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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. Overall, the decrease in inequality resulted from a decrease in transitory differentials in Germany, France, UK and Ireland, in permanent differentials in Belgium and Spain, and in both components in Denmark and Austria. The increase in inequality reflects an increase in permanent differentials in Luxembourg, Italy, Greece and Finland, and an increase in both components in Portugal and Netherlands. The decrease in inequality was accompanied by an increase in mobility only in Denmark, Belgium and Spain. Except for Netherlands and Portugal, all countries recording an increase in inequality experienced also a decrease in mobility.

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 these issues in a comparative manner.

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, 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 and 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 the 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, assumed to be independent of each other. 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.

A rise in permanent inequality is 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, 1958, 1962, 1974; Hause, 1980).

An increase in transitory inequality can 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, both, increase the demand for skills, and 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)

3.2. 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:

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

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:

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

Since 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 permanent earnings inequality. 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 (σ_y^2), as a measure of earnings dispersion, is composed both from a permanent and transitory dispersion ($\sigma_\mu^2 + \sigma_v^2$). The covariances 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} is interpreted as time-varying return to skills or skill price, its increase suggests that the relative labour market advantage of high-skilled 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 the 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 instability.

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 greater dispersion of unobserved labour quality within younger cohorts, resulting from unequal school quality. Some studies rejected the hypothesis that the return to education is the same across cohorts. These differences 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.

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

where $\gamma_{jc},\ j = 1, 2$ 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)

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

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 φ_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 a random walk process in age, 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 of human capital investments or labour market conditions through implicit contacts. In this model, current earnings are a sufficient statistic for future earnings.

Thirdly, previous research found that the transitory component of earnings is 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.

3.3. Earnings Mobility

Another aspect relevant for 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.

Earnings mobility is a very complex phenomenon, and the ways of measuring it are diverse. We look at the degree of immobility, measured by the ratio between permanent and transitory inequality, following Kalwij and Alessie (2003). This measure offers also a summary of the evolution in the structure of inequality: a(n) decrease (increase) in the immobility ratio indicates an increase (decrease) in earnings mobility, equivalent with a(n) decrease (increase) in the relative share of permanent differentials in the overall inequality. This mobility index captures non-directional earnings movements and can be interpreted as the opportunity to improve one’s position in the distribution of lifetime earnings.

An increase in cross-sectional inequality accompanied by a decrease in earnings mobility is expected to have negative implications for long-run or lifetime earnings differentials, as it shows that over time low wage men get worse off both in terms of their relative earnings position and in terms of their opportunity to escape low wage trap. Thus it is reasonable to expect that cross-sectional earnings differentials will be enhanced in a lifetime perspective.

An increase in cross-sectional inequality accompanied by an increase in earnings mobility has uncertain implications for long-run or lifetime earnings differentials. Over time low wage men get worse off in terms of their relative earnings position, but better off in terms of the opportunity to escape low wage trap in a lifetime perspective. Thus earnings mobility could either enhance or decrease lifetime earnings differentials compared with the cross-sectional ones.

A decrease in cross-sectional inequality accompanied by an increase in earnings mobility is expected to have positive implications for lifetime earnings differentials, as over time low wage men better their relative earnings position and their opportunity to escape low wage trap in a lifetime perspective. Thus, lifetime earnings differentials are expected to be reduced compared with annual differentials.

A decrease in cross-sectional inequality accompanied by a decrease in earnings mobility has uncertain implications for lifetime earnings differentials, as over time low wage men get better off in terms of their relative earnings position, but worse off in terms of their opportunity to escape low wage trap in a lifetime perspective. Thus, lifetime earnings differentials could be either reduced or enhanced compared with annual differentials.

It becomes obvious that the question regarding the link between earnings mobility and earnings inequality does not have a straight forward answer and mobility is not always beneficial. It depends on the underlying factors: "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. Dickens (1999) Nonetheless, no controversy surrounds the fact that mobility is beneficial when it helps low paid individuals to improve their income position in the long-term or lifetime income distribution.

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 to avoid the selection bias associated with women's earnings.

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.

We apply the weighting system recommended by Eurostat, namely the "base weights" of the last wave observed for each 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.

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

[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.

Earnings are expressed in real log net 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 (2009a, 2009b). Mean hourly earnings appear to increase in all countries except for Austria where it records a slight decrease.

In general, as illustrated by Table 1, 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

In this section, we 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 permanent and transitory components of earnings over the sample period and their impact on the overall level of earnings inequality.

5.1. Econometric Earnings Specification

In order to differentiate lifecycle dynamics from secular changes in earnings inequality, earnings differentials are explored by cohort. Earnings are de-trended for each cohort. The empirical specification of earnings follows the structure:

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

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} adjust for year, age and cohort effects in a less restrictive way than the preliminary regressions typically used, which assume that age and cohort effects within any year can be approximated by a polynomial in age.(Baker and Solon, 2003) 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}, in a similar manner with time series, following MaCurdy(1981) and MaCurdy (1982). The graphical inspection of the autocovariance structure of earnings, 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;

(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.

Our model incorporates these features. Feature (i) suggests the presence of an AR(1) process, but the presence of feature (iii) calls for a more complex ARMA (1, 1). Feature (ii) is captured by the presence of the permanent component. Feature (iv) 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

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

structure of earnings in feature (v) is captured by modelling the permanent individual component as random walk and/or random growth in age. Cohort heterogeneity (vi) is incorporated by parameters that allow the permanent and transitory components to vary between cohorts.

To avoid choosing a model specification that is inconsistent with the data, we start with a broad class of models for r_{ict} and employ preliminary data analysis procedures to choose among competing specifications. The following general specification encompasses the relevant aspects of earnings dynamics considered above.

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

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

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

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 the individual age-profile heterogeneity, called also a random growth (Moffitt and Gottschalk, 1995; Baker, 1997), where μ_i and φ_i are time invariant individual-specific intercept and slopes with variance σ_μ^2 and σ_φ^2. The parameterization of the permanent component includes also a random walk process in age (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.

The transitory component follows an ARMA(1,1) process (equation (11)), 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} the white-noise mean-reverting transitory shocks. The variances $\sigma_{0,c}^2$ measure 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 captured by 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 by cohort. $\gamma_{jc},\ \ j=1,2$ are cohort loading factor, normalized to 1 for the oldest cohort 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, 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 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 they have experienced different period effects. Therefore such a strong assumption is untenable.

Following MaCurdy (1981, 1982), the cohort initial transitory variances are treated as 4 additional parameters to be estimated. The covariance structure for the first sample period takes the form:

$$
\begin{aligned}
&Var(Y_{ic0}) = \\
&= E(r_{ic0}r_{ic0}) = \sigma_{\mu}^2 + \sigma_{\varphi}^2 E(age_{i0}^2) + 2\operatorname{cov}(\mu_i\varphi_i)E(age_{i0}) + (a_0-20)^2\sigma_{\pi}^2 + Var(v_{i0})\ \ if\ t=0
\end{aligned}
\qquad (12),
$$

where a_0 is the central age of the cohort c in the first wave.

The covariance structure for subsequent years is expressed as follows:

[4] 1994 refers to t=0

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

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

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

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

where a_t is the central age of the cohort c in period t.

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

5.3. Estimation of Covariance Structures

The parameters of the models are fit to the covariance structure for each cohort using equally weighted minimum distance methods of estimation. The methodology is similar with 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:

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

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 $\sum_{c=1}^{4}\frac{t_c(t_c+1)}{2} - p = 144 - p$, $\mathbf{R}^{-1} = (\mathbf{WVW'})^{-1}$ **and** $\mathbf{W} = \mathbf{I} - \mathbf{G}(\mathbf{G'AG})^{-1}\mathbf{G'A}$. 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 the BIC criterion: the smaller the value of BIC, the better the fit.

$$BIC = (SSE \cdot 144^{k/144}) / (144 - k)$$

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.

In the beginning of the sample period, the overall inequality, measured by the variance of log hourly earnings, is the highest in Portugal, followed by Ireland, Spain, France, Luxembourg, UK, Greece, Germany, Austria, Italy, Belgium, Netherlands, Finland and Denmark. Overall inequality decreases over the sample period in Germany, Denmark, Belgium, France, UK, Ireland, Spain and Austria, and increases in Netherlands, Luxembourg, Greece, Portugal and Finland. Following these changes, in 2001, Portugal still records the highest inequality, followed by Luxembourg, France, Greece, Spain, UK, Italy, Germany, Ireland, Netherlands, Finland, Belgium, Austria and Denmark.

[6] $k_1 > k_2$

The scope of this study is to decompose earnings inequality for each country into the permanent and transitory inequality, and conclude which of these components is the main factor triggering the evolution of overall inequality over time.

The overall autocovariance structure of earnings (Figure 1) displays both similar and diverging patterns across countries. The common pattern across all countries is that all lags autocovariances show in general a 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 (Table 2) and all lags autocovariances (Figure 1) vary over time, which signals the presence of nonstationarity in the dynamic structure of earnings.

In all countries, the autocovariances display different patterns across cohorts (Figure 2), supporting the hypothesis of cohort heterogeneity with respect to individual earnings dynamics. In most countries, the variance of earnings for all cohorts follows the evolution of the overall variance. Mixed trends across cohorts are observed in Germany – where the variance increased for the cohorts born in 1941-1950 and 1961-1970 -, in Belgium – where the variance increased for the youngest cohort -, in France - where the variance increased for the cohort born in 1961-1970 -, in UK – where the variance increased for the youngest two cohorts -, in Spain - where the variance increased for the youngest and the oldest cohorts, and in Finland - where the variance decreased for the youngest cohort.

The evolution of the variance 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 are the autocovariances. 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. Lifecycle autocovariances are illustrated in Figure 3. They are positive and evolve at different rates over the life cycle. The smoothed lifecycle profiles illustrate that, on average, all lags autocovariances increase with age at a decreasing rate, which is consistent with the presence of a permanent component of earnings that rises with age at a diminishing rate. (Dickens, 2000).

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

[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.

reported estimates of the variances represent the exponent of the parameter and the reported standard errors correspond to the parameter estimates.[8]

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

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 play 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%[9] 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

[8] The SE column reports the standard error for the parameter estimate. Where I report the exp(estimate), the SE corresponds to the log(exp(estimate)) = estimate

[9] $4.89 = 100 \cdot \sqrt{\sigma_{\varphi}^{2}}$

the returns to the permanent component vary to a large extent across countries. One common feature is that they reflect the 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 increased in Germany and Finland. The trends over time differ between countries, some record 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 the return to skills, in Greece every second year, in Spain 1995 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 lower than the variance at subsequent ages, suggesting the presence of larger permanent shocks at older 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. Year by year, France records an increase in the returns to skills until 1997 and again in 2001, Luxembourg until 2000, Belgium in 1996 and 2000, Austria during most of the period, except 1998-1999, and Portugal in 1996, 1998 and 2000.

The estimates of the cohort-specific shifters for the permanent earnings are highly significant in all countries. The trends, however, differ between countries. A monotonic increase over the lifecycle is observed 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 lifecycle. 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 decreases over the life cycle in UK, Ireland, Italy, Greece and Finland. This may be due to younger cohorts having more heterogeneous skills or experiencing larger permanent shocks even without a larger dispersion of skills. This could be the case if the labour market has become tougher over time, as in the case of the Italian case, 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 Italy, Greece and Spain, where it follows an ARMA(1,1). Except for Spain, Portugal and Austria, 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, 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 the variance of subsequent shocks in all countries, except Luxembourg, Ireland, the oldest three cohorts in UK, and the middle two cohorts in Finland. Overall, the variance of initial conditions increases over the lifecycle in Denmark, Belgium, France, Luxembourg, UK, Italy, Greece and Finland, suggesting that the initial variance plays a larger role in the formation of earnings differentials for the oldest cohort compared with the youngest. The opposite is observed in Germany, Netherlands and Ireland.

The pattern of the heteroskedstic initial conditions, however, is not monotonic across cohorts. In Luxembourg, UK, Italy, and Finland it follows an 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 and Netherlands the pattern of the heteroskedstic initial conditions records a sharp drop for the second youngest cohort, an increase for the second oldest and a small drop for the oldest cohort. In Denmark, Belgium, Ireland and Greece, the variance of initial conditions records an increase for the second youngest cohort, a drop for the second oldest and an increase for the oldest 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 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.[10]

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 all countries, except Luxembourg and Ireland.

The estimates of the cohort-specific shifters for the transitory earnings are highly significant in all countries. They indicate that earnings volatility is 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 is expected, given that

[10] 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.

younger people experience in general more frequent job changes, and consequently less stable earnings.

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 $\chi^2$was of 23668.02, 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 $\text{cov}(\mu,\varphi) = 0$), 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.

Assuming away the random walk in the permanent component was rejected by the Wald test in Denmark (χ^2=115.65, df=1) Incorporating a random walk in the permanent component was rejected in Portugal, and leaded to identification problems in Belgium, France, Luxembourg and

Austria. 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 and 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

Having estimated a suitable error component model for earnings in each country, next we use these parameters estimates to decompose earnings inequality into its permanent and transitory components, assess their absolute and relative contribution to the evolution of overall inequality, and estimate earnings mobility over the sample period, by cohort.

There is a fundamental conceptual underidentification of time, life-cycle, and cohort effects due to the exact multicollinearity of time, age, and birth year. Our decompositions control for cohort effects, but the age and period effects are confounded. Since our scope is to decompose within-cohort inequality into the two components, the lifecycle effect is considered part of the permanent component, and thus its specific identification was disregarded.

8.1. Absolute Decomposition

Figure 4 illustrates the absolute decomposition of the variance, together with the actual and predicted variance of earnings by cohort. The decomposition by cohort identifies how inequality and its components are affected by labour market changes at different lifecycle stages. For all countries, the evolution of the predicted variance follows closely the evolution of the actual variance, confirming the fit of the country models, indicated by the 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 and the oldest 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 for the youngest cohort. These are countries where wages appear to be more responsive to market forces.

The pattern of the absolute decomposition of the overall variance varies between countries and cohorts. Nevertheless, some common traits emerge. Permanent variance is higher and transitory variance is lower, the older is the cohort, which is consistent with the evidence of lifecycle earnings divergence showing that older cohorts experience a lower earnings volatility compared with younger cohorts. Similar results are found by Dickens (2000) and Ramos (1999, 2003) for UK, Cervini and Ramos (2006) for Spain, and Capellari (2003) for Italy.

The decrease in the overall cross-sectional inequality is the result of decreasing permanent and transitory differentials in Denmark and Austria, of decreasing permanent differentials with offsetting effect over the increasing transitory differentials in Belgium and Spain, and of decreasing transitory differentials with offsetting effects over the increasing permanent differentials in Germany, France, UK and Ireland. In most countries, these trends are consistent across cohorts. Mixed trends across cohorts are observed in: Denmark - where the transitory variance increased for the second oldest cohort -, Belgium – where both component decreased for the oldest cohort and the increase in the transitory variance dominated for the youngest cohort -, Spain – where the increase in the transitory variance dominated for the oldest and the youngest cohort -, Germany - where both components increased for the 1941-1950 and 1961-

1970 cohorts, and decreased for the cohort 1951-1960 -; France – where both components increased for the second youngest cohort -, Ireland - where both components decreased for the oldest cohort -, and UK – where both components decreased for the oldest cohort, and the increase in inequality for the youngest two cohorts was determined by an increase in the permanent variance for the cohort 1961-1970 and by an increase in the transitory variance for the cohort 1971-1980.

In Luxembourg, Italy, Greece and Finland, the exacerbation of permanent differentials, meaning the increase in returns to skills was the dominant factor behind the increase in overall inequality, offsetting the decrease in transitory differentials, whereas in Portugal and Netherlands both components increased. These trends are consistent across cohorts, except for the youngest cohort in Luxembourg and Italy, and the second oldest cohort in Greece - where both components increased -, the youngest two cohorts in Netherlands - where permanent differentials decreased -, and Finland - where both components decreased.

To summarize these trends we averaged permanent and transitory variance across cohorts: the decrease in overall inequality was driven by a decrease in both components in Denmark and Austria, by a decrease in permanent differentials in Belgium and Spain, and by a decrease in transitory differentials in Germany, France, UK and Ireland. The exacerbation of overall inequality was the result of increasing permanent differentials in Luxembourg, Italy, Greece and Finland, and of an increase in both components in Portugal and Netherlands.

Comparing with national results, Cervini and Ramos (2006) obtained similar results with respect to overall within-cohort inequality in Spain, however differed in respect of the component trends.

Daly and Valletta's (2005) findings for Germany and the UK are reasonably consistent with those reported here. For the UK, for the period 1994-1999, our results are only partially in line with Ramos (2003). First, the sharp increase he found in 1999 is not present in our data or in other recent studies[11]. Second, between 1994 and 1998, he got a similar trend in actual inequality for the oldest two cohorts, but the trends in the two components differ, which might result from the mismatch between the trends in actual and predicted variances.

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[11] Our trend in overall inequality is consistent also with Cholezas and Tsakloglou (2008), which compared hourly earnings inequality across EU using ECHP.

For Ireland, Doris et al.'s (2008) results for overall and transitory inequality are in line ours. For permanent inequality, only the oldest cohort matches their trend. The findings for Italy are consistent with Capellari (2003).

Following these changes, the ranking in permanent and transitory dispersion for all countries by cohort in 2001 are illustrated in Figure 5. The figures are in ascending order for the transitory variance. For the oldest three cohorts, the highest permanent inequality is observed in Portugal, and for the youngest cohort in Luxembourg. Denmark, Belgium and Austria have the lowest permanent dispersion across all cohorts. Portugal, Greece and Spain have the highest transitory variance for all cohorts, except the youngest one, where Netherlands is the highest. The lowest transitory variance is observed in Denmark for the oldest cohort, in Finland for the middle cohorts, and in Ireland for the youngest cohort.

We summarize the changes in country ranking in permanent and transitory inequality over the sample period by reporting the averages across cohorts. In 1994, the highest average permanent inequality[12] 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, Belgium, Denmark, Netherlands, Italy and Portugal. In 1995, Austria and Luxembourg had a middle ranking in permanent inequality and a top ranking[13] in transitory inequality. In 1996, Finland had the second lowest permanent inequality and a middle ranking in transitory inequality.

In 2001 the rankings looks slightly different. Portugal records the highest average 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.

8.2. Relative decomposition – Structure of Inequality

Figure 6 illustrates the evolution of the structure of inequality, expressed by the relative decomposition of the overall predicted variance of earnings into its permanent and transitory components.

[12] Average permanent variance and transitory variance represent average across cohorts.
[13] Among the highest four.

Figure 7 translates these trends into earnings immobility, measured as the ratio between permanent variance and transitory variance following Kalwij and Alessie (2003). An increase in the immobility ratio indicates a decrease in earnings mobility, equivalent to an increase in the share of the permanent differentials in overall inequality. This mobility index captures non-directional earnings movements and can be interpreted as the opportunity to improve one's position in the distribution of lifetime earnings.

The pattern of the relative decomposition of the overall variance and the trends in earnings immobility vary between countries and cohorts. Nevertheless, some common traits emerge. Inequality in the permanent component of earnings accounts 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, for the youngest cohort, temporary inequality has a dominant share in overall inequality, which reinforces that earnings volatility is higher at younger ages. (Figure 6) The same pattern was found by Capelari (2003), Ramos (2003) and Cervini and Ramos (2006).

Similarly, in all countries, the degree of immobility is higher for older cohorts compared with younger cohorts, which suggests that the opportunity to improve one's position in the earnings distribution is lower the older is the cohort. (Figure 7)

Figure 8 summarizes the country ranking with respect to earnings persistency and earnings immobility over the sample period, by cohort. The higher the share of permanent inequality, the higher the immobility. In the first wave, for the oldest cohort, the highest share of the permanent component (the lowest mobility) is in Germany (97%), followed by Portugal, Spain, Netherlands, Italy, Ireland, Denmark, France and UK with shares between 85% and 60 %, and the rest with shares between 60% and 49%. For the cohort 1951-1960, the highest permanent share (the lowest mobility) is in Portugal (89%), followed by Spain, Germany, Ireland, Netherlands, Belgium, UK, Italy, Denmark and France with shares between 78% and 60%, and the rest with shares between 58% (Greece) and 47% (Finland).

For the 1961-1970 cohort, the highest permanent shares (the lowest mobility) are in Netherlands and Portugal (77%), followed by Spain, France and Germany - with shares between 68% and 64% -, Luxembourg, UK, Belgium, Austria and Ireland - with shares between 56% and 42% -, and the rest with shares between 40% (Denmark) and 21% (Greece). For the cohort 1971-1981, the highest permanent share is recorded in UK (52%), followed by Luxembourg (45%), Greece, Finland, Ireland, Portugal, Italy and Spain - with shares between 38% and 25% -, and the rest with shares between 18% (Netherlands) and 2% (Belgium).

Turning to Figure 6 and Figure 7 we observe that among the countries with decreasing inequality, in Denmark, Belgium and Spain the structure of inequality and earnings mobility by cohort did not change much in 2001 compared with 1994. The share of the permanent component decreased – the immobility ratio decreased, thus mobility increased - for all cohorts in Spain, for all cohorts except the second youngest in Denmark, and for the youngest three cohorts in Belgium. For the other countries with decreasing inequality, the structure of inequality changed to a large extent and led to an increase in the share of the permanent inequality – an increase in the immobility ratio, thus a decrease in mobility- for all cohorts, except the oldest in Germany and the youngest in UK.

Most countries with increasing inequality recorded an increasing share of permanent inequality – an increasing immobility ratio, thus decreasing mobility – for all cohorts. Netherlands, Portugal, and the youngest cohort in Luxembourg and Finland, however, are exceptions.

The results for Germany over 1994-1999 and for UK over 1994-1998 are in line with Daly and Valletta (2005), which found increasing shares of permanent differentials. For UK, Ramos(2003) found decreasing shares between 1994-1999 for all cohorts. For Spain, our results are at odds with Cervini and Ramos (2006), which found increasing shares of permanent inequality for all cohorts. For Ireland, our results are in line with Doris et al. (2008). For Italy, the results are in line with Capelari (2003).

Following these changes, the structure of inequality and earnings immobility in 2001 is summarized in Figure 8. For the oldest cohort, the highest share of permanent inequality implying the highest earning persistency (lowest mobility) is found in Luxembourg, France, Germany, Italy, Ireland, Portugal and Spain, with rates between 82% and 73%. Greece, Netherlands, Finland, UK and Austria are less persistent with values between 70% and 60%. The least persistent – most mobile - are Denmark and Belgium, where permanent variance accounts for 56-58% of the overall variance.

For the 1951-1960 cohort, the highest persistency – lowest mobility - is recorded by the same countries, including UK and Finland, with shares between 85% and 71%, followed by Greece, Austria and Netherlands with shares between 68% and 61%, and lastly Belgium (56%) and Denmark (49%). For the 1961-1970 cohort in Luxembourg, Ireland and Finland permanent variance accounts for 79% to 70% of the overall variance, followed by UK, France, Germany, Italy and Portugal with shares between 66% and 63%, by Spain, Greece and Austria with shares between 58% and 56%, and by Belgium, Netherlands and Denmark with shares between 45% and 42%.

For the youngest cohort, the variance is dominantly transitory in all countries, except Ireland where the transitory variance accounts for 46% of the overall variance, suggesting that Irish youngsters have the lowest degree of earnings mobility in Europe. The most volatile earnings are found in Belgium, where 98.5% of the variance is transitory. Next follow Denmark and Netherlands where transitory variance accounts for 89% of the overall variance; Spain, Austria and Portugal, with transitory shares between 84% and 81%; Germany, France, Finland, Italy and UK with transitory shares between 72% and 63%; Greece and Luxembourg where transitory inequality accounts for 56% of the variance.

Based on Daly and Valetta (2007) the contribution of permanent variance to the overall inequality is of 54% for the US, 58% for Germany and 52% for Great Britain over the 1990's. For UK, over 1994-1999, Ramos (2003) found a lower persistency than us: the permanent component varied from about 60% to 30-40% for people born after 1960, and from 50% to 30-40% for people born between 1941 and 1960. For Spain, over 1994-2000, Cervini and Ramos (2006) found an increasing contribution from 60% and 70% to 90% and 80% for people born in 1944-1953 and 1954-1963, and from 30% to 40% for people born after 1964. For Ireland, Doris et al. (2008) reported an average permanent share of 71%.

The evolution of the two components, both in absolute and relative terms, and of earnings immobility was not monotonic. Most countries experienced a turnaround after 1996-1999. The labour market explanations for these changes are explored in Sologon and O'Donoghue (2009c).

To sum up, the decrease in inequality was accompanied by an increase in mobility (decrease in immobility ratio) only in Denmark, Belgium and Spain. In a few countries some cohorts diverged from the general trend. The youngest cohort recorded an increase in inequality accompanied by an increase in mobility (decrease in immobility ratio) in Belgium, Spain, and UK. The second youngest cohort recorded a decrease in inequality accompanied by a decrease in mobility (increase in immobility ratio) in Denmark, and an increase in inequality accompanied by a decrease in mobility (increase in immobility ratio) in Germany, France and UK. The oldest cohort recorded an increase in inequality accompanied by an increase in mobility (decrease in immobility ratio) in Germany and Spain, and a decrease in inequality accompanied by a decrease in mobility (increase in immobility ratio) in Belgium.

Except for Netherlands and Portugal, all countries recording an increase in inequality experienced also a decrease in mobility (increase in immobility ratio). This trend is valid across cohorts, which suggests that the changes in the labour market affected all workers in a similar way. The youngest cohort in Luxembourg and Finland are exceptions: the increase in inequality in Luxembourg and the decrease in inequality in Finland was accompanied by an increase in mobility (decrease in immobility ratio).

Averaged across cohorts, earnings mobility[14] decreased over time in most countries, except Denmark, Belgium, Spain, Netherlands and Portugal. In 2001, Denmark has the highest average earnings mobility, followed by Belgium, Netherlands, Austria, Spain, Greece, Finland, UK, France, Germany, Italy, Portugal, Ireland and Luxembourg. (Figure 9)

Based on Figure 10, which illustrates the average inequality and average immobility in 2001, ranked in ascendant order of the average inequality, the level of cross-sectional inequality appears to be positively[15] associated with the level of earnings immobility. Denmark, Belgium and Austria have the lowest inequality and the lowest immobility in 2001. Thus, assuming that lifetime mobility will act towards reducing lifetime differentials, we expect these countries to trigger the lowest degree of lifetime inequality. The lifetime inequality ranking between Austria and Netherlands, however, is undetermined. Finland is expected to trigger a lower lifetime inequality than Italy, UK, Ireland, Germany, Luxembourg and Portugal; Netherlands a lower lifetime inequality than UK, Ireland, Denmark, Greece, Spain, Luxembourg, France and Portugal; UK a lower lifetime inequality than Ireland Germany, Luxembourg, France and Portugal; Ireland a lower lifetime inequality than Luxembourg; Germany a lower lifetime

[14] Average Immobility=Average Permanent Variance/Average Transitory Variance

[15] The correlation coefficient indicates a strong positive association (0.5864), sig at 5% level of confidence.

inequality than Luxembourg and Portugal; Greece and Spain a lower lifetime inequality than Luxembourg, France and Portugal; and France a lower lifetime inequality than Portugal.

These expectations, however, are based on the strong assumption that lifetime mobility will act towards reducing lifetime differentials.

9. CONCLUDING REMARKS

We explored the extent to which the changes in cross-sectional earnings inequality in 14 EU countries over the period 1994 and 2001 reflect changes in transitory and/or permanent earnings inequality and the potential link with earnings mobility. The analysis was broken down by cohorts to identify the potential consequences of the labour market changes occurred after 1995 on earnings persistency and mobility at different lifecycle stages.

Overall earnings inequality, measured by the variance in log hourly earnings, decreased in Germany, Denmark, Belgium, France, UK, Ireland, Spain, Austria and increased in Netherlands, Luxembourg, Italy, Greece, Portugal and Finland. For all countries, both in relative and absolute terms, individual earnings inequality contains a highly permanent component for the oldest three cohorts and a highly transitory component for the youngest cohort. This is consistent with the evidence of lifecycle earnings divergence showing that earnings volatility is higher at younger ages. The degree of immobility is higher for older cohorts compared with younger cohorts, which suggests that the older the cohort, the lower the opportunity to improve one's position in the distribution of lifetime earnings.

Overall, the decrease in inequality resulted from a decrease in transitory differentials in Germany, France, UK and Ireland, in permanent differentials in Belgium and Spain, and in both components in Denmark and Austria. The increase in inequality reflects an increase in permanent differentials in Luxembourg, Italy, Greece and Finland, and an increase in both components in Portugal and Netherlands. The decrease in inequality was accompanied by an increase in mobility only in Denmark, Belgium and Spain. Except for Netherlands and Portugal, all countries recording an increase in inequality experienced also a decrease in mobility.

More important are the welfare implications of these trends. We start with the countries recording a decrease in overall inequality. In Denmark, Belgium and Spain, mobility appears to be beneficial: in 2001, low wage individuals are better off both in terms of their relative wage and in terms of the opportunities to escape the low-wage trap in a lifetime perspective. Thus in a lifetime perspective, Denmark, Belgium and Spain are expected to reduce lifetime earnings differentials compared with annual differentials.

In Austria, Germany, France, UK and Ireland, in 2001, low-wage individuals are worse off in terms of the opportunity to escape the low-wage trap, but their relative position in the earnings distribution is improved compared with the 1st wave. For these countries mobility is expected to play a decreasing role in reducing lifetime inequality, therefore annual differentials have a high chance of being preserved in a lifetime perspective.

The inequality and mobility behaviour across cohorts differ from the general trend in a few countries. The youngest cohort recorded an increase in inequality accompanied by an increase in mobility in Belgium, Spain, and UK, suggesting that in 2001 young low wage workers are worst of in terms of their relative wage, but better off in terms of their opportunity to improve their earnings position in a lifetime perspective. Hence, the reforms might have increased employment and wage flexibility among young workers. The second youngest cohort recorded a decrease in inequality accompanied by a decrease in mobility in Denmark, and an increase in inequality accompanied by a decrease in mobility in Germany, France and UK. The oldest cohort recorded an increase in inequality accompanied by an increase in mobility in Germany and Spain, suggesting that in 2001 older low wage workers are worst off in terms of their relative wage, but better off in terms of their opportunity to escape low-wage trap. This might result from increased employment and wage flexibility among older workers. In Belgium, the oldest cohort recorded a decrease in inequality accompanied by a decrease in mobility, suggesting that in 2001, among older workers, low wage workers are better off in terms of their relative wage, but worst off in terms of the opportunity to escape low-wage trap in a lifetime perspective.

Among countries recording an increase in earnings inequality, in Luxembourg, Italy, Greece, and Finland, 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. Thus we can expect these countries to increase lifetime earnings differentials compared with annual differentials. Netherlands and Portugal record widening wages differentials accompanied by increased opportunity of low wage individuals to improve their position in the distribution of lifetime earnings. Thus, for Netherlands and Portugal, earnings mobility could either decrease or exacerbate lifetime earnings differentials compared with annual ones.

These trends are valid across cohorts, suggesting that the changes in the labour market affected all workers in a similar way. Two exceptions are Finland, where for the youngest cohort inequality decreased and was accompanied by an increase in mobility, and Luxembourg, where for the youngest cohort inequality increased and was accompanied by an increase in mobility.

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 EU labour market changes after 1995. Hence, future research could explore the role of labour market factors in explaining cross-national differences in permanent and transitory inequality, and earnings mobility, a topic neglected by the existing literature.

10. TABLES AND FIGURES

Table 1. Inflows Inflows and Outflows of Individuals in the Sample - Germany

	1994	1995	1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings	25018	26059	25806	24889	23290	22955	21909	20703
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year								
	Frequencies	23956	25224	24197	22814	22321	21290	20107
	%	66.99	67.37	66.2	63.01	64.84	64.86	64.39
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year								
Unemployed	Frequencies	3448	3461	4119	3932	3055	2787	2766
Inactive	%	9.64	9.24	11.27	10.86	8.87	8.49	8.86
Attrition	Frequencies	1885	2182	1892	3280	2951	2924	2830
	%	5.27	5.83	5.18	9.06	8.57	8.91	9.06
Missing Wage	Frequencies	6470	6576	6345	6180	6100	5826	5524
	%	18.09	17.56	17.36	17.07	17.72	17.75	17.69
Total	Frequencies	35759	37443	36553	36206	34427	32827	31227
	%	100	100	100	100	100	100	100

Table 1. Inflows and Outflows of Individuals in the Sample – Denmark

	1994	1995	1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings	20899	20399	19190	19062	17321	16235	15678	15380
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year								
	Frequencies	19854	18527	18110	16442	15334	14865	14642
	%	68.74	66.59	69.43	66.23	67.41	69.6	71.6
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year								
Unemployed	Frequencies	1535	1744	951	899	732	658	958
Inactive	%	5.31	6.27	3.65	3.62	3.22	3.08	4.68
Attrition	Frequencies	2440	3096	2914	3603	2922	2133	1775
	%	8.45	11.13	11.17	14.51	12.85	9.99	8.68
Missing Wage	Frequencies	5054	4454	4110	3881	3759	3703	3074
	%	17.5	16.01	15.76	15.63	16.53	17.34	15.03
Total	Frequencies	28883	27821	26085	24825	22747	21359	20449
	%	100	100	100	100	100	100	100

Table 1. Inflows and Outflows of Individuals in the Sample – Netherlands

		1994	1995	1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings		20221	22100	22892	22753	22863	23233	24065	24130
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year									
	Frequencies		20578	21328	21221	21055	20545	21026	21341
	%		69.07	71.37	68.68	67.52	67.24	68.56	69.59
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year									
Unemployed	Frequencies		2418	2356	2536	2120	1984	1840	1689
Inactive	%		8.12	7.88	8.21	6.8	6.49	6	5.51
Attrition	Frequencies		2941	1889	2591	3562	3984	4301	4891
	%		9.87	6.32	8.39	11.42	13.04	14.02	15.95
Missing Wage	Frequencies		3857	4310	4550	4448	4042	3502	2745
	%		12.95	14.42	14.73	14.26	13.23	11.42	8.95
Total	Frequencies		29794	29883	30898	31185	30555	30669	30666
	%		100	100	100	100	100	100	100

Table 1. Inflows and Outflows of Individuals in the Sample – Belgium

		1994	1995	1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings		35342	34367	33280	32378	31129	29414	28087	26538
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year									
	Frequencies		33277	32384	31564	30575	28731	27460	25790
	%		63.43	63.65	64.38	63.88	64.28	65.15	64.38
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year									
Unemployed	Frequencies		3810	5127	4378	3601	3040	3090	2540
Inactive	%		7.26	10.08	8.93	7.52	6.8	7.33	6.34
Attrition	Frequencies		4145	3798	3473	4803	4421	3851	4930
	%		7.9	7.46	7.08	10.04	9.89	9.14	12.31
Missing Wage	Frequencies		11228	9573	9614	8882	8504	7748	6798
	%		21.4	18.81	19.61	18.56	19.03	18.38	16.97
Total	Frequencies		52460	50882	49029	47861	44696	42149	40058
	%		100	100	100	100	100	100	100

Table 1. Inflows and Outflows of Individuals in the Sample – Luxembourg

		1995	1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings		15829	13695	14489	13403	14075	12667	12992
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year								
	Frequencies		13417	12498	13190	12257	12402	11457
	%		64.75	69.48	69.33	69.81	68.71	70.39
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year								
Unemployed	Frequencies		1765	1559	1505	1408	1246	954
Inactive	%		8.52	8.67	7.91	8.02	6.9	5.86
Attrition	Frequencies		3423	1663	2109	1913	2346	1940
	%		16.52	9.25	11.09	10.9	13	11.92
Missing Wage	Frequencies		2116	2267	2220	1980	2057	1926
	%		10.21	12.6	11.67	11.28	11.4	11.83
Total	Frequencies		20721	17987	19024	17558	18051	16277
	%		100	100	100	100	100	100

Table 1. Inflows and Outflows of Individuals in the Sample – France

	1994	1995	1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings	20137	19270	19042	17906	14467	14012	13760	14212
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year								
	Frequencies	19143	18197	17243	14014	12209	12080	12468
	%	62.47	64.76	62	52.08	54.24	55.54	60.8
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year								
Unemployed	Frequencies	3259	3042	3426	3006	2607	2072	1995
Inactive	%	10.64	10.83	12.32	11.17	11.58	9.53	9.73
Attrition	Frequencies	3371	2213	2785	5584	3531	3786	2658
	%	11	7.88	10.01	20.75	15.69	17.41	12.96
Missing Wage	Frequencies	4871	4646	4358	4304	4162	3811	3385
	%	15.9	16.53	15.67	16	18.49	17.52	16.51
Total	Frequencies	30644	28098	27812	26908	22509	21749	20506
	%	100	100	100	100	100	100	100

Table 1. Inflows and Outflows of Individuals in the Sample – UK

	1994	1995	1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings	24949	25329	25495	26010	26145	25750	25674	25264
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year								
	Frequencies	24511	24848	25303	25278	25006	24881	24467
	%	64.59	66.31	67.06	67.04	67.36	68.33	68.58
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year								
Unemployed	Frequencies	4712	5053	4663	4140	3941	3607	3595
Inactive	%	12.42	13.48	12.36	10.98	10.62	9.91	10.08
Attrition	Frequencies	1836	966	1169	2073	1919	2153	2105
	%	4.84	2.58	3.1	5.5	5.17	5.91	5.9
Missing Wage	Frequencies	6888	6605	6597	6213	6257	5774	5510
	%	18.15	17.63	17.48	16.48	16.85	15.86	15.44
Total	Frequencies	37947	37472	37732	37704	37123	36415	35677
	%	100	100	100	100	100	100	100

Table 1. Inflows and Outflows of Individuals in the Sample – Ireland

	1994	1995	1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings	13937	13221	12590	12515	12435	12091	10745	9727
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year								
	Frequencies	12750	12217	12212	12020	11668	10236	9507
	%	49.99	50.04	52.41	53.13	54.1	51.63	54.65
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year								
Unemployed	Frequencies	4930	4723	4254	3374	2905	2185	2307
Inactive	%	19.33	19.35	18.26	14.91	13.47	11.02	13.26
Attrition	Frequencies	2167	2115	1600	1936	2516	3288	2362
	%	8.5	8.66	6.87	8.56	11.66	16.59	13.58
Missing Wage	Frequencies	5656	5359	5235	5292	4480	4116	3220
	%	22.18	21.95	22.47	23.39	20.77	20.76	18.51
Total	Frequencies	25503	24414	23301	22622	21569	19825	17396
	%	100	100	100	100	100	100	100

Table 1. Inflows and Outflows of Individuals in the Sample – Italy

	1994	1995	1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings	32633	32236	32111	29661	28865	26993	26912	25170
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year								
	Frequencies	30946	31028	28717	27188	25717	25348	24139
	%	51.58	51.19	47.18	47.34	46.87	48.73	48.86
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year								
Unemployed	Frequencies	7900	7799	7670	6627	6890	5662	5027
Inactive	%	13.17	12.87	12.6	11.54	12.56	10.88	10.18
Attrition	Frequencies	3175	2947	5922	6030	5941	5399	5920
	%	5.29	4.86	9.73	10.5	10.83	10.38	11.98
Missing Wage	Frequencies	17978	18836	18559	17585	16325	15610	14315
	%	29.96	31.08	30.49	30.62	29.75	30.01	28.98
Total	Frequencies	59999	60610	60868	57430	54873	52019	49401
	%	100	100	100	100	100	100	100

Table 1. Inflows and Outflows of Individuals in the Sample – Greece

	1994	1995	1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings	27974	27654	26150	24865	22675	22001	21335	21929
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year								
	Frequencies	26868	25946	24385	21815	20357	20443	21342
	%	45.83	45.69	44.98	42.09	43.52	46.06	49.72
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year								
Unemployed	Frequencies	7537	6813	6419	4523	4489	4427	3858
Inactive	%	12.86	12	11.84	8.73	9.6	9.97	8.99
Attrition	Frequencies	4417	4392	4347	7892	6222	4159	2363
	%	7.53	7.73	8.02	15.23	13.3	9.37	5.5
Missing Wage	Frequencies	19802	19640	19068	17599	15707	15352	15365
	%	33.78	34.58	35.17	33.96	33.58	34.59	35.79
Total	Frequencies	58624	56791	54219	51829	46775	44381	42928
	%	100	100	100	100	100	100	100

Table 1. Inflows and Outflows of Individuals in the Sample – Spain

	1994	1995	1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings	22559	21863	21296	20975	20371	20580	19898	20185
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year								
	Frequencies	21460	20521	20329	19456	19679	19167	19352
	%	47.6	48.29	48.49	48.63	52.13	52.12	56.06
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year								
Unemployed	Frequencies	8419	8230	7353	5970	5083	4512	4761
Inactive	%	18.67	19.37	17.54	14.92	13.46	12.27	13.79
Attrition	Frequencies	4467	3000	4120	4327	3188	3922	3052
	%	9.91	7.06	9.83	10.81	8.44	10.66	8.84
Missing Wage	Frequencies	10741	10742	10121	10259	9802	9176	7357
	%	23.82	25.28	24.14	25.64	25.96	24.95	21.31
Total	Frequencies	45087	42493	41923	40012	37752	36777	34522
	%	100	100	100	100	100	100	100

Table 1. Inflows and Outflows of Individuals in the Sample – Portugal

		1994	1995	1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings		14653	15450	15379	15087	14837	14569	14604	14550
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year									
	Frequencies		13892	14538	14321	13977	13921	13952	13942
	%		57.84	57.5	57.32	56.98	59.12	60.83	62.16
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year									
Unemployed	Frequencies		2187	2264	2396	2019	2067	1843	1702
Inactive	%		9.11	8.95	9.59	8.23	8.78	8.04	7.59
Attrition	Frequencies		1701	1908	1918	2346	1956	1617	1575
	%		7.08	7.55	7.68	9.56	8.31	7.05	7.02
Missing Wage	Frequencies		6236	6573	6350	6189	5602	5525	5211
	%		25.97	26	25.42	25.23	23.79	24.09	23.23
Total	Frequencies		24016	25283	24985	24531	23546	22937	22430
	%		100	100	100	100	100	100	100

Table 1. Inflows and Outflows of Individuals in the Sample – Austria

		1994	1995	1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings			17944	17789	17199	16209	15162	13816	13056
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year									
	Frequencies			16472	16384	15634	14551	13403	12601
	%			67.96	68.2	67.49	67.2	66.51	68.21
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year									
Unemployed	Frequencies			1209	1231	906	790	803	843
Inactive	%			4.99	5.12	3.91	3.65	3.98	4.56
Attrition	Frequencies			2195	2080	2435	2470	2409	1794
	%			9.06	8.66	10.51	11.41	11.95	9.71
Missing Wage	Frequencies			4361	4330	4189	3842	3538	3235
	%			17.99	18.02	18.08	17.74	17.56	17.51
Total	Frequencies			24237	24025	23164	21653	20153	18473
	%			100	100	100	100	100	100

Table 1. Inflows and Outflows of Individuals in the Sample – Finland

		1996	1997	1998	1999	2000	2001
Number of individuals with positive earnings		15811	15845	15895	15546	13329	13057
Absolute number and proportion of individuals who report positive earnings in current year conditional on being in the sample in previous year							
	Frequencies		15246	15345	14753	12756	12588
	%		55.95	57.2	59.29	53.83	64.16
Absolute number and proportion of individuals who report no earnings in current year conditional on being in the sample in the previous year							
Unemployed	Frequencies		3446	2327	1657	1326	1267
Inactive	%		12.65	8.67	6.66	5.6	6.46
Attrition	Frequencies		1933	3219	2658	5219	1708
	%		7.09	12	10.68	22.02	8.71
Missing Wage	Frequencies		6623	5937	5814	4398	4057
	%		24.31	22.13	23.37	18.56	20.68
Total	Frequencies		27248	26828	24882	23699	19620
	%		100	100	100	100	100

Table 2. 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[16]	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	3.70	3.74	3.84	3.92	3.99	4.08	4.31	4.46
	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.

[16] Gross Amounts

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	0.0078	0.2653	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
$\exp(estimate) = \sigma_\pi^2$			0.0001	0.0745										
Time shifters, $\lambda_{1,1994} = 1$														
$\lambda_{1,1995}$	1.0734	0.0084	0.9709	0.0203	0.9735	0.0158	0.9421	0.0116	1.0511	0.0129	1		0.9915	0.0082
$\lambda_{1,1996}$	1.1503	0.0112	0.9241	0.0201	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	0.8193	0.0214	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	0.8070	0.0231	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	0.7048	0.0228	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	0.6578	0.0251	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	0.6657	0.0235	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	1.2694	0.0339	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	1.6459	0.1164	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	1.4783	0.2034	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	0.2604	0.2961	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	0.0314	0.0851	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	0.0224	0.0813	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	0.0334	0.0740	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	0.0269	0.0712	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	0.5459	0.0135	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	0.2591	0.0373	0.4936	0.0756	0.2941	0.0226	0.2517	0.0739	1		0.8214	0.0418
$\lambda_{2,1996}$	0.3801	0.1088	0.2477	0.0382	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	0.2497	0.0375	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	0.2187	0.0326	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	0.2923	0.0428	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	0.2838	0.0420	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	0.2566	0.0380	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	1.1306	0.0269	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	1.1604	0.0228	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	1.8221	0.0340	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		5710.0156		2492.7787		17769.4220		1756.3574		1632.2320		2597.3157	
LogL	459.2576		513.2610		486.0084		540.0406		421.9693		318.4753		520.5053	

Note: The SE column reports the standard error for the parameter estimate. Where I report the exp(estimate), the SE corresponds to the log(exp(estimate)) = estimate

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		
$\exp(estimate) = \sigma_{0,40-50}^{2}$	0.0709	0.0825	0.0314	0.0898	0.0791	0.0516							0.0550	0.0743
$\exp(estimate) = \sigma_{0,51-60}^{2}$	0.0688	0.0966	0.0422	0.0619	0.0574	0.0702							0.0588	0.0701
$\exp(estimate) = \sigma_{0,61-70}^{2}$	0.0942	0.0869	0.0521	0.0592	0.1011	0.0436							0.0707	0.0727
$\exp(estimate) = \sigma_{0,71-80}^{2}$	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 shifters, $\lambda_{2,1994} = 1$														
$\lambda_{2,1995}$	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 shifters, $\gamma_{2,40-50} = 1$														
$\gamma_{2,51-60}$	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	

Note: SE column reports the standard error for the parameter estimate. Where I report the exp(estimate), the SE corresponds to the log(exp(estimate)) = estimate

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, $\sigma_0^2 = \sigma_{0,cohort}^2$	0.0287	3737.4586	408.9498	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

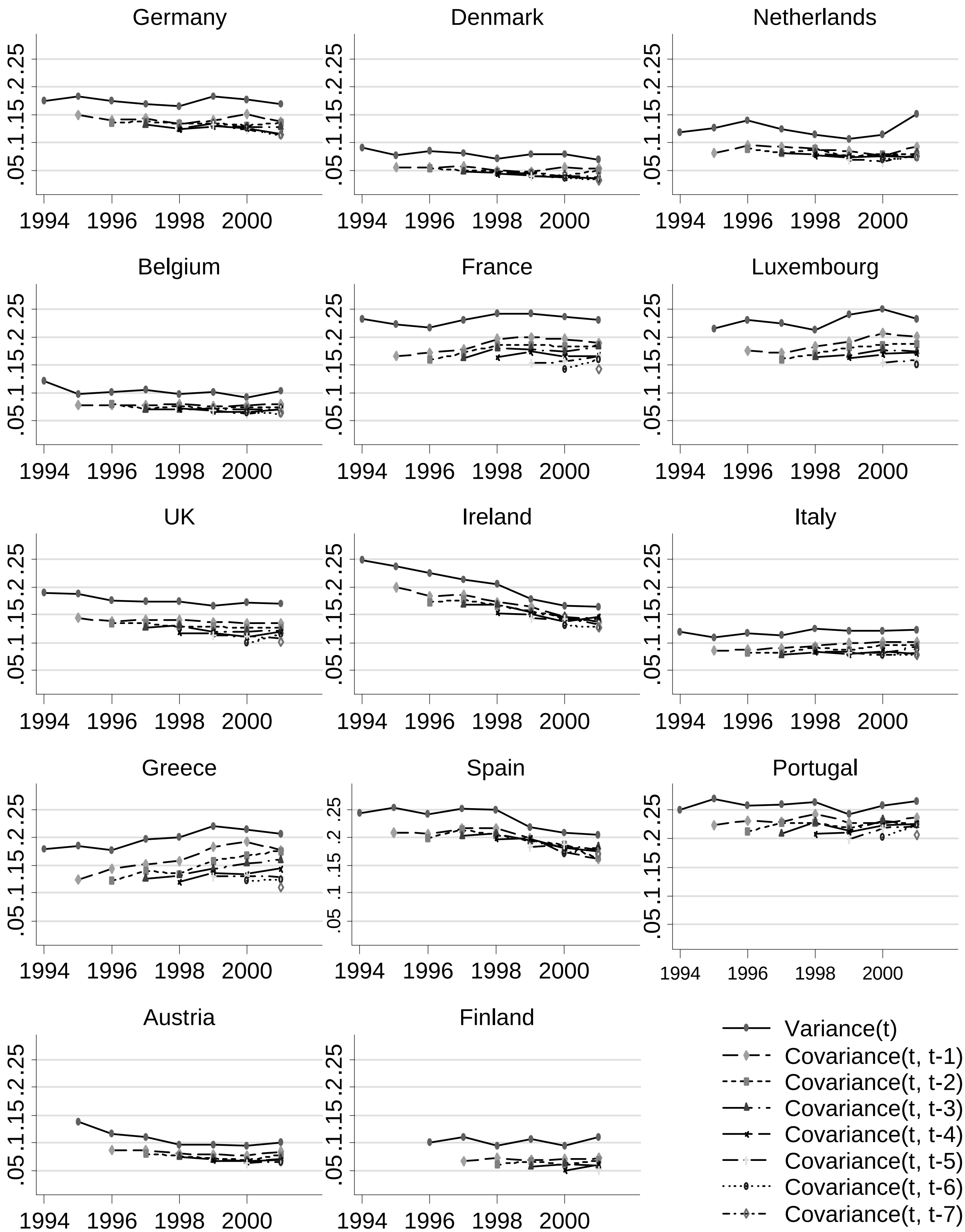

Figure 1. Overall Autocovariance Structure of Hourly Earnings: Years 1994-2001

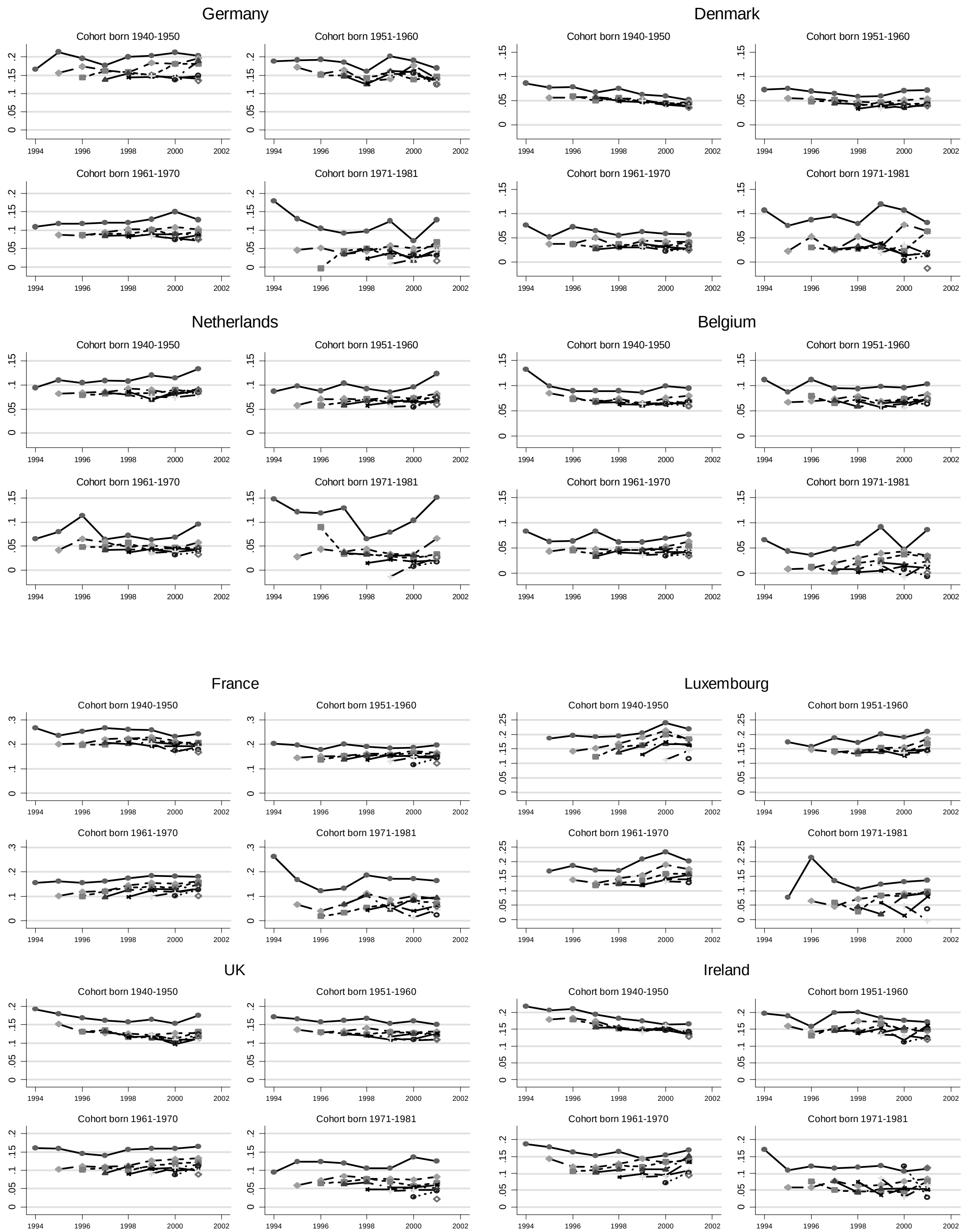

Figure 2. Autocovariance Structure of Hourly Earnings for Selected Cohorts: years 1994-2001

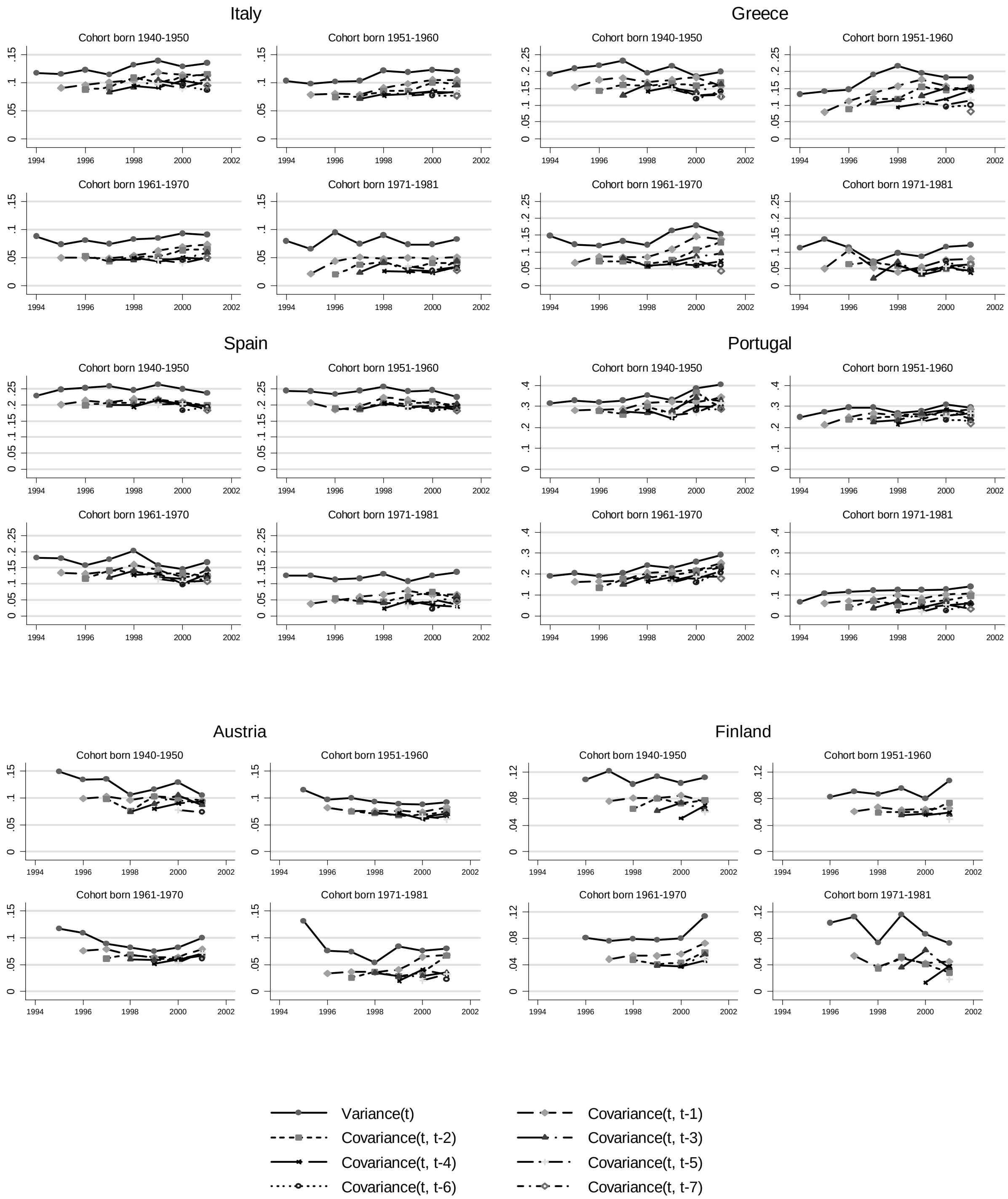

Figure 2. (Continued)

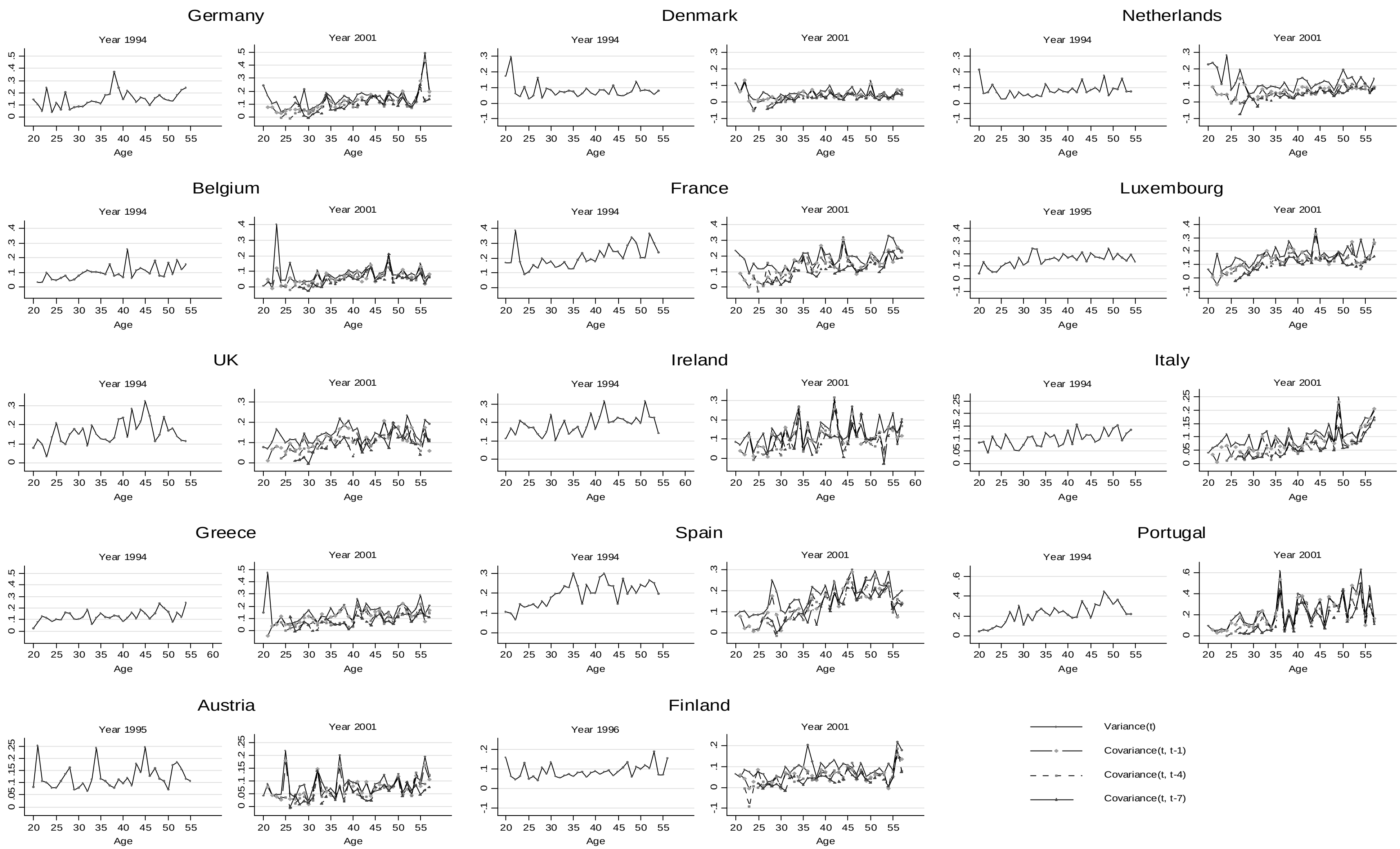

Figure 3. Lifecycle Autocovariances for Selected Years: First and Last Wave, by Country

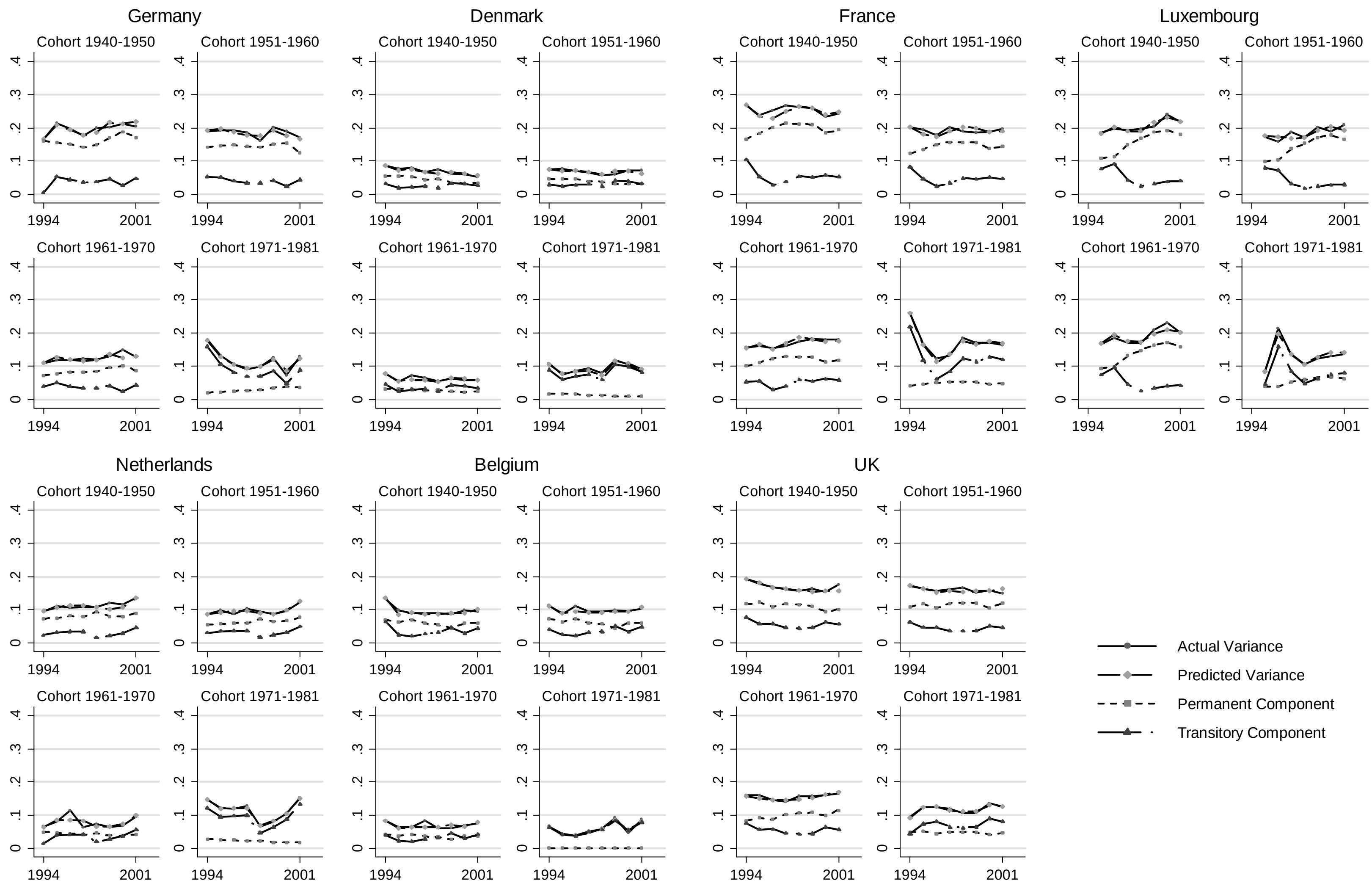

Figure 4. Actual and Predicted Variance of Earnings with Permanent and Transitory Predicted Components for Selected Cohorts: 1994-2001

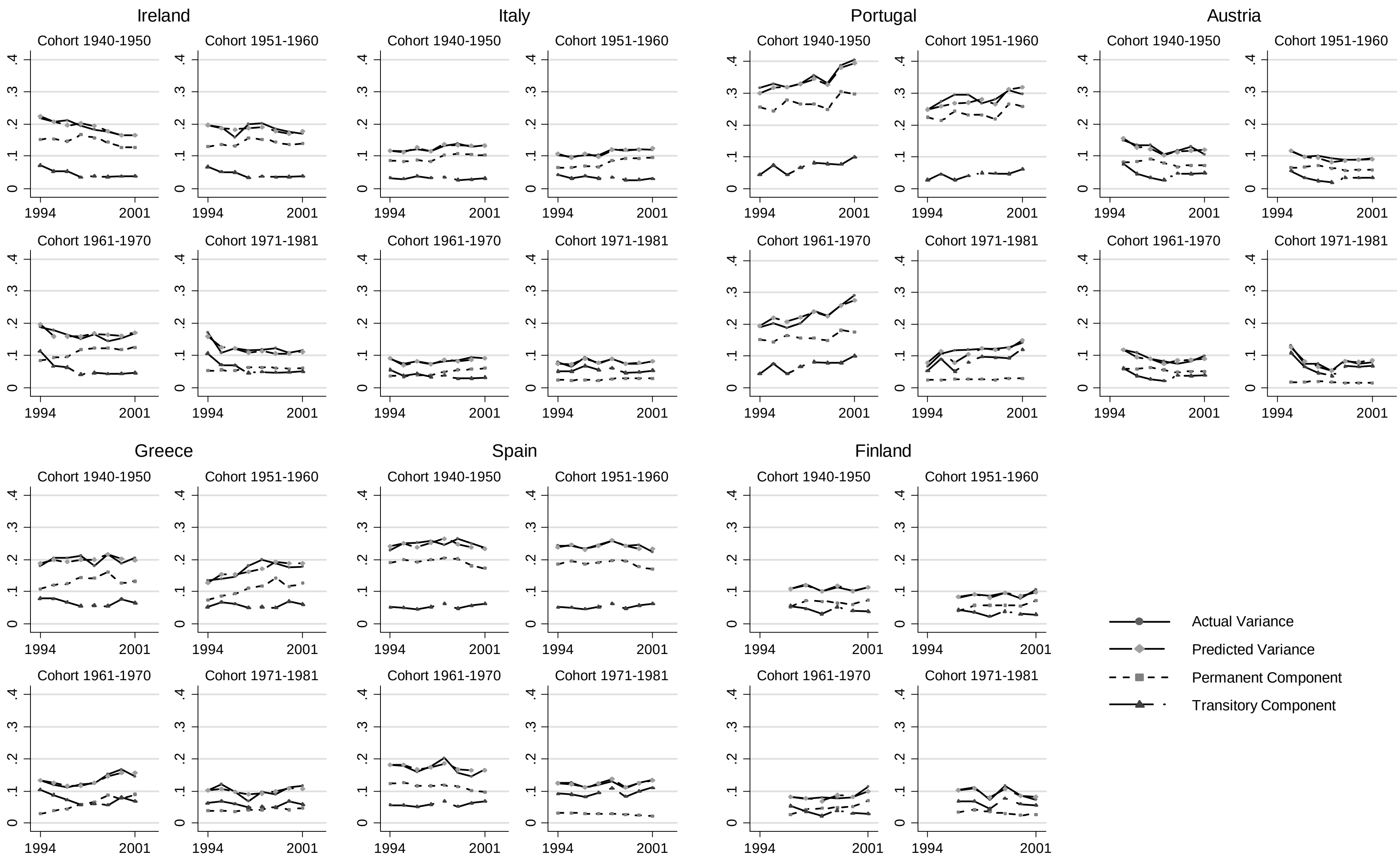

Figure 4 (Continued)

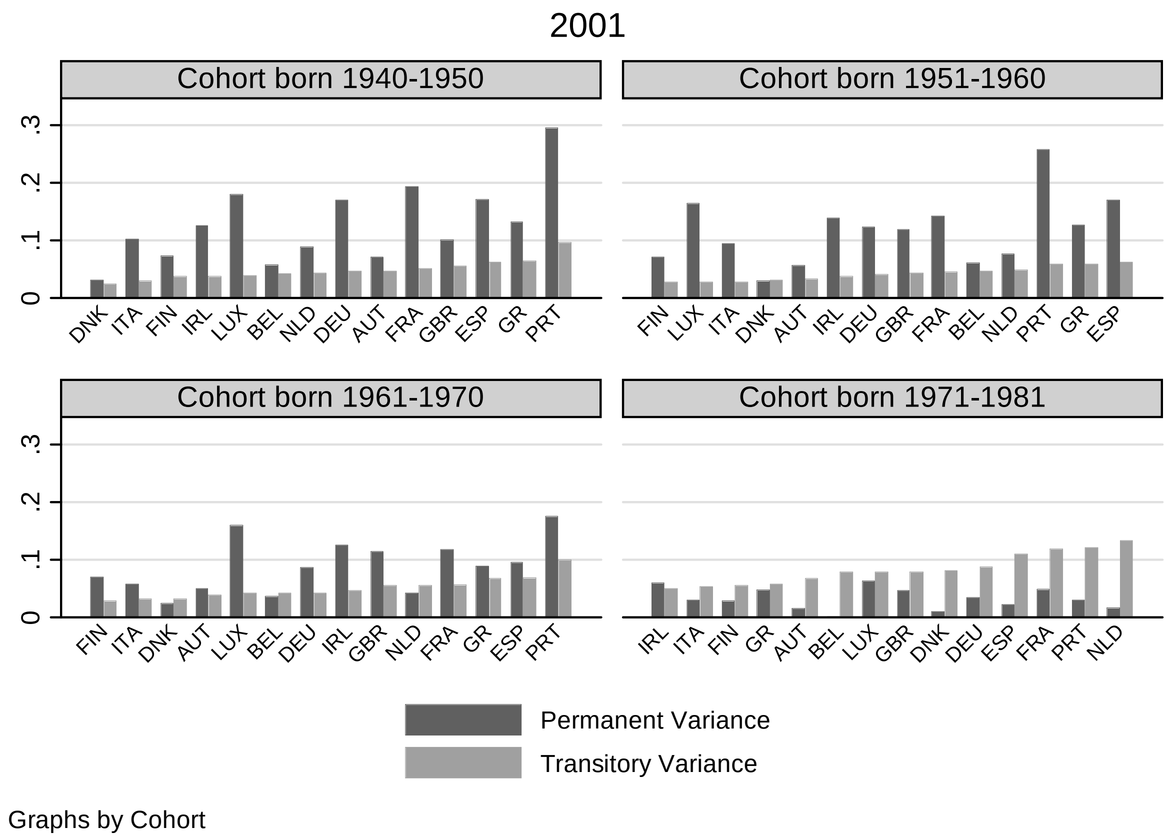

Figure 5. Permanent and Transitory Variance for Selected Cohorts in 2001

Note: The figures are in ascending order for the transitory variance.

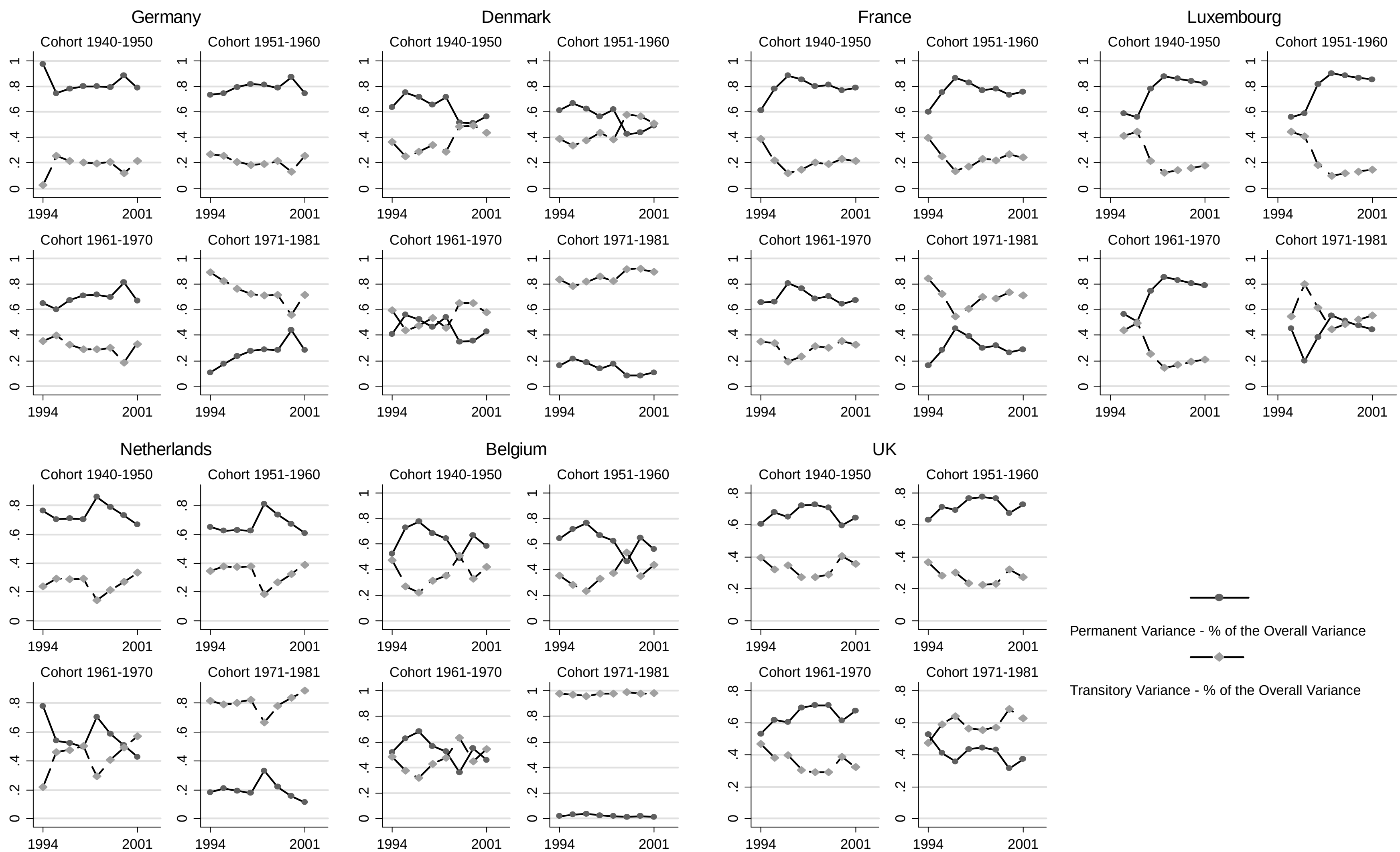

Figure 6. Predicted Permanent and Transitory Variance as % of Predicted Overall Variancefor Selected Cohorts: 1994-2001

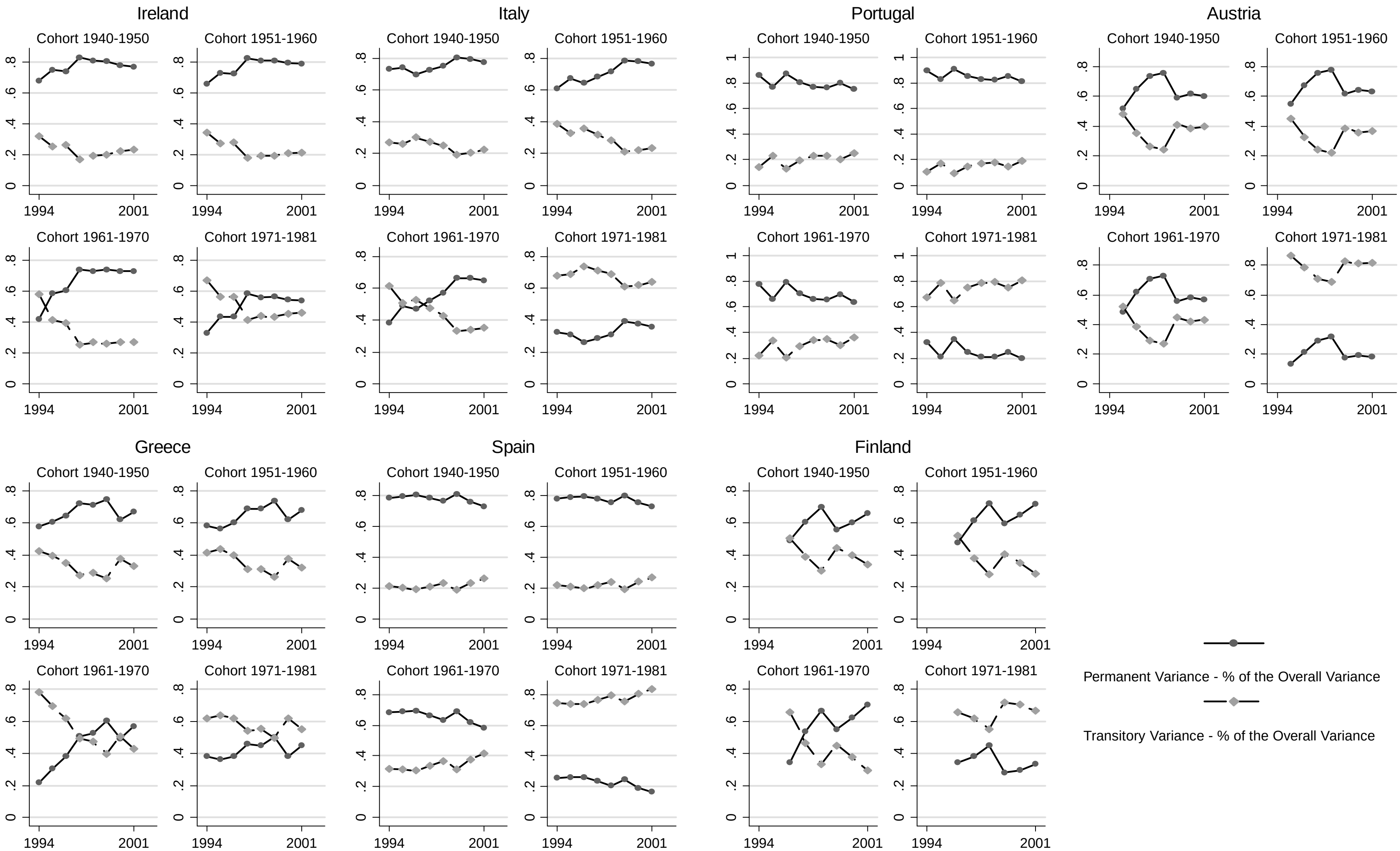

Figure 6. (Continued)

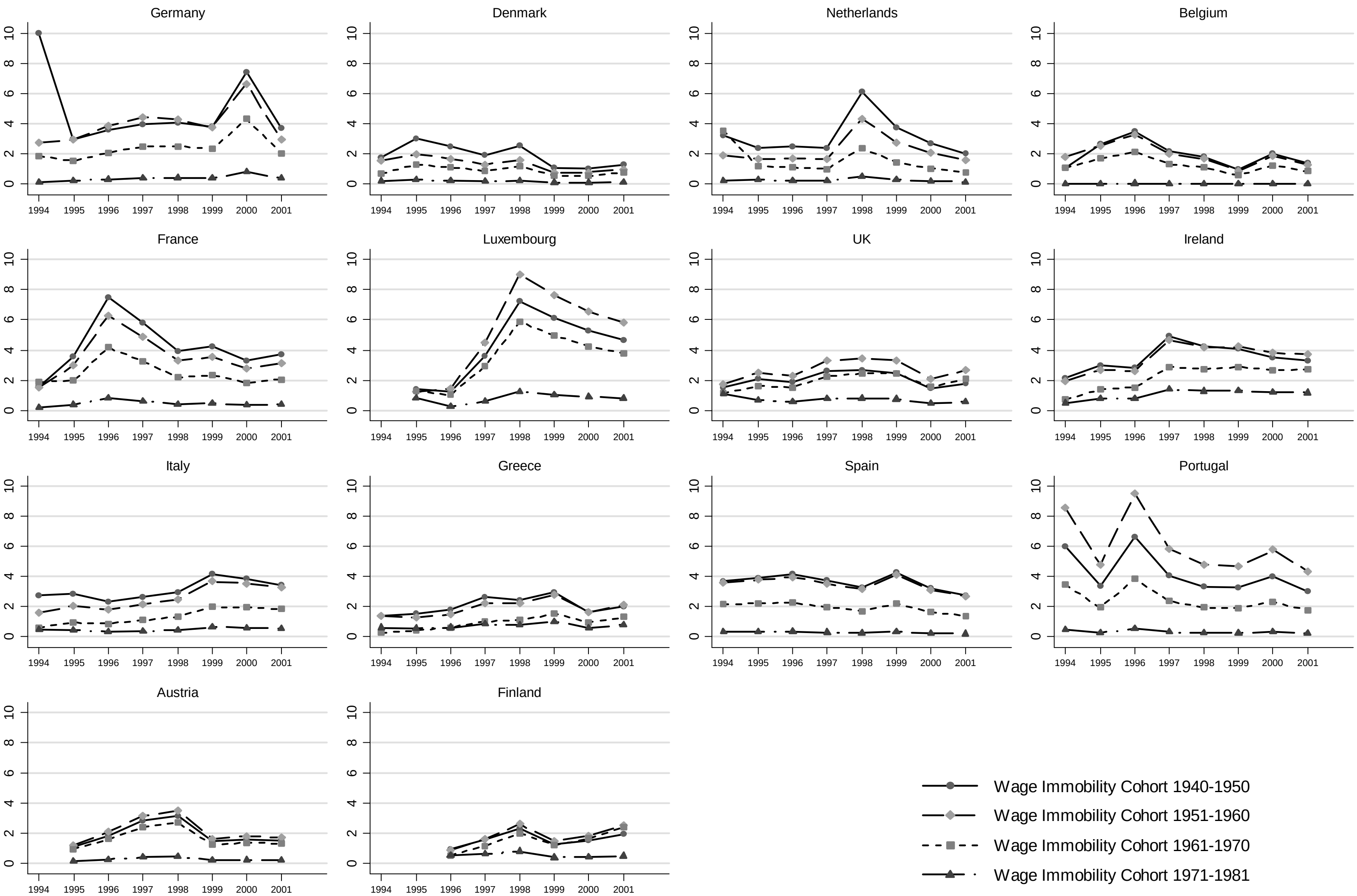

Figure 7. Ratio Between Permanent Variance and Transitory Variance Over Time For Selected Cohorts

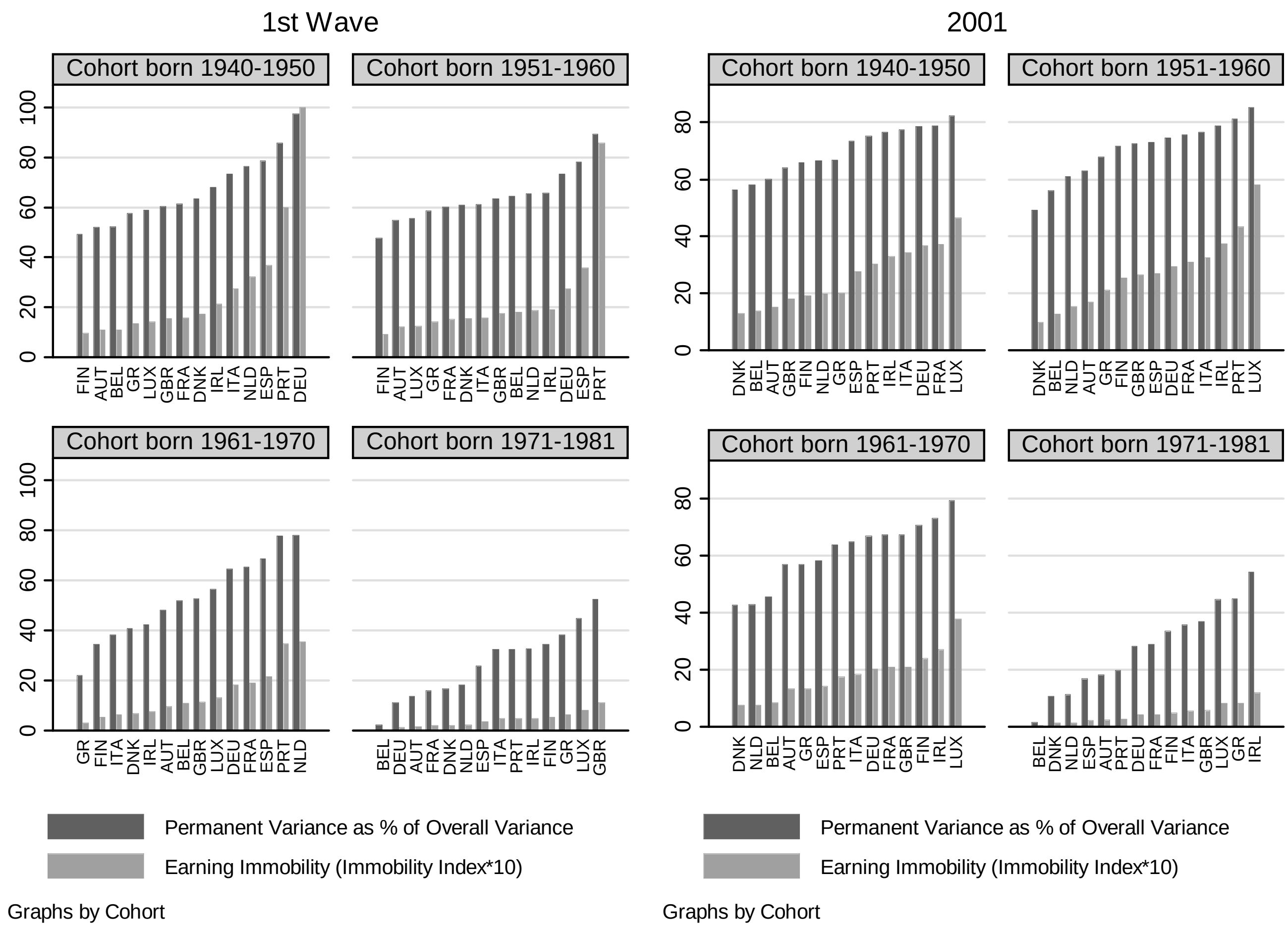

Figure 8. Permanent Inequality - % of the Overall Inequality and Earnings Immobility for Selected Cohorts over Time

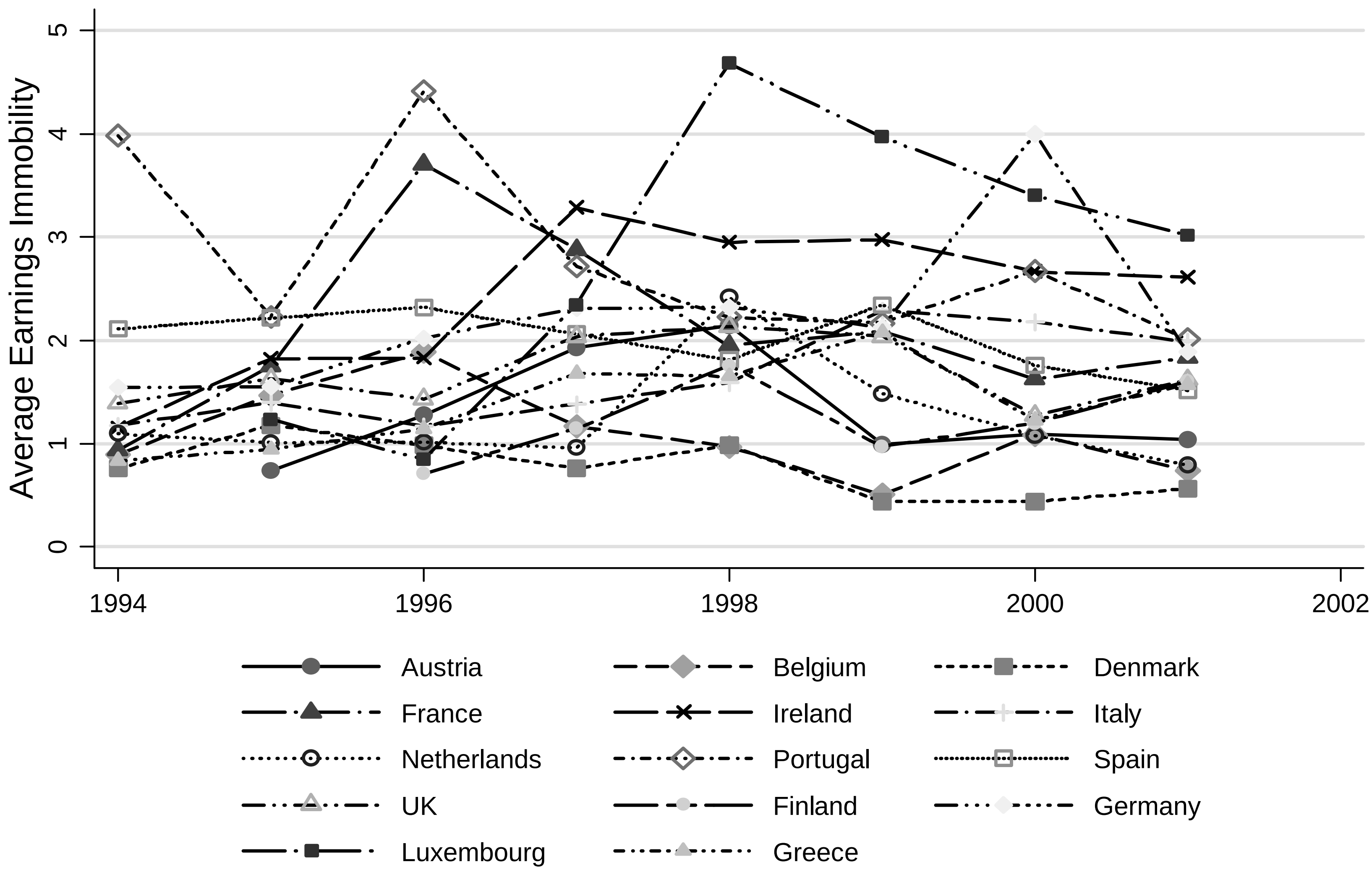

Figure 9. Average Earnings Immobility – Ratio between Average Permanent Variance and Average Transitory Variance over Time

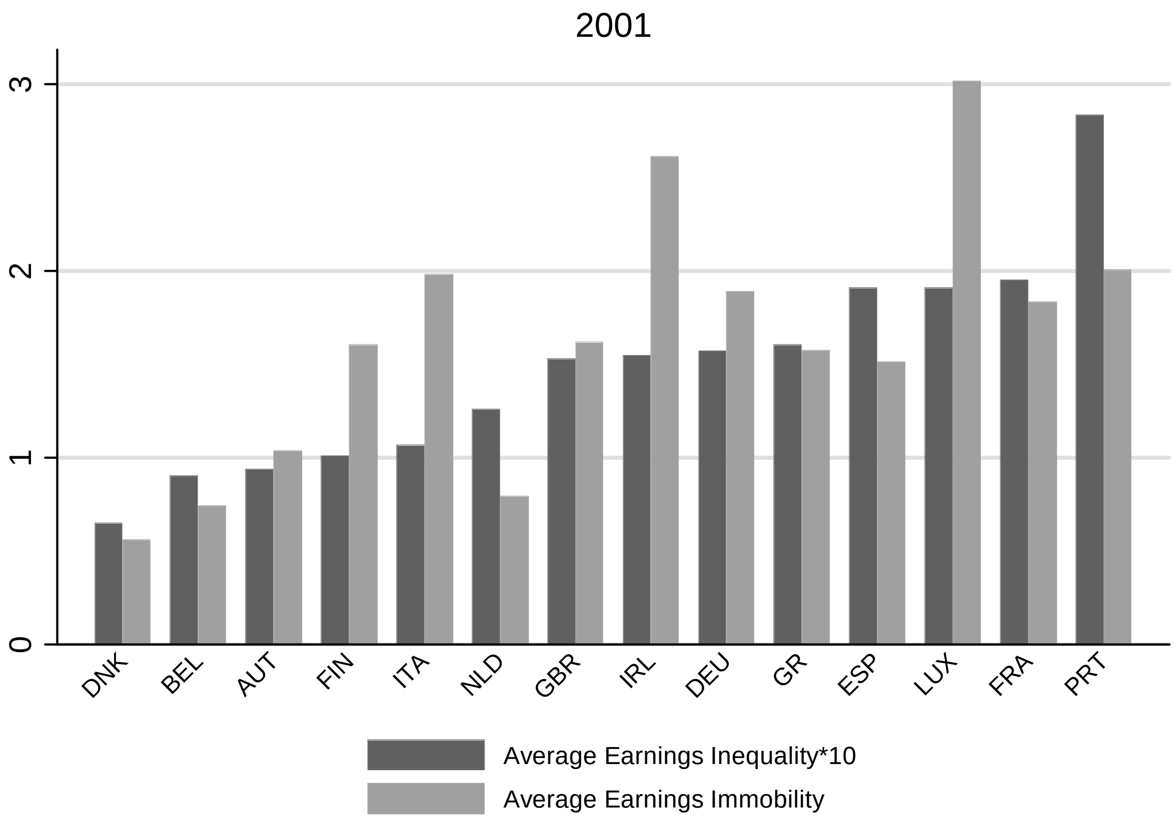

Figure 10. Average Earnings Inequality and Average Earnings Immobility Ratio in 2001

Note: The figures are in ascending order for the Average Earnings Inequality, rescaled by multiplying with 10.

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002	Gassmann, F.	How to Improve Access to Social Protection for the Poor? Lessons from the Social Assistance Reform in Latvia