the end. The opposite holds for France, where the oldest and the youngest cohorts have the highest initial variances.

In Germany, Netherlands, France and Finland the pattern of the heteroskedstic initial conditions illustrates a general decreasing trend over the lifecycle, suggesting that the initial variance plays a larger role in the formation of earnings differentials for the youngest cohort compared with the oldest. In Belgium the reverse holds: the heteroskedastic cohort initial conditions appear to play the largest role in the formation of earnings differentials for the oldest cohort and the smallest for the youngest cohort.

The magnitude of the autoregressive parameter varies between countries. A large autoregressive parameter, which suggests that shocks are persistent, is recorded in Spain with 26.9% of a shock still present after 8 years, in Portugal with 8.5% and in Austria with 5.7%. A moderate autoregressive parameter suggesting that shocks die out rather quickly is recorded in Italy with 2.8% of a shock still present after 8 years, in Belgium with 2.4%, and in Greece with 1.4%. A very small autoregressive parameter is present in Luxembourg, Ireland, Finland, Netherlands, Germany, France, UK and Denmark, where between 0.0008% and 0.8% of a shock is still present after 8 years. The negative sign of the MA component implies that the autocovariances decline sharply over the first period, confirming the trends observed in the previous section for Italy, Greece and Spain.[9]

The time-specific loading factors for the transitory component are highly significant and display a higher variation than for the permanent component in all countries. The trends of the transitory inequality vary to a large extent across countries. These estimates show that overall the transitory variance decreased over the sample period in Germany, Denmark, Netherlands, Belgium, France, UK, Italy, Greece, Spain, Portugal, Austria and Finland. It increased in Luxembourg and Ireland.

The estimates of the cohort-specific shifters for the transitory earnings are highly significant in all countries. The estimates of the cohort-specific shifters for the temporary component indicate that earnings volatility appears to be higher for younger cohorts, thus confirming the pattern observed in the dynamic description of the autocovariance structure of earnings, where autocovariances were found to be lower for younger cohorts. This result is expected, given that younger people experience in general more frequent job changes, and consequently less stable earnings.

[9] For the other countries, the MA component was either rejected by the data or could not be identified due to the low number of waves.

Alternative model specifications

Table 4 introduces the alternative model specifications for each country to justify the choice for the preferred models. Through these models, we tested whether the restrictions imposed by previous studies hold for each country.

First compared with the simple canonical model, our country-models revealed a significant improvement, both with respect to SSR and the Newey chi-squared goodness of fit. Moreover, the overall Wald test showed that, for each country, the restrictions imposed by the canonical model do not hold in the data. In Germany, assuming away the restrictions imposed by the canonical model decreased the χ^2 .with 46764.97at a cost of 26 degrees of freedom. Similarly, in Denmark the decrease in χ^2 was of 23505.49, in Netherlands of 21880.65, in Belgium of 28937.06, in France of 6602.395, in Luxembourg of 33598.94, in UK of 9651.35, in Ireland of 22338.56, in Italy of 10858.77, in Greece of 23150.67, in Spain of 9833.018, in Portugal of 35182.5, in Austria of 12829.92 and in Finland of 5733.26. We then tested these restrictions in turn.

If we assume away the random growth in the permanent component ($\sigma_{\varphi}^2 = 0$ and $\mathrm{cov}(\mu,\varphi) = 0$), the Wald test on this restrictions clearly rejects the null in Germany ($\chi^2 =$ 859.6255 , df=2), Netherlands ($\chi^2 = 178.7331$, df=3), UK ($\chi^2 = 185.2973$, df=2), Ireland ($\chi^2 = 8.8093$, df=2), Italy ($\chi^2 = 65.2755$, df=2), Spain ($\chi^2 = 28.2711$, df=2), Finland ($\chi^2 = 99.2208$, df=2). In Greece, this assumption leads to an unidentified model. Identification problems from incorporating a random growth are found in Belgium, France, Luxembourg, Portugal and Austria.

Incorporating a random walk in the permanent component leaded to identification problems in Belgium, France, Luxembourg and Austria. Based on the Wald test, in Portugal and Denmark, the random walk was rejected by the data. However, in Denmark, given that the random walk was highly significant and the SSR is lower than without the random walk, we decided to keep it. Among the countries that favoured the random growth, the random walk either triggered some identification problems or a higher BIC than the model incorporating a random growth.

Based on Wald test, the restriction of homogenous initial conditions ($\sigma_0^2 = \sigma_{0,40-50}^2 = \sigma_{0,51-60}^2 = \sigma_{0,61-70}^2 = \sigma_{0,71-80}^2$) was rejected in Germany ($\chi^2 = 125.1595$, df=5), Denmark ($\chi^2 = 436.3263$, df=3), Netherlands ($\chi^2 = 207.3169$, df=3), Belgium ($\chi^2 = 1063.161$, df=3), France ($\chi^2 = 61.0812$, df=3), Luxembourg (($\chi^2 = 268.491$, df=3), Ireland ($\chi^2 = 8.8093$, df=2), Italy ($\chi^2 = 70.1507$, df=3) and Greece ($\chi^2 = 172.1103$, df=3). Assuming heterogeneous initial conditions worsened the fit of the model in Portugal and Austria, as illustrated by the increase of 11613.2, respectively 152.77 in χ^2 . Similarly was obtained in Finland, however given that in our preferred model the SSR is smaller and the parameter estimates are significant, we decided to keep the specification. Assuming heterogenous initial conditions leaded to convergence or identification problems in UK and Spain.

Introducing an MA(1) component besides the AR(1) improved significantly the fit of the model in Italy ($\chi^2 = 323.1314$, df=1), Greece ($\chi^2 = 121.2267$, df=1) and Spain ($\chi^2 = 47.9717$, df=1). MA(1) component was rejected in Luxembourg and Portugal, as suggested by the increase of 1.073, respectively 4015.76 in χ^2 . In rest, this specification failed to converge or suffered from identification problems.

8. Inequality Decomposition into Permanent and Transitory Inequality

8.1.Absolute Decomposition

Having estimated a suitable error component model for earnings in each country, next we use these parameters estimates to decompose the variance-covariance structure of earnings into its permanent and transitory components, assess their relative importance and analyse their contribution to the evolution of the overall inequality over the sample period. Basically, we want to assess which is the component that plays the largest role in the declining/rising overall cross-sectional inequality between 1994 and 2001.

The decomposition of the variance, together with the actual and predicted variance of earnings by cohort are presented in Figure 3. A summary of the evolution of the two components is offered in Figure 4 which illustrates the degree of immobility, measured as the ratio between the average permanent variance across cohorts and the average transitory variance across cohorts.

For all countries, the evolution of the predicted variance follows closely the evolution of the actual variance, which is not surprising given the high fit of the models indicated by the very low sum of square residuals. Earnings inequality measured by the actual variance decreased overall in Germany, except for the cohorts born in 1941-1950 and 1961-1970 where it increased; in Denmark; in Belgium, except for the youngest cohort where it increased; in France, except for the cohort born in 1961-1970; in UK, except for the youngest two cohorts where it increased; in Ireland; in Spain except the youngest cohort, and in Austria. Earnings inequality measured by the actual variance increased overall for all cohorts in Netherlands, Luxembourg, Italy, Greece, Portugal and Finland, except the youngest cohort. These are countries where wages appear to be more responsive to market forces.

In 1994, the highest permanent inequality was recorded in Portugal and Spain, followed by France, Ireland, Germany, UK, Greece, Italy, Netherlands, Belgium and Denmark. The highest transitory variance was recorded in France, Ireland, Greece, UK, Germany, Spain, Denmark, Belgium, Netherlands, Italy and Portugal. The rankings in immobility reveal that Denmark was the most mobile, followed by Greece, Belgium, France, Netherlands, Ireland, Italy, UK, Germany, Spain and Portugal.

In 2001 the rankings looks slightly different. Portugal records the highest permanent differentials, followed by Luxembourg, France, Spain, Ireland, Germany, Greece, UK, Italy, Finland, Netherlands, Austria, Belgium and Denmark. In terms of transitory inequality, Portugal appears to be the most dispersed, followed by Spain, Netherlands, France, Greece, UK, Germany, Belgium, Luxembourg, Austria, Ireland, Denmark, Finland and Italy. Denmark has still the highest earnings mobility, followed by Belgium, Netherlands, Austria, Spain, Greece, Finland, UK, France, Germany, Italy, Portugal, Ireland and Luxembourg. As expected, countries with the lowest mobility are among the countries with the highest permanent differentials.

The decrease in cross-sectional inequality was accompanied by a decrease in the importance of the permanent component relative to the transitory component, and consequently an increase in mobility in Denmark, Belgium and Spain.(Figure 4) Among the three, Spain is the most immobile, which is consistent with the fact that Spain is characterised by a degree of permanent inequality more than twice the value for the other two countries, and a higher share of the permanent component. In Denmark, the decrease in cross-sectional inequality appears to be the result of decreasing both permanent and transitory differentials, whereas in Belgium and Spain, the decrease in cross-sectional inequality appears to be determined by a decrease in the permanent variance, which offset the increase in the transitory variance. (Figure 3)

Hence, the increase in mobility helped individuals improve their position in permanent earnings distribution and consequently reduced overall inequality.

In Germany, France, UK, Ireland and Austria, the decrease in cross-sectional inequality was accompanied by an increase in the importance of the permanent component relative to the transitory component, and therefore a decrease in earnings mobility.(Figure 4) Thus, in these countries, mobility cannot be considered the driving force for the decrease in overall inequality.

In Germany, France, UK and Ireland, the decrease in the overall inequality was the result of an increase in permanent differentials and a decrease in transitory differentials, whereas in Austria both components decreased. Different trends are observed by cohorts. (Figure 3)

The increase in cross-sectional inequality was accompanied by an increase in mobility in Netherlands and by a decrease in mobility in Luxembourg, Italy, Greece, Portugal, and Finland. (Figure 4)

In Netherlands the increase in overall inequality was the result of an increase in both components. (Figure 3) Transitory inequality was exacerbated over time for all cohorts, whereas the trends in the permanent inequality differ to a large extent between cohorts. In this case, mobility actually exacerbates overall cross-sectional inequality, suggesting an increase in the earnings volatility.

In Luxembourg, Italy, Greece and Finland the increase in the overall cross-sectional inequality appears to be the result of an increase in permanent inequality which offset the decrease in transitory inequality. (Figure 3) Therefore the exacerbation of permanent differentials, meaning the increase in returns to skills was the dominant factor behind the increase in overall inequality. In Portugal, both components increased over time, the permanent component at a higher rate than the transitory component.

8.2.Relative decomposition

Figure 5 illustrates the relative decomposition of the overall predicted variance of earnings into its permanent and transitory components. The pattern of decomposition of the overall variance varies between cohorts and countries. However, some common traits emerge. Inequality in the permanent component of earnings appears to account for a higher share of the overall variance the older the cohort is, which is consistent with the evidence of lifecycle earnings divergence showing that older cohorts experience a lower earnings volatility compared with younger cohorts. Moreover, inequality in the temporary component of earnings accounts for the highest share for the youngest cohort, which reinforces the expectation that earnings volatility is higher at younger ages.

In countries which recorded a decrease in inequality accompanied by an increase in mobility – Denmark, Belgium and Spain - the structure of inequality did not change much in 2001 compared with 1994. Mixed trends across cohort are observed in Denmark and Belgium, whereas in Spain the share of permanent inequality decreased slightly for all cohorts. However, its evolution is not monotonic. A turnaround in the evolution of the share of permanent inequality is observed around 1998-1999, when the share started decreasing in Denmark and Spain, following the increase over the period 1994-1998.

In Denmark, in 2001, for the oldest two cohorts the persistent variance accounts for roughly 50%-60% of the overall variance, for the cohort born between 1961-1970 40%, whereas for the youngest cohort the variance is mostly transitory (90%). In Belgium, the rates are similar with Denmark for the oldest two cohorts and higher with roughly 10 percentage points for the rest. In Spain, the share of the permanent component is higher with roughly 10 percentage points for the oldest two cohorts and with roughly 20 percentage points for the youngest two than in Belgium.

In countries that recorded a decrease in inequality and mobility - Germany, France, UK, Ireland and Austria -, the structure of inequality over the sample period changed to a large extent and led to an increase in the share of the permanent inequality for all cohorts, except the oldest in Germany and the youngest in UK. Similar with previous countries, its evolution is not monotonic.

In France and Ireland, a significant turnaround occurred in 1996, respectively 1997, when the share of permanent inequality started to decrease and implicitly mobility to increase. In Austria, 1998 market the year of the turnaround. Until 1998, the share of permanent inequality increased sharply and was accompanied by a large drop in wage mobility. The share dropped and mobility increased in 1999, followed by stable evolution thereafter.

In 2001, in Germany compared with Spain, the share of the permanent component for the oldest two cohorts is higher with roughly 10 percentage points, roughly equal for the second youngest cohort and higher with 10 percentage points for the youngest. Therefore, in Germany, the persistency of earnings is higher than in Spain, and implicitly than in Belgium and Denmark. For France, the share of the persistent component is similar with Germany. In UK, the share of the persistent differentials was similar with Spain. In Ireland, the structure of inequality is similar with Germany, except for the youngest cohort where the share of the permanent component is almost double, suggesting a lower earnings volatility for Irish than for German youngsters. In Austria permanent differentials account for 60% of the overall variance for the oldest three cohorts and for 20% for the youngest one. These rates place Austria as the country with the lowest earnings persistency among the ones which recorded a decrease in earning inequality.

In countries that recorded an increase in inequality and mobility – Netherlands - the share of the permanent inequality decreased over time. A significant changed occurred after 1998, when the share of permanent inequality started decreasing and offset the increasing trend which dominated the period before 1998.

In countries that recorded an increase in inequality and a decrease in mobility – Luxembourg, Italy, Portugal, Greece and Finland – the share of permanent inequality increased over time. For all these countries, a turning point in the evolution of the share of permanent inequality appears to have occurred around 1998-1999.

In 2001, Luxembourg has the highest shares of the permanent component among all countries recording an increase in overall inequality: roughly 80% for the oldest three cohorts and 40% for the youngest one. Next, in terms of earnings persistency in 2001, we find Italy, with slightly lower shares for all cohorts. In Portugal, the structure is very similar with Italy, except for the youngest cohort, for which the share is half the one in Italy, signalling a higher earnings volatility for youngsters in Portugal. In Greece, the share of the persistent component is lower with roughly 10 percentage points for the oldest two cohorts, similar for the second youngest cohort and more than double for the youngest cohort than in Portugal. This suggests that earnings volatility for the youngest cohort is lower than in Portugal and is similar with Luxembourg and Italy. In Finland, the share of the permanent component for the oldest two and the youngest cohorts is similar with Greece, whereas for the second youngest the share is higher with roughly 10 percentage points than in Greece.

9. CONCLUDING REMARKS

The purpose of this study was to analyze what are the driving forces behind the changes in the distribution of labour market income across 14 EU countries over the period 1994-2001 using ECHP. Earnings inequality, as measured by the variance in log earnings was found to decrease in Germany, Denmark, Belgium, France, UK, Ireland, Spain, Austria and to increase in Netherlands, Luxembourg, Italy, Greece, Portugal and Finland. We examined the extent to which these changes in cross-sectional inequality were determined by changes in transitory and/or in permanent earnings differentials.

For all countries individual earnings inequality contains a highly permanent component for the oldest three cohorts and a highly transitory component for the youngest cohort. Regarding the structure of inequality, the permanent component appears to account for a higher share of the overall variance the older the cohort is. This is consistent with the evidence of lifecycle earnings divergence showing that older cohorts experience a lower earnings volatility compared with younger cohorts. Moreover, inequality in the temporary component of earnings accounts for the highest share for the youngest cohort, which reinforces the expectation that earnings volatility is higher at younger ages.

Increases in inequality appear to reflect increases in permanent differentials in Luxembourg, Italy, Greece and Finland, and increases in both components in Portugal and Netherlands. Decreases in inequality appear to result from decreases in transitory differentials in Germany, France, UK and Ireland, in permanent differentials in Belgium and Spain and in both components in Denmark and Austria. In most countries, increases in inequality appear to be accompanied by decreases in mobility, except for Netherlands. Decreases in inequality are accompanied by increases in mobility only in Denmark, Belgium and Spain.

More important are the welfare implications of these trends. In Luxembourg, Italy, Greece, Finland and Portugal, it appears that besides the widening wages differentials, low wage individuals find it harder to better their position in the wage distribution in 2001 compared with the first wave. Hence, in 2001, low wage individuals are worse off both in terms of the relative wage they receive and in terms of the opportunity of escaping the low-pay trap. In Netherlands, mobility appears to exacerbate cross-sectional inequality, meaning that the rich might have gotten richer and the poor poorer. In Denmark, Belgium and Spain, mobility appears to be beneficial. In 2001, low wage individuals are better off both in terms of the relative wage they receive and in terms of the opportunities to escape the low-wage trap. In Austria, Germany, France, UK and Ireland, low-wage individuals are worse off in 2001 in terms of the opportunity to escape the low-wage trap, but their relative position in the earnings distribution is improved, most probably because of the reduction in wage differentials between the top and the bottom of the distribution. The reduction in mean wage in Austria might signal a reduction in top incomes.

The evolution of the inequality structure and earnings mobility was not monotonic. Most countries experienced a sharp turnaround around 1996-1999 which could be linked with the turnaround in the institutional and policy framework experienced by EU countries after 1995. Hence, an interesting topic for future research is to explore the role of labour market factors in explaining cross-national differences in permanent inequality, transitory inequality and earnings mobility. Moreover, the link between earnings mobility and the two components can be explored more in depth by looking at different mobility measures, including long and short period mobility.

10. Tables and Figures

Table 1. Mean hourly earnings and number of individuals with positive earnings

		1994	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**
Germany	Mean	9.43	9.49	9.61	9.52	9.57	9.48	9.60	9.72
	N	25018	26059	25806	24889	23290	22955	21909	20703
Denmark	Mean	10.89	11.40	11.58	11.61	11.86	11.85	12.02	12.08
	N	20899	20399	19190	19062	17321	16235	15678	15380
Netherlands	Mean	9.69	9.56	9.59	9.70	10.02	9.88	10.04	9.91
	N	33277	32384	31564	30575	28731	27460	25790	33277
Belgium	Mean	8.48	8.82	8.71	8.75	8.81	8.83	8.92	9.10
	N	20221	22100	22892	22753	22863	23233	24065	24130
Luxembourg	Mean		16.18	15.81	16.73	17.39	17.15	17.22	17.10
	N		15829	13695	14489	13403	14075	12667	12992
France[10]	Mean	10.23	9.92	9.87	10.05	10.33	10.60	10.55	10.87
	N	20137	19270	19042	17906	14467	14012	13760	14212
UK	Mean	8.16	8.11	8.22	8.34	8.68	9.01	9.21	9.68
	N	24949	25329	25495	26010	26145	25750	25674	25264
Ireland	Mean	9.30	9.54	9.76	10.02	10.43	10.84	11.69	12.44
	N	13937	13221	12590	12515	12435	12091	10745	9727
Italy	Mean	7.16	6.91	6.96	7.05	7.29	7.37	7.28	7.32
	N	32633	32236	32111	29661	28865	26993	26912	25170
Greece	Mean	4.95	5.03	5.23	5.59	5.63	5.85	5.70	5.77
	N	27974	27654	26150	24865	22675	22001	21335	21929
Spain	Mean	6.83	6.95	7.09	6.89	7.18	7.37	7.45	7.42
	N	22559	21863	21296	20975	20371	20580	19898	20185
Portugal	Mean	9.08	8.33	8.37	8.49	8.55	8.55	8.54	9.08
	N	14653	15450	15379	15087	14837	14569	14604	14550
Austria	Mean		9.08	8.33	8.37	8.49	8.55	8.55	8.54
	N		17944	17789	17199	16209	15162	13816	13056
Finland	Mean			7.89	8.01	8.41	8.45	8.66	8.86
	N			15811	15845	15895	15546	13329	13057

Note: Mean hourly earnings are expressed in Euro.

[10] Gross Amounts

Table 2. Number and share of individuals present in the sample in year $t-1$ which record positive earnings in year t

		1995	1996	1997	1998	1999	2000	2001
Germany	Freq.	23956	25224	24197	22814	22321	21290	20107
	%	66.99	67.37	66.2	63.01	64.84	64.86	64.39
Denmark	Freq.	19854	18527	18110	16442	15334	14865	14642
	%	68.74	66.59	69.43	66.23	67.41	69.6	71.6
Belgium	Freq.	33277	32384	31564	30575	28731	27460	25790
	%	63.43	63.65	64.38	63.88	64.28	65.15	64.38
Netherlands	Freq.	20578	21328	21221	21055	20545	21026	21341
	%	69.07	71.37	68.68	67.52	67.24	68.56	69.59
Luxembourg	Freq.		13417	12498	13190	12257	12402	11457
	%		64.75	69.48	69.33	69.81	68.71	70.39
France	Freq.	19143	18197	17243	14014	12209	12080	12468
	%	62.47	64.76	62	52.08	54.24	55.54	60.8
UK	Freq.	24511	24848	25303	25278	25006	24881	24467
	%	64.59	66.31	67.06	67.04	67.36	68.33	68.58
Ireland	Freq.	12750	12217	12212	12020	11668	10236	9507
	%	49.99	50.04	52.41	53.13	54.1	51.63	54.65
Italy	Freq.	30946	31028	28717	27188	25717	25348	24139
	%	51.58	51.19	47.18	47.34	46.87	48.73	48.86
Greece	Freq.	26868	25946	24385	21815	20357	20443	21342
	%	45.83	45.69	44.98	42.09	43.52	46.06	49.72
Spain	Freq.	21460	20521	20329	19456	19679	19167	19352
	%	47.6	48.29	48.49	48.63	52.13	52.12	56.06
Portugal	Freq.	13892	14538	14321	13977	13921	13952	13942
	%	57.84	57.5	57.32	56.98	59.12	60.83	62.16
Austria	Freq.		16472	16384	15634	14551	13403	12601
	%		67.96	68.2	67.49	67.2	66.51	68.21
Finland	Freq.			15246	15345	14753	12756	12588
	%			55.95	57.2	59.29	53.83	64.16

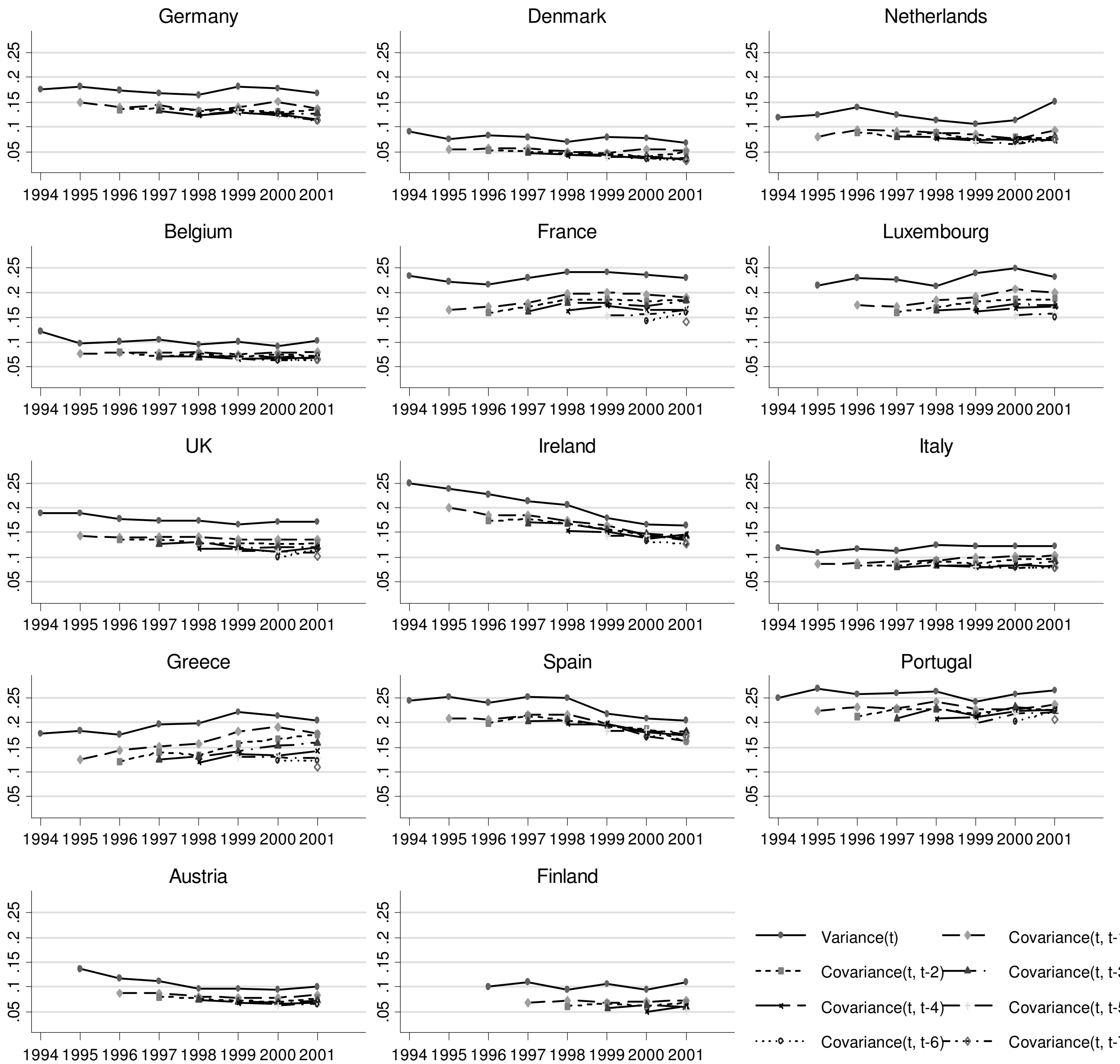

Figure 1. Overall Autocovariance Structure of Hourly Earnings: Years 1994-2001

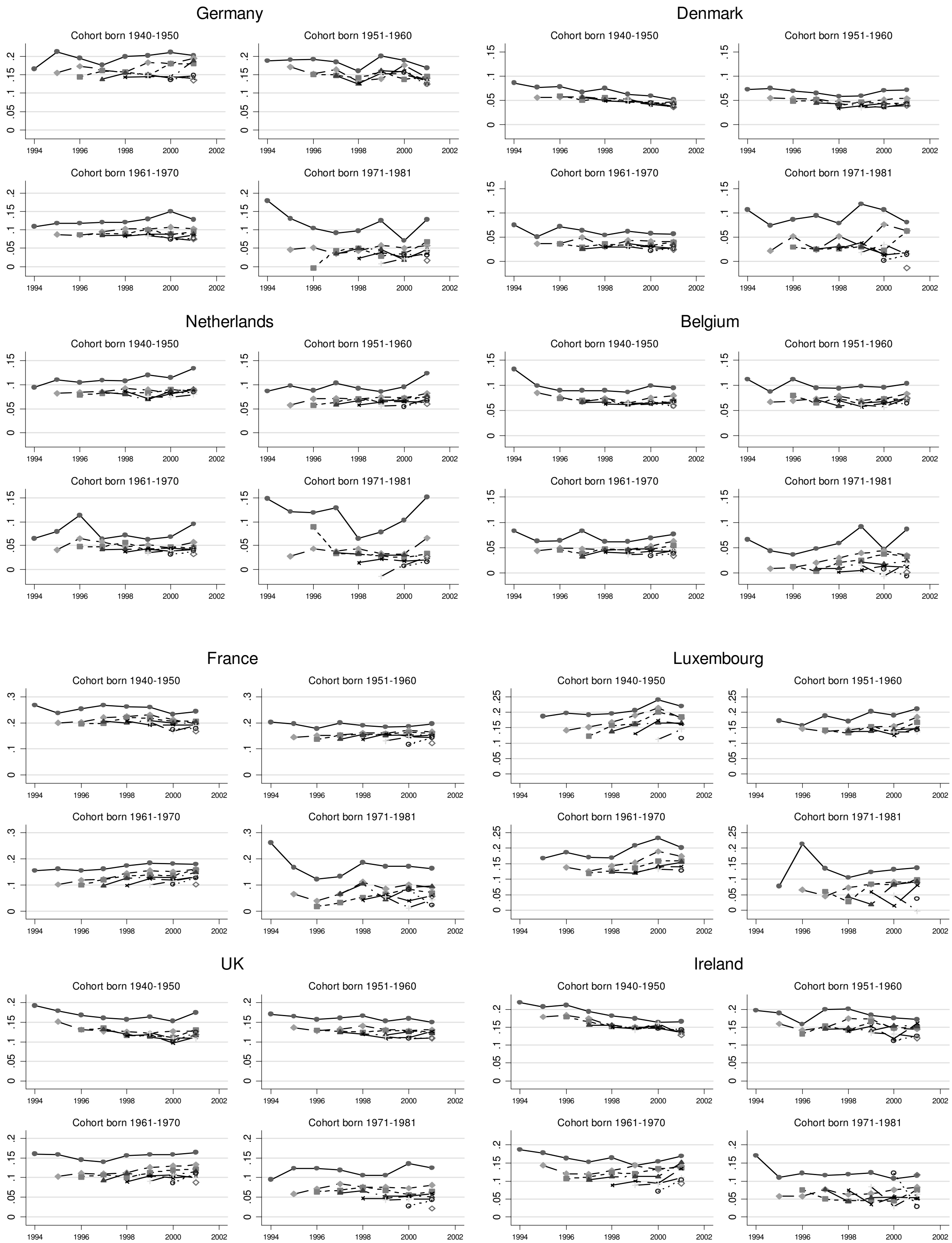

Figure 2. Autocovariance Structure of Hourly Earnings for Selected Cohorts: years 1994-2001

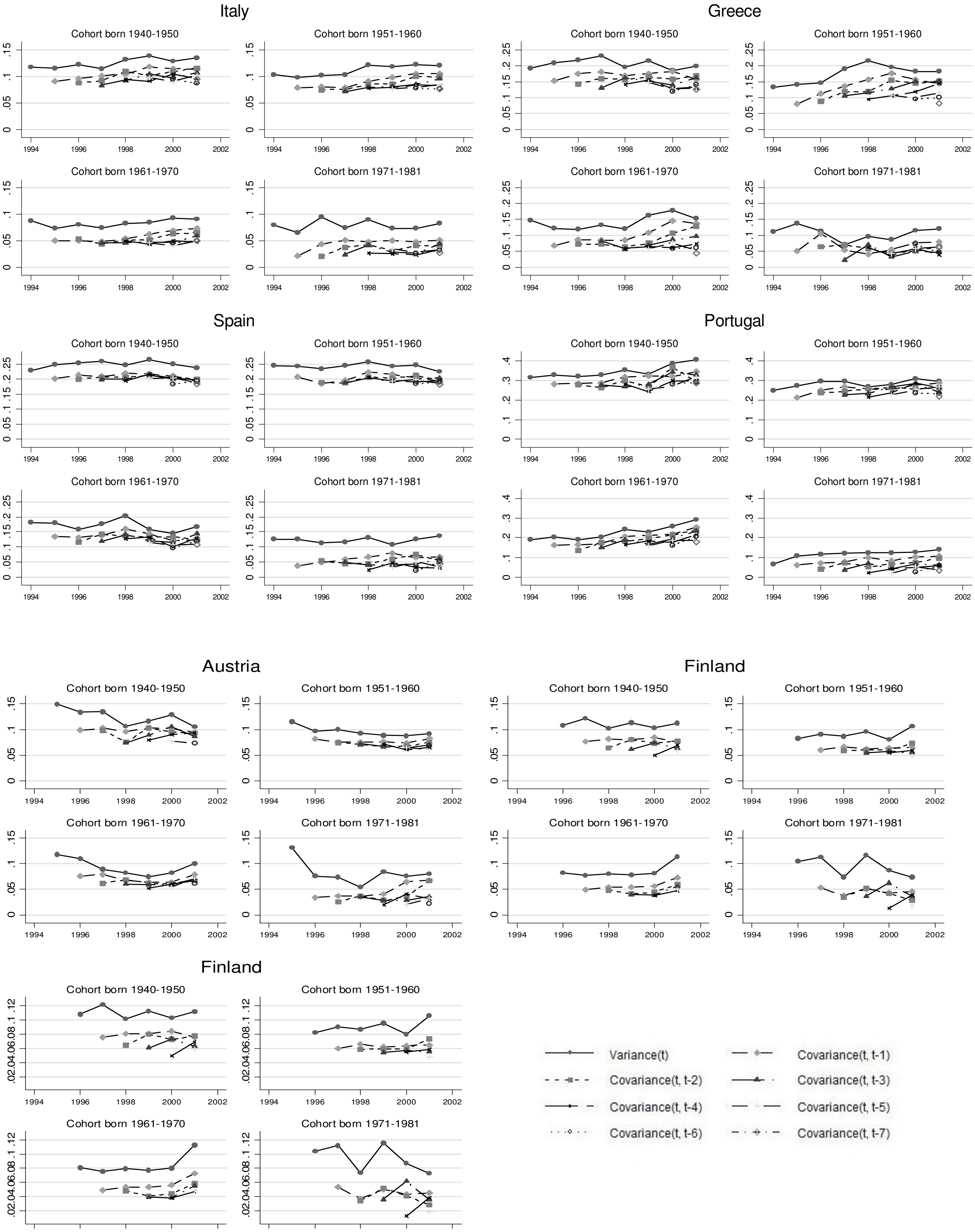

Figure 2. Autocovariance Structure of Hourly Earnings for Selected Cohorts: years 1994-2001 *(continued)*

Table 3. Error-Components Models for Log Real Hourly Earnings

	Germany RG+AR1		Denmark RW+AR1		Netherlands RG+AR1		Belgium PI+AR1		France PI+AR1		Luxembourg PI+AR1		UK RG+AR1	
	Param.	SE	Param.	SE	Param.	SE	Param.	SE	Param.	SE	Param.	SE	Param.	SE
Permanent Component														
$\exp(estimate) = \sigma_{\mu}^{2}$	7.2609	0.0867	0.0097	0.5891	0.1913	0.0905	0.0698	0.0246	0.1653	0.0293	0.1071	0.0251	0.0467	0.2467
$\exp(estimate) = \sigma_{\varphi}^{2}$	0.0024	0.0968			0.0002	0.0797							0.0001	0.1032
$\mathrm{cov}(\mu, \varphi)$	-0.1313	0.0121			-0.0052	0.0005							-0.0022	0.0004
$\exp(estimate) = \sigma_{\pi}^{2}$			0.0014	0.1494										
Time shifters, $\lambda_{1,1994} = 1$														
$\lambda_{1,1995}$	1.0734	0.0084	1.0185	0.0210	0.9735	0.0158	0.9421	0.0116	1.0511	0.0129	1		0.9915	0.0082
$\lambda_{1,1996}$	1.1503	0.0112	0.9910	0.0209	0.9748	0.0172	1.0041	0.0122	1.1058	0.0130	1.0215	0.0220	0.9070	0.0103
$\lambda_{1,1997}$	1.2028	0.0142	0.9011	0.0231	0.9334	0.0159	0.9225	0.0145	1.1338	0.0144	1.1810	0.0208	0.9228	0.0126
$\lambda_{1,1998}$	1.2720	0.0215	0.9022	0.0256	0.9876	0.0169	0.8915	0.0160	1.1295	0.0173	1.2493	0.0222	0.8936	0.0146
$\lambda_{1,1999}$	1.4078	0.0188	0.7953	0.0257	0.8963	0.0184	0.7853	0.0162	1.1257	0.0181	1.3205	0.0248	0.8571	0.0154
$\lambda_{1,2000}$	1.5155	0.0222	0.7431	0.0287	0.8749	0.0193	0.9245	0.0170	1.0581	0.0188	1.3425	0.0314	0.7802	0.0163
$\lambda_{1,2001}$	1.4744	0.0280	0.7643	0.0264	0.9096	0.0208	0.9207	0.0156	1.0842	0.0186	1.2977	0.0222	0.7982	0.0175
Cohort shifters, $\gamma_{1,40-50} = 1$														
$\gamma_{1,51-60}$	0.4401	0.0145	1.0630	0.0306	1.2748	0.0424	1.0127	0.0138	0.8589	0.0139	0.9557	0.0189	1.4131	0.0301
$\gamma_{1,61-70}$	0.2031	0.0088	1.0950	0.0704	1.3168	0.1144	0.7776	0.0105	0.7796	0.0131	0.9396	0.0183	2.0459	0.0992
$\gamma_{1,71-80}$	0.0856	0.0046	0.9890	0.1467	0.7891	0.0704	0.1425	0.0387	0.5000	0.0178	0.5933	0.0183	2.4514	0.2435
Transitory Component														
$\exp(estimate) = \sigma_{\varepsilon}^{2}$	0.2578	0.5741	0.1315	0.2626	0.1262	0.3096	0.2439	0.1523	0.7969	0.5779	0.0186	0.1671	0.0702	0.1110
$\exp(estimate) = \sigma_{0}^{2}$														

$\exp(estimate)=\sigma^2_{0,40-50}$	0.0044	0.7316	0.0368	0.0732	0.0228	0.0913	0.0639	0.0437	0.1039	0.0491	0.0753	0.0638	0.0764	0.0437
$\exp(estimate)=\sigma^2_{0,51-60}$	0.0562	0.0887	0.0255	0.0810	0.0271	0.1208	0.0357	0.0663	0.0913	0.0902	0.1064	0.1109	0.0789	0.0605
$\exp(estimate)=\sigma^2_{0,61-70}$	0.0419	0.0940	0.0349	0.0725	0.0112	0.2073	0.0392	0.0535	0.0486	0.0843	0.0672	0.1136	0.0750	0.0681
$\exp(estimate)=\sigma^2_{0,71-80}$	0.0832	0.0679	0.0284	0.0705	0.0406	0.0962	0.0347	0.0596	0.0956	0.0966	0.0225	0.1220	0.0313	0.1179
ρ	0.3583	0.0223	0.5472	0.0732	0.3289	0.0118	0.6280	0.0104	0.3993	0.0254	0.2389	0.0161	0.4512	0.0125
θ														
Time shifters, $\lambda_{2,1994}=1$														
$\lambda_{2,1995}$	0.4531	0.1298	0.3697	0.0502	0.4936	0.0756	0.2941	0.0226	0.2517	0.0739	1		0.8214	0.0418
$\lambda_{2,1996}$	0.3801	0.1088	0.3548	0.0508	0.4839	0.0771	0.2396	0.0181	0.1703	0.0504	1.9774	0.1487	0.8135	0.0475
$\lambda_{2,1997}$	0.3480	0.1008	0.3531	0.0483	0.4839	0.0756	0.2677	0.0202	0.1963	0.0572	1.4402	0.1377	0.7179	0.0406
$\lambda_{2,1998}$	0.3511	0.1013	0.3077	0.0409	0.3287	0.0505	0.2784	0.0209	0.2373	0.0676	1.0818	0.0915	0.7025	0.0359
$\lambda_{2,1999}$	0.3886	0.1121	0.4086	0.0543	0.3875	0.0605	0.3371	0.0255	0.2284	0.0650	1.2422	0.1019	0.7140	0.0377
$\lambda_{2,2000}$	0.2918	0.0841	0.3980	0.0538	0.4541	0.0710	0.2704	0.0201	0.2432	0.0696	1.3644	0.1127	0.8482	0.0482
$\lambda_{2,2001}$	0.3957	0.1147	0.3595	0.0484	0.5629	0.0877	0.3255	0.0257	0.2346	0.0675	1.4003	0.1195	0.7977	0.0453
Cohort shifters, $\gamma_{2,40-50}=1$														
$\gamma_{2,51-60}$	0.9547	0.0299	1.1521	0.0265	1.0459	0.0294	1.0555	0.0189	0.9383	0.0293	0.8573	0.0355	0.8949	0.0171
$\gamma_{2,61-70}$	0.9643	0.0268	1.2128	0.0205	1.1180	0.0313	0.9996	0.0140	1.0469	0.0303	1.0445	0.0429	0.9938	0.0182
$\gamma_{2,71-80}$	1.3832	0.0411	1.8237	0.0325	1.7278	0.0464	1.3569	0.0233	1.5123	0.0465	1.4318	0.0595	1.1898	0.0224
SSR	0.0143		0.0068		0.0099		0.0047		0.0240		0.0222		0.0061	
χ^2	2473.7073		5872.5492		2492.7787		17769.4220		1756.3574		1632.2320		2597.3157	
LogL	459.2576		512.8864		486.0084		540.0406		421.9693		318.4753		520.5053	

Table 3. Error-Components Models for Log Real Hourly Earnings *(continued)*

	Ireland RG+AR1		Italy RG+ARMA(1,1)		Greece RG+ARMA(1,1)		Spain RG+ ARMA(1,1) $\sigma_0^2 = \sigma_{0,cohort}^2$		Portugal PI+AR1, $\sigma_0^2 = \sigma_{0,cohort}^2$		Austria PI+AR1, $\sigma_0^2 = \sigma_{0,cohort}^2$		Finland RG+AR1	
	Param.	SE	Param.	Param.	Param.	SE	Param.	SE	Param.	SE	Param.	SE	Param.	SE
Permanent Component														
$\exp(estimate) = \sigma_\mu^2$	0.0564	0.3502	0.0325	0.0325	0.0779	0.0915	0.294	0.059	0.2561	0.0303	0.0811	0.0449	0.0616	0.2703
$\exp(estimate) = \sigma_\varphi^2$	0.0002	0.1435	0.00008	0.00008	0.0002	0.0582	0.000	0.000					0.0001	0.1399
$\mathrm{cov}(\mu, \varphi)$	-0.0029	0.0007	-0.0014	-0.0014	- 0.0034	0.0003	-0.006	0.001					- 0.0023	0.0005
Time shifters, $\lambda_{1,1994} = 1$														
$\lambda_{1,1995}$	0.9784	0.0114	0.9529	0.0112	1.0205	0.0145	1.010	0.012	0.9767	0.0119	1			
$\lambda_{1,1996}$	0.9230	0.0126	0.9548	0.0184	0.9970	0.0194	0.973	0.017	1.0414	0.0124	1.0112	0.0244	1	
$\lambda_{1,1997}$	0.9602	0.0167	0.9085	0.0212	1.0386	0.0229	0.972	0.022	1.0176	0.0140	1.0570	0.0287	1.1265	0.0193
$\lambda_{1,1998}$	0.9141	0.0185	0.9868	0.0267	1.0104	0.0239	0.976	0.027	1.0187	0.0157	0.9843	0.0291	1.0778	0.0232
$\lambda_{1,1999}$	0.8559	0.0193	0.9983	0.0292	1.0606	0.0238	0.959	0.032	0.9875	0.0171	0.9081	0.0379	1.0173	0.0274
$\lambda_{1,2000}$	0.7928	0.0215	0.9704	0.0307	0.9236	0.0227	0.898	0.036	1.0925	0.0194	0.9403	0.0391	0.9554	0.0266
$\lambda_{1,2001}$	0.7770	0.0249	0.9476	0.0335	0.9267	0.0207	0.867	0.040	1.0758	0.0199	0.9425	0.0384	1.0297	0.0309
Cohort shifters, $\gamma_{1,40-50} = 1$														
$\gamma_{1,51-60}$	1.3594	0.0443	1.2272	0.0463	1.3261	0.0233	1.162	0.074	0.9340	0.0178	0.8921	0.0198	1.3819	0.0485
$\gamma_{1,61-70}$	2.0128	0.1621	1.3857	0.1189	1.9371	0.0811	0.988	0.120	0.7691	0.0162	0.8354	0.0262	2.4403	0.1705
$\gamma_{1,71-80}$	2.9811	0.4996	1.5606	0.2008	3.9268	0.4940	0.475	0.078	0.3140	0.0203	0.4591	0.0293	2.9792	0.7975
Transitory Component														
$\exp(parameter) = \sigma_\varepsilon^2$	0.0285	0.1649	0.0582	0.0758	0.1183	0.0750	0.099	0.006	0.2584	0.2067	0.4830	0.1811	0.0555	0.2197
$\exp(estimate) = \sigma_0^2$							0.052	0.004	0.0428	0.0974	0.0751	0.0652		

$\exp(estimate)=\sigma^2_{0,40-50}$	0.0709	0.0825	0.0314	0.0898	0.0791	0.0516							0.0550	0.0743
$\exp(estimate)=\sigma^2_{0,51-60}$	0.0688	0.0966	0.0422	0.0619	0.0574	0.0702							0.0588	0.0701
$\exp(estimate)=\sigma^2_{0,61-70}$	0.0942	0.0869	0.0521	0.0592	0.1011	0.0436							0.0707	0.0727
$\exp(estimate)=\sigma^2_{0,71-80}$	0.0801	0.1015	0.0283	0.0919	0.0695	0.1269							0.0464	0.1098
ρ	0.2912	0.0229	0.6438	0.0428	0.5995	0.0346	0.849	0.024	0.7785	0.0149	0.7009	0.0292	0.2904	0.0195
θ			-0.2506	0.0204	-0.1487	0.0242	-0.364	0.007						
Time loading factors, $\lambda_{2,1994}=1$														
$\lambda_{2,1995}$	1.2269	0.0938	0.7692	0.0239	0.7991	0.0261	0.907	0.027	0.5061	0.0525	1			
$\lambda_{2,1996}$	1.2789	0.1050	0.8238	0.0294	0.6992	0.0277	0.815	0.024	0.3117	0.0367	0.2929	0.0291	1	
$\lambda_{2,1997}$	1.0434	0.0818	0.7296	0.0241	0.6171	0.0280	0.842	0.024	0.3536	0.0383	0.2089	0.0224	0.8849	0.0977
$\lambda_{2,1998}$	1.0924	0.0853	0.7536	0.0264	0.6269	0.0275	0.887	0.023	0.3723	0.0397	0.1724	0.0196	0.7069	0.0809
$\lambda_{2,1999}$	1.0595	0.0821	0.6516	0.0242	0.6106	0.0256	0.760	0.021	0.3555	0.0371	0.2270	0.0223	0.9301	0.0957
$\lambda_{2,2000}$	1.0816	0.0876	0.6656	0.0225	0.7195	0.0287	0.821	0.022	0.3484	0.0362	0.2203	0.0220	0.8191	0.0861
$\lambda_{2,2001}$	1.1093	0.0968	0.6998	0.0234	0.6657	0.0287	0.856	0.023	0.3921	0.0400	0.2248	0.0229	0.7937	0.0852
Cohort specific factors, $\gamma_{2,40-50}=1$														
$\gamma_{2,51-60}$	0.9889	0.0352	0.9894	0.0204	0.9608	0.0179	1.004	0.025	0.7800	0.0383	0.8410	0.0254	0.8609	0.0253
$\gamma_{2,61-70}$	1.0987	0.0403	1.0324	0.0217	1.0187	0.0183	1.051	0.025	1.0102	0.0399	0.8986	0.0280	0.8714	0.0252
$\gamma_{2,71-80}$	1.1532	0.0458	1.3299	0.0278	0.9443	0.0256	1.330	0.030	1.1072	0.0409	1.1979	0.0416	1.2070	0.0349
SSR	0.0273		0.0017		0.0146		0.0094		0.0288		0.0052		0.0038	
χ^2	2116.2117		1576.2281		3824.4496		1984.9587		3737.5070		2229.2852		945.1045	
LogL	412.7881		611.7874		458.0054		489.8478		408.9498		399.6179		300.6177	

Table 4. Alternative Model Specifications

	Alternative Model	SSR	Chi2	LogL	Parameters
Germany	PI+AR1	.0171	3333.3328	446.4264	27
	PI+AR1, $\sigma_0^2 = \sigma_{0,cohort}^2$	0.0168	2598.8668	447.7299	26
	Canonical Model	0.3314	43238.681	233.051	2
Denmark	PI+AR1	0.0069	5825.6657	511.8177	27
	RW+AR1, $\sigma_0^2 = \sigma_{0,cohort}^2$	0.0069	6308.8755	511.6101	25
	Canonical model	0.0273	29378.035	412.7862	2
Netherlands	PI+AR1	.0104	2671.5118	482.3131	27
	RG+AR, $\sigma_0^2 = \sigma_{0,cohort}^2$	.0107	2700.0947	480.0743	26
	Canonical model	0.0769	24373.43	338.163	2
Belgium	PI+AR1, $\sigma_0^2 = \sigma_{0,cohort}^2$	0.005	18832.583	533.4292	24
	Canonical model	0.0751	46706.478	339.8958	2
France	PI+AR1, $\sigma_0^2 = \sigma_{0,cohort}^2$	0.0255	1817.4386	417.7385	24
	Canonical model	0.3668	8599.1199	225.739	2
Luxembourg	PI+AR1, $\sigma_0^2 = \sigma_{0,cohort}^2$	0.026	1900.723	309.4077	22
	PI+ARMA(1,1)	0.0222	1633.305	318.5007	26
	Canonical model	0.2064	35231.176	193.6939	2
UK	PI+AR1	0.0072	2782.613	508.905	27
	Canonical model	0.1062	12248.666	314.9804	2
Ireland	PI+AR1	0.0323	2125.021	400.506	27
	RG+AR1, $\sigma_0^2 = \sigma_{0,cohort}^2$	0.0276	2324.4346	412.13	26
	Canonical model	0.2028	24662.992	268.4008	2
Italy	PI+ARMA(1,1)	0.002	1641.5036	598.0915	28
	RG+ARMA(1,1), $\sigma_0^2 = \sigma_{0,cohort}^2$	0.002	1646.3788	598.1981	27
	RG+AR1	0.002	1899.3595	600.8606	29
	Canonical model	0.097	12434.997	12434.997	2
Greece	RG+ARMA(1,1), $\sigma_0^2 = \sigma_{0,cohort}^2$	0.0153	3996.5599	454.4974	27
	RG+AR1	0.0147	3945.6763	457.1551	29
	Canonical model	0.2507	26975.122	253.1378	2
Spain	PI+ARMA(1,1), $\sigma_0^2 = \sigma_{0,cohort}^2$	0.0098	2013.2298	486.3516	25
	RG+AR1, $\sigma_0^2 = \sigma_{0,cohort}^2$	0.0109	2032.9304	478.5467	26
	Canonical model	0.551	11817.977	196.4497	2
Portugal	RW+AR1, $\sigma_0^2 = \sigma_{0,cohort}^2$	0.0273	5456.5912	412.8313	25
	PI+AR1	0.0274	15350.702	412.4226	27
	PI+ARMA(1,1), $\sigma_0^2 = \sigma_{0,cohort}^2$	0.0261	7753.2688	415.9961	25
	Canonical model	1.208	38920.003	139.9288	2
Austria	PI+AR1	0.0049	2382.0622	402.5245	25
	Simple model	0.0539	15059.202	268.8687	2
Finland	PI+AR1	0.0049	1044.3253	290.5622	23
	RG+AR1, $\sigma_0^2 = \sigma_{0,cohort}^2$	0.0039	947.6261	298.9057	22
	Canonical model	0.0197	6678.3651	231.7795	2

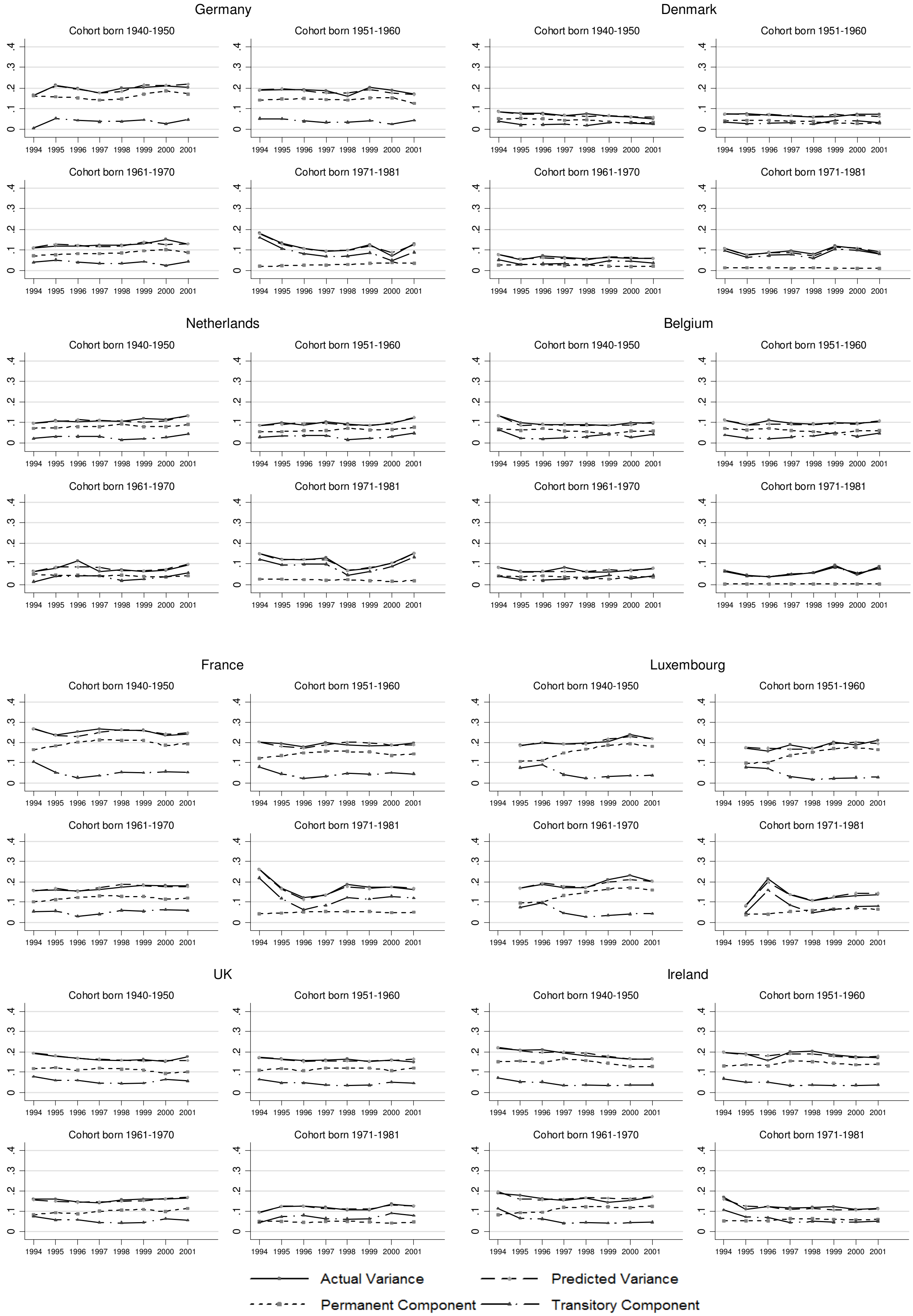

Figure 3. Actual and Predicted Variance of Earnings with Permanent and Transitory Predicted Components for Selected Cohorts: 1994-2001

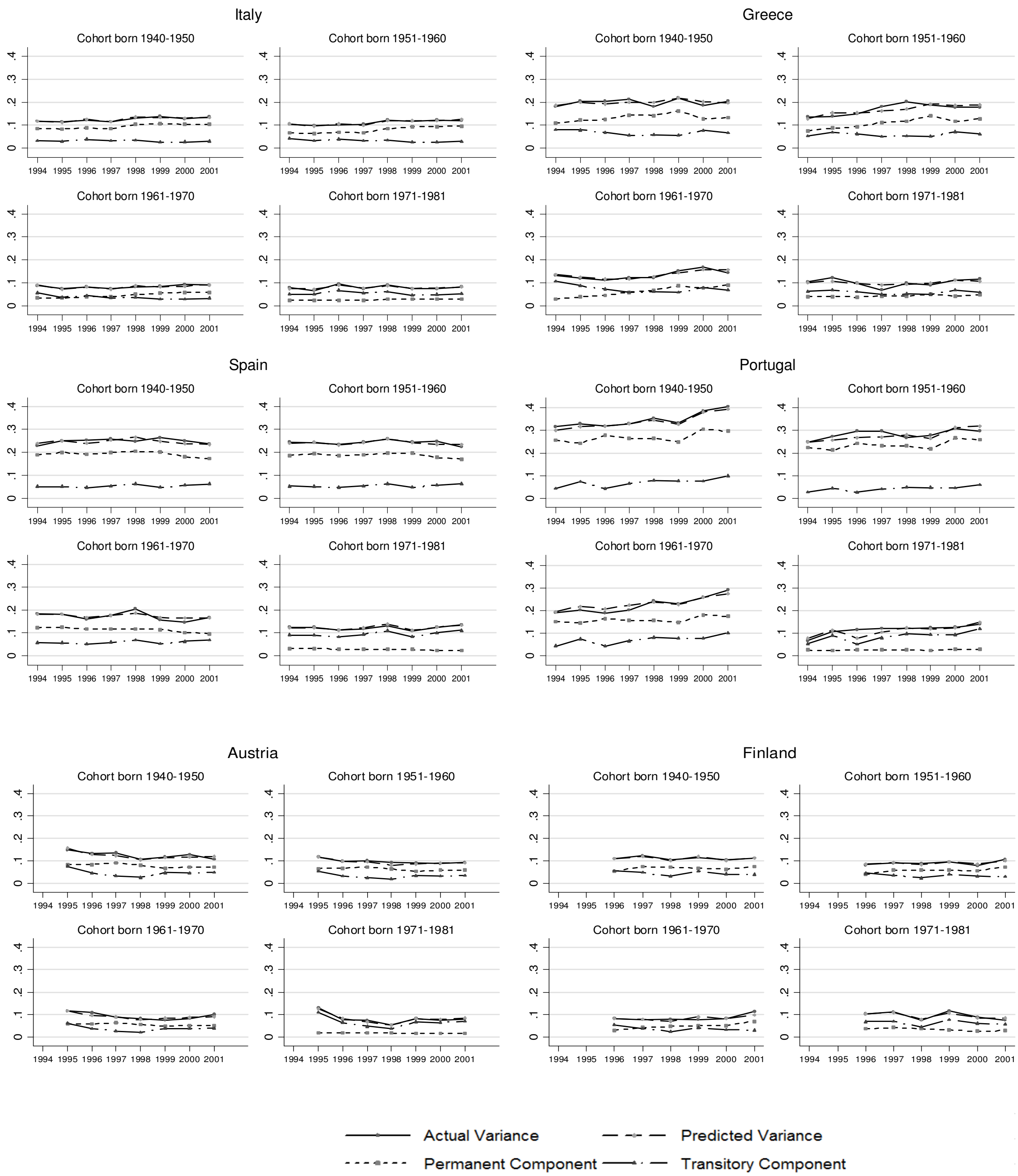

Figure 3. Actual and Predicted Variance of Earnings with Permanent and Transitory Predicted Components for Selected Cohorts: 1994-2001 *(continued)*

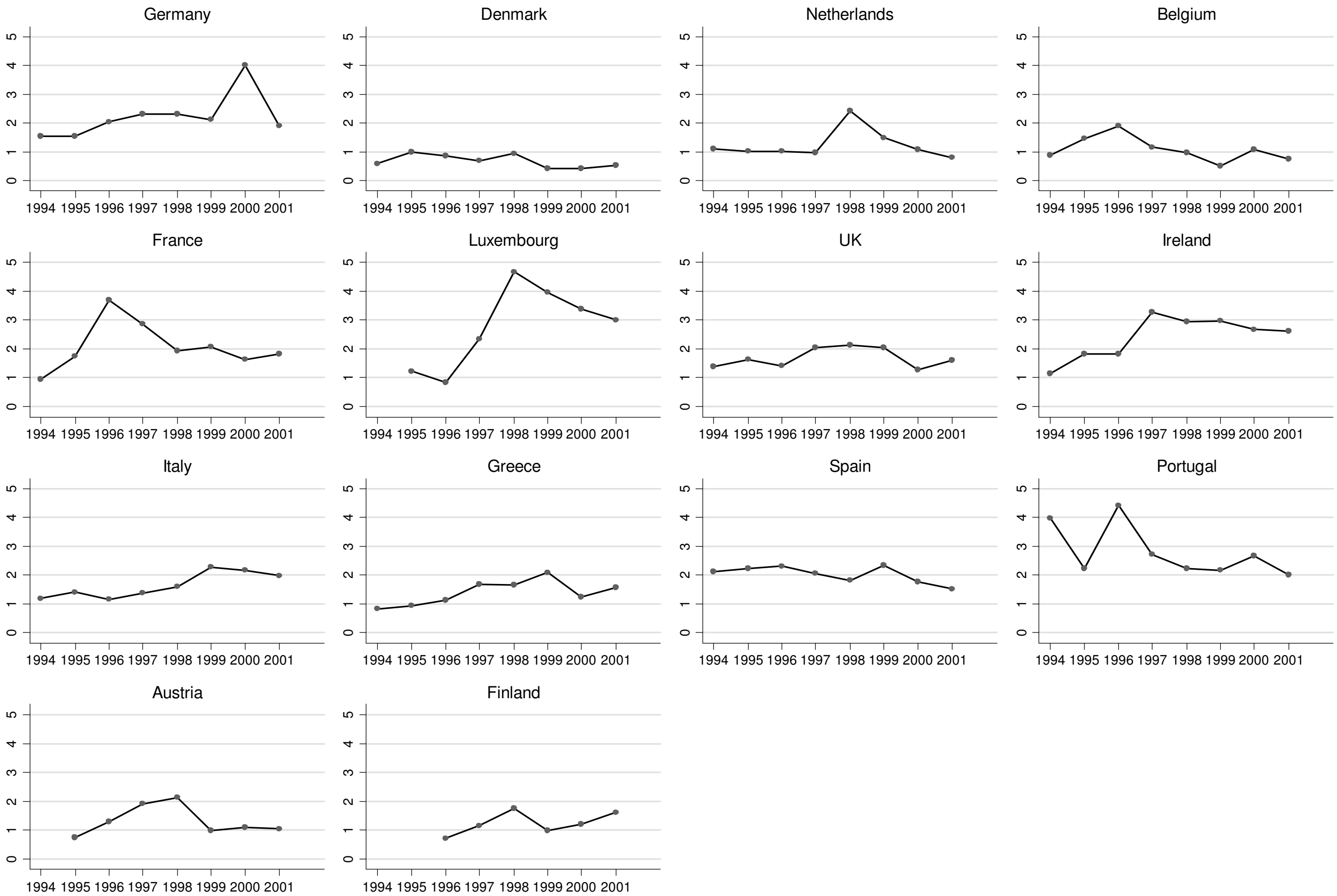

Figure 4. Ratio Between Permanent Variance and Transitory Variance Over Time For Selected Cohorts

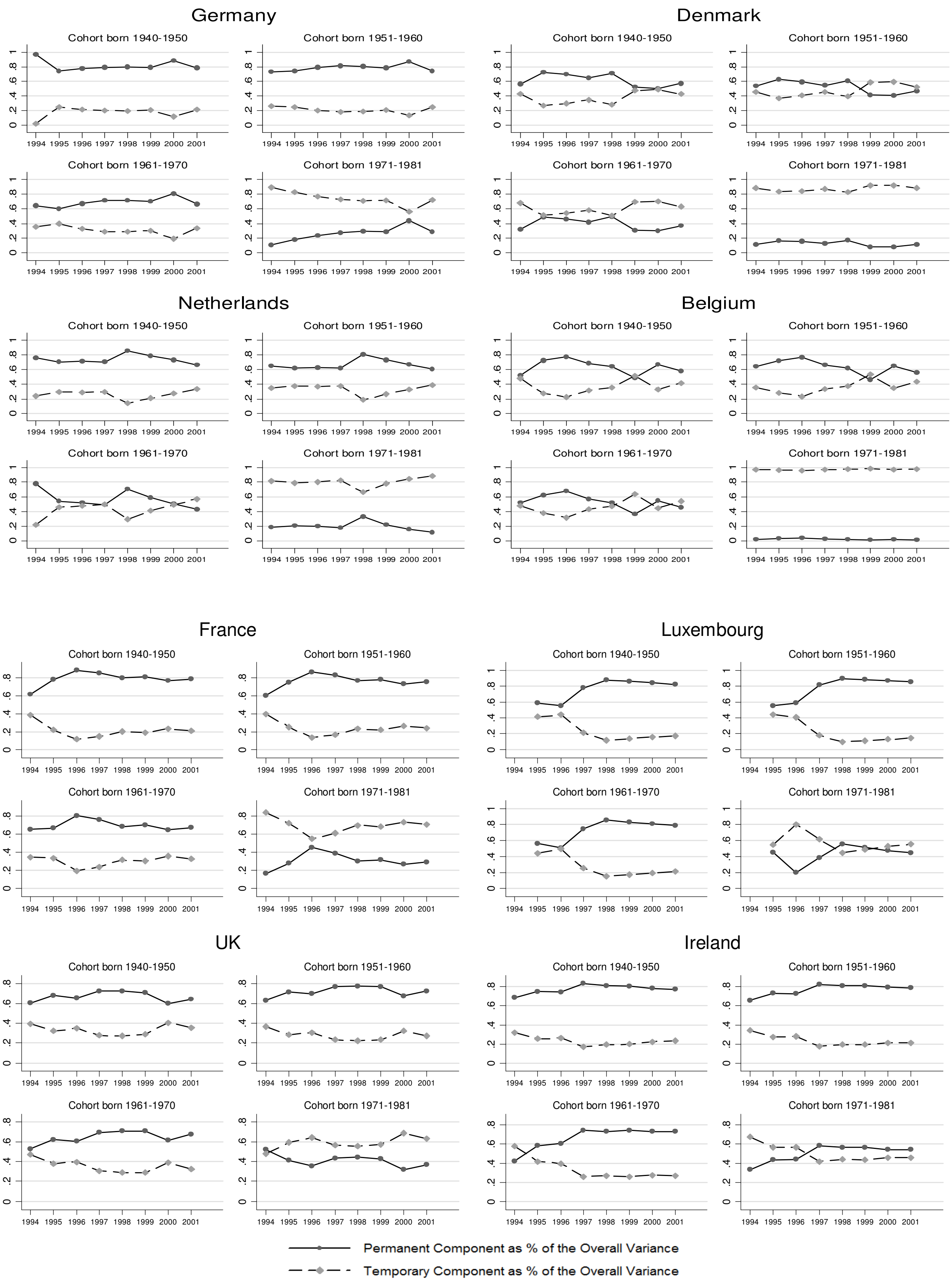

Figure 5. Predicted Permanent and Transitory Variance as % of Predicted Overall Variance for Selected Cohorts: 1994-2001

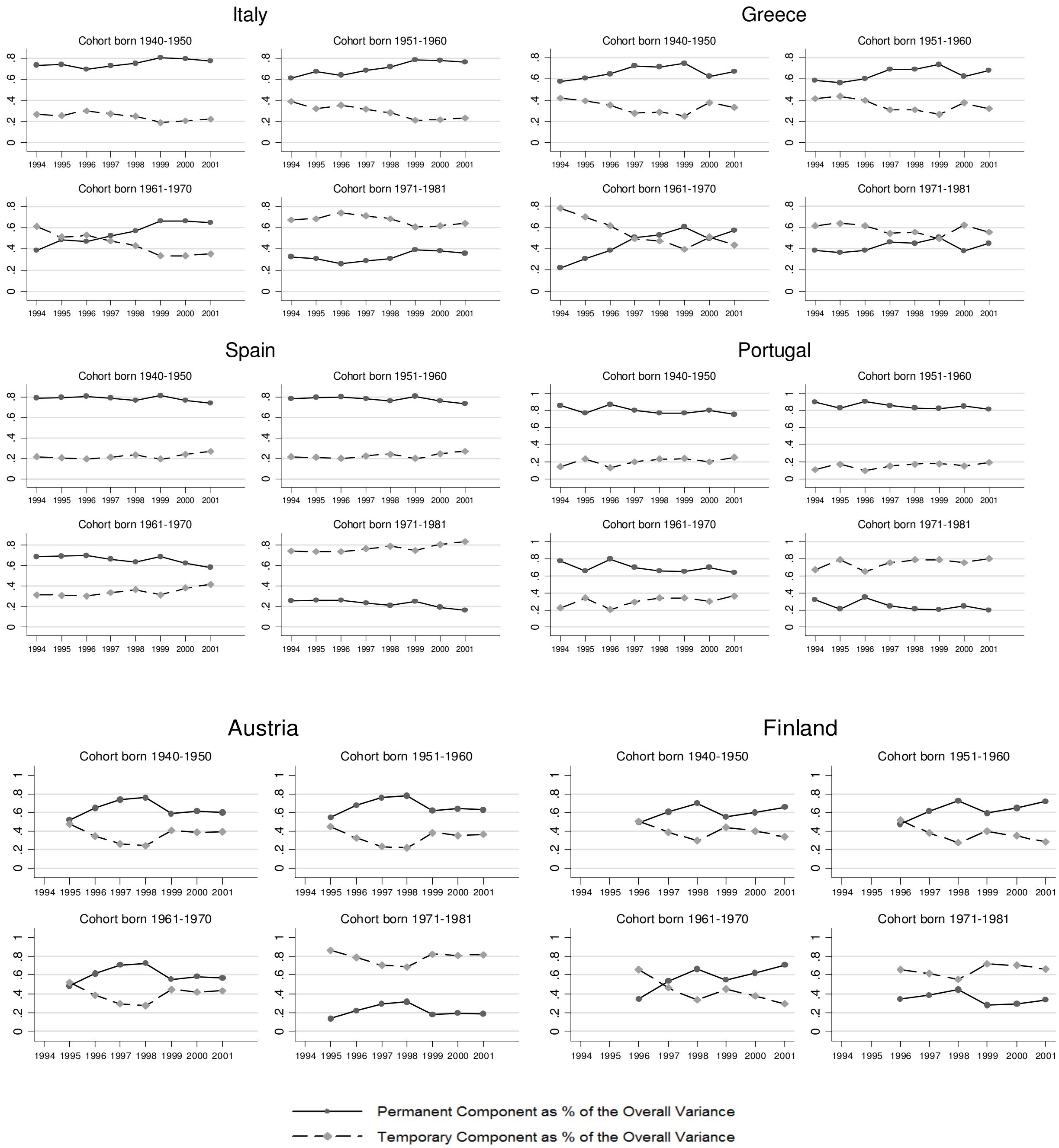

Figure 5. Predicted Permanent and Transitory Components of Earnings as % of Predicted Overall Variance for Selected Cohorts: 1994-2001 *(continued)*

11. ANNEX

11.1. The Specification of the covariance structure of earnings

The covariance structure for the first sample period takes the form:

$$\begin{aligned}
&Var(Y_{ic0}) = E(r_{ic0}r_{ic0}) = \\
&= E[\gamma_{1c}^2\lambda_{10}^2(\mu_i + \varphi_i age_{i0} + u_{ia})^2] + E(\gamma_{2c}^2\lambda_{20}^2 v_{i0}v_{i0}) = \\
&= \gamma_{1c}^2\lambda_{1,0}^2 E(\mu_i^2 + \varphi_i^2 age_{i0}^2 + 2\mu_i\varphi_i age_{i0} + u_{ia}^2) + \gamma_{2c}^2\lambda_{2,0}^2 Var(v_{i0}) = \\
&= \sigma_\mu^2 + \sigma_\varphi^2 E(age_{i0}^2) + 2\operatorname{cov}(\mu_i\varphi_i)E(age_{i0}) + (a-20)\sigma_\pi^2 + Var(v_{i0}) \;\; if\; t=0
\end{aligned} \tag{18}$$

The covariance structure implied by the model introduced in the previous section takes the following form. The variance of the process can be expressed as follows:

$$\begin{aligned}
&Var(Y_{ict}) = E(r_{ict}r_{ict}) = \\
&= E[\gamma_{1c}^2\lambda_{1t}^2(\mu_i + \varphi_i age_{it} + u_{iat})^2] + E(\gamma_{2c}^2\lambda_{2t}^2 v_{it}v_{it}) = \\
&= \gamma_{1c}^2\lambda_{1t}^2 E(\mu_i^2 + \varphi_i^2 age_{it}^2 + 2\mu_i\varphi_i age_{it} + u_{iat}^2) + \gamma_{2c}^2\lambda_{2t}^2 Var(v_{it}) = \\
&= \gamma_{1c}^2\lambda_{1t}^2[\sigma_\mu^2 + \sigma_\varphi^2 E(age_{it}^2) + 2\operatorname{cov}(\mu_i\varphi_i)E(age_{it}) + \sigma_\pi^2(a-20)] + \gamma_{2c}^2\lambda_{2t}^2 E[(\rho v_{it-1} + \varepsilon_{it} + \theta\varepsilon_{it-1})^2] = \\
&= \gamma_{1c}^2\lambda_{1t}^2[\sigma_\mu^2 + \sigma_\varphi^2 E(age_{it}^2) + 2\operatorname{cov}(\mu_i\varphi_i)E(age_{it}) + \sigma_\pi^2(a-20)] + \\
&+ \gamma_{2c}^2\lambda_{2t}^2[\rho^2 Var(v_{it-1}) + \sigma_\varepsilon^2(1 + 2\rho\theta + \theta^2)] \;\; if\; t>0
\end{aligned} \tag{19}$$

Where
$$\begin{aligned}
&Var(\mu_{i,20,t-(a-20)}) = \sigma_{\mu_{20}}^2 \\
&Var(\mu_{iat}) = Var(\mu_{i,a-1,t-1}) + \sigma_\pi^2 = Var(\mu_{i,20,t-(a-20)}) + (a-20)\sigma_\pi^2
\end{aligned} \tag{20}$$

$\sigma_{\mu_{20}}^2$ is estimated as part of σ_μ^2.

$$\begin{aligned}
&Cov(Y_{ict}Y_{ict-s}) = E(r_{ict}r_{ict-s}) = \\
&= E[\gamma_{1c}^2\lambda_{1t}\lambda_{1t-s}(\mu_i + \varphi_i age_{it} + u_{iat})(\mu_i + \varphi_i age_{it-s} + u_{i,a-s,t-s})] + E(\gamma_{2c}^2\lambda_{2t}\lambda_{2t-s} v_{it}v_{it-s}) = \\
&= \gamma_{1c}^2\lambda_{1t}\lambda_{1t-s} E[\mu_i^2 + \varphi_i^2 age_{it}age_{it-s} + \mu_i\varphi_i(age_{it} + age_{it-s}) + u_{iat}u_{i,a-s,t-s}] + \gamma_{2c}^2\lambda_{2t}\lambda_{2t-s} Cov(v_{it}v_{it-s}) = \\
&= \gamma_{1c}^2\lambda_{1t}\lambda_{1t-s}\{\sigma_\mu^2 + \sigma_\varphi^2 E(age_{it})E(age_{it-s}) + \operatorname{cov}(\mu_i\varphi_i)[E(age_{it}) + E(age_{it-s})] + \sigma_\pi^2(a-s-20)\} + \\
&+ \gamma_{2c}^2\lambda_{2t}\lambda_{2t-s} E[(\rho v_{it-1} + \varepsilon_{it} + \theta\varepsilon_{it-1})v_{it-s}] = \\
&= \gamma_{1c}^2\lambda_{1t}^2\{\sigma_\mu^2 + \sigma_\varphi^2 E(age_{it})E(age_{it-s}) + \operatorname{cov}(\mu_i\varphi_i)[E(age_{it}) + E(age_{it-s})] + \sigma_\pi^2(a-s-20)\} + \\
&+ \gamma_{2c}^2\lambda_{2t}\lambda_{2t-s}[\rho Cov(v_{it-1}, v_{it-s})] \;\; if\; t>0 \;\;\&\;\; s>1
\end{aligned} \tag{21}$$

$$
\begin{aligned}
&Cov(\mu_{iat},\mu_{i,a-s,t-s}) = Cov(\mu_{i,a-1,t-1},\mu_{i,a-s-1,t-s-1}) + \sigma_\pi^2 = \\
&= Cov(\mu_{i,a-(a-s-20),t-(a-s-20)},\mu_{i,20,t-(a-20)}) + (a-s-20)\sigma_\pi^2 = \\
&= \sigma_{\mu_{20}}^2 + (a-s-20)\sigma_\pi^2
\end{aligned}
\qquad (22)
$$

Where

$$
Cov(\mu_{iat},\mu_{i,20,t-(a-20)}) = \sigma_{\mu_{20}}^2
$$

$$
\begin{aligned}
&Cov(Y_{ict}Y_{ict-1}) = E(r_{ict}r_{ict-1}) = \\
&= E[\gamma_{1c}^2\lambda_{1t}\lambda_{1t-1}(\mu_i+\varphi_i age_{it}+u_{ia})(\mu_i+\varphi_i age_{it-1}+u_{ia-1})] + E(\gamma_{2c}^2\lambda_{2t}\lambda_{2t-1}v_{it}v_{it-1}) = \\
&= \gamma_{1c}^2\lambda_{1t}^2\{\sigma_\mu^2+\sigma_\varphi^2 E(age_{it})E(age_{it-1}) + \operatorname{cov}(\mu_i\varphi_i)[E(age_{it})+E(age_{it-1})] + \sigma_\pi^2(a-1-20)\} \\
&+\gamma_{2c}^2\lambda_{2t}\lambda_{2t-1}\{\rho Var(v_{it-1})+\theta\sigma_\varepsilon^2)\}\ \ if\ t>0\ \ \&\ \ s=1
\end{aligned}
\qquad (23)
$$

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Contents

1. Introduction 1
2. Literature Review 2
3. Theoretical Model of the determinants of wage differentials 5
   3.1. Determinants of earnings inequality 5
   3.2. Earnings Mobility 10
4. Data 11
5. Econometric specification and Estimation method of covariance structures 12
   5.1. Econometric Earnings Specification 13
   5.2. Specification of the Covariance Structure of Earnings 15
   5.3. Estimation of Covariance Structures 16
   5.4. Strategy for model specification 19
6. The dynamic autocovariance structure of hourly earnings 21
7. Results of Covariance Structure Estimation 24
   7.1. Error component model estimation results 24
8. Inequality Decomposition into Permanent and Transitory Inequality 30
   8.1. Absolute Decomposition 30
   8.2. Relative decomposition 32
9. Concluding remarks 35
10. Tables and Figures 37
11. Annex 52
    11.1. The Specification of the covariance structure of earnings 52
12. References 54

Figures

Figure 1. Overall Autocovariance Structure of Hourly Earnings: Years 1994-2001 39
Figure 2. Autocovariance Structure of Hourly Earnings for Selected Cohorts: years 1994-2001 40
Figure 3. Actual and Predicted Variance of Earnings with Permanent and Transitory Predicted Components for Selected Cohorts: 1994-2001 47
Figure 4. Ratio Between Permanent Variance and Transitory Variance Over Time For Selected Cohorts 49
Figure 5. Predicted Permanent and Transitory Variance as % of Predicted Overall Variance 50

Tables

Table 1. Mean hourly earnings and number of individuals with positive earnings......................37
Table 2. Number and share of individuals present in the sample in year $t-1$ which record positive earnings in year t 38
Table 3. Error-Components Models for Log Real Hourly Earnings 42
Table 4. Alternative Model Specifications 46