The Dynamics of Individual Male Earnings in Great Britain: 1991-1999

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ABSTRACT

In this paper I analyse the dynamic structure of earnings in Great Britain for the period 1991-1999 by decomposing the earnings covariance structure into its permanent and transitory components. Using information on monthly earnings of male full-time employees from the first nine waves of the British Household Panel Study I find that earnings inequality increases over the Nineties. However, earnings mobility may have also increased. That is, for this period earnings persistence falls. Surprisingly, I also find that relative earnings persistence declines over the life cycle, which implies lower mobility for younger cohorts. This evidence is at odds with previous literature on earnings dynamics both for Britain and other OECD countries. Unlike recent studies, I also consider the effects of observed characteristics on the covariance structure of log earnings and find that human capital and job related characteristics account for nearly all persistent earnings differences and that the transitory component is highly persistent.

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Non-technical Summary

Earnings inequality has markedly increase over the last twenty-five years in Great Britain. This increase in cross sectional inequality is well documented. However we still know very little about the dynamic nature of those individual earnings differences. From a longitudinal perspective, such a widening in earnings dispersion is partly due to individual differences that persist over time and partly due to transitory differences

Such distinction is important since permanent and transitory earnings differences have different economic implications. Permanent differences imply little or no earnings mobility and possibly a rigid labour market in where the starting position is crucial for determining individual's life cycle earnings profile and their position in the earnings distribution over time. Alternatively if cross-section inequality is largely due to short run transitory differences, over time, the burden of inequality can be seen as being shared more equally among individuals.

In this paper I analyse some dynamic aspects of earnings inequality in Great Britain for the period 1991-1999 by decomposing the earnings covariance structure into its permanent and transitory components. Using information on monthly earnings of male full-time employees from the first nine waves of the British Household Panel Study I find that earnings inequality increases over the Nineties and follow rather closely the business cycle.

The study of the dynamic processes governing such a widening in individual earnings dispersion indicates that both persistent and transitory differences account for increasing earnings inequality. At the beginning of the Nineties, the persistent component plays a somewhat larger rôle. However, in the course of the decade, earnings dispersion becomes more transitory and much less persistent. Thus earnings volatility within the distribution has increased over the Nineties.

Surprisingly, I also find that relative earnings persistence declines over the life cycle, which implies lower mobility for younger cohorts. This evidence contrasts with previous literature on earnings dynamics both for Britain and other OECD countries, which have found the transitory and persistent components to play a very similar rôle in accounting for increasing earnings dispersion, and smaller earnings persistency for younger cohorts.

To start exploring the causes of the increases in long-run inequality and instability I analyse the residuals from a first-stage regression which nets out the effects of human capital and job related characteristics from log earnings. The results suggest that these covariates account most earnings persistency

1. Introduction

The rising earnings inequality trends experienced over the last twenty-five years in Britain as well as many other OECD countries have motivated a substantial amount of contributions which try to understand the statics and dynamics of this reality. Over the last decade a growing body of literature —mainly for the US— has shown that such widening in earnings dispersion is partly due to individual differences that persist over time and partly due to transitory differences.[1]

Such distinction is important since permanent and transitory earnings differences have different economic implications. Permanent differences imply little or no earnings mobility and possibly a rigid labour market in where the starting position is crucial for determining individual's life cycle earnings profile and their position in the earnings distribution over time. Alternatively if cross-section inequality is largely due to short run transitory differences, over time, the burden of inequality can be seen as being shared more equally among individuals. From a policy perspective, the degree of persistence in individual earnings differences also tells us to what extent low earnings is a lasting or one-off experience.

In this paper I use the first nine waves of the British Household Panel Study (BHPS) to analyse the dynamic structure of individual earnings in Great Britain for the period 1991-1999. Thus, I provide new evidence on the dynamics of individual earnings for the second half of the Nineties in an analysis that covers the whole last decade. According to the BHPS data, cross-section earnings differences grew substantially over this period. To study the dynamic aspects of this increase in earnings differences, I decompose individual earnings into its permanent and transitory components by fitting error component models to the covariance structure of individual earnings. Unlike recent studies, I also examine the effects of observed variables (*i.e.* observable heterogeneity) on the covariance structure of log earnings.

My findings suggest that earnings mobility may have also increased over the Nineties. That is, for this period earnings persistence falls. Surprisingly, I also find that relative earnings persistence increases over the life cycle, which implies lower mobility for older cohorts. When I make use of the observed variables, persistent earnings differences are mostly accounted for by human capital and job related characteristics, and the transitory component is highly persistent.

The rest of the paper is structured as follows. In the next section I describe the data and present some relevant evidence on earnings statics and dynamics. That is, cross-section earnings inequality and a descriptive analysis of the covariance structure of earnings. Section 3 contains a brief discussion of some models of earnings dynamics and estimation methods. Section 4 presents the main empirical results from fitting those models to the BHPS data and analyses its implications in terms of the permanent-transitory decomposition of individual earnings. Finally, section 5 summarises and discusses the main findings.

2. The Data

The dynamic nature of the analysis requires longitudinal data. I employ the first nine waves of the British Household Panel Study (BHPS).[2] Following the practice of most previous studies I analyse only males. In particular, the sample is restricted to full-time male employees who reported positive earnings in at least one of the nine waves.[3] Therefore, individuals are allowed to enter the panel at any wave and to re-enter the panel if they do exit. Such a sample selection produces an unbalanced panel since not all persons are present for all nine waves. The final sample consists of 4,777 individuals and a total of 22,660 individual-year observations.

To separate life cycle effects from time effects, I partition the sample into 4 age cohorts.[4] The oldest cohort comprises those individuals born before 1941, so they are aged 50 years or more in 1991 when wave 1 takes place. The other two cohorts contain those born between 1941 and 1950, and between 1951 and 1960. The youngest cohort contains males born after 1961, that is, aged less than 31 in 1991.

The earnings measure is the log of the usual monthly earnings or salary payment before tax and other deductions in the current main job, deflated by the consumer price index. Unlike recent studies, this earnings measure is *not* derived from hourly wages.[5] In the BHPS, individuals report the amount they earn and the length of the period that amount covers—period length ranges from a week to a year. Monthly earnings are derived from these two questions.[6]

Permanent earnings differences may be due to the effect of time-invariant observables such as education but also to time-invariant unobservable factors such as ability or effort. On the other hand, serially correlated transitory differences may reflect the effect of serially correlated independent observable variables or the effect of transitory observable variables whose effects persist for more than one period, but also the effect of serially correlated random shocks which may be attributed to unobservables such as luck or even measurement error.

The use of log earnings, y, as the definition of earnings does not allow us to know which is the contribution to permanent and transitory earnings differences of the variables we do observe. However, the use of log earnings residuals from a first-stage earnings regression can help us determine such contributions, since the first-stage regression takes account of the effect of the observable variables on earnings and, thus, nets out their contribution to permanent and transitory earnings differences.

My strategy is to work with two definitions of earnings: log of earnings, y, and residuals from an earnings regressions, ω, with a set of human capital and job related covariates ($\mathbf{X}$).[7] Log earnings residuals are estimated by OLS separately for each cohort on the data pooled over individuals and waves. Regression results are presented in Appendix Table A1.

Description of the statics and dynamics of earnings differences

According to standard inequality measures, cross-section inequality of earnings grows over the Nineties —see Figure 1.[8] Note that earnings dispersion is procyclical, closely following the evolution of the GDP growth rate. Such a cross-section picture, however, does not tell us anything about the dynamics of individual earnings or about the relative importance of the permanent and transitory components of earnings.

In order to analyse the dynamics of individual earnings and to assess to which extent earnings differences persist over time, I estimate the covariance matrix of the log-earnings for each cohort.[9] The covariance matrix contains 180 unique elements (9 variances and 36 covariances for each one of the four cohorts). A first insight into the dynamic nature of individual earnings can be obtained from direct observation of the actual variances and covariances —not shown. The covariances are all positive and quite large in magnitude relative to the variances. The relative magnitude of the covariances differ across cohorts: on average, relative covariances of any lag length, are larger for the younger cohorts than for the older one. This evidence points to a substantial persistence of earnings differences, which is to be larger for younger cohorts —since (longer lag) covariances mainly reflect the permanent component of earnings.

A further and compact description of the covariance matrix can be obtained by pooling all covariances and regressing them on a set of dummies for lag length, calendar time (wave) and birth cohort using OLS.[10] As Table 1 shows, only the first lag coefficient is statistically significant, suggesting that transitory shocks are not very persistent. Calendar time dummies pick up the trend in earnings dispersion shown in Figure 1. This trend somehow parallels the labour market behaviour in terms of unemployment rates. Male unemployment rose to 12.4 percent in 1993 (picked up by the 1993 dummy, statistically significant only at 10%) and monotonically decreased thereafter until 1999. This evidence, then, suggests a weak inverse relationship between earnings dispersion and unemployment. Cohort estimates show that earnings variances and covariances are larger for older cohorts, especially for individuals born before 1941. That is, earnings dispersion seems to increase over the life cycle, being notably higher for the oldest cohort.

3. Error Component Models

The last section described some stylised facts about individual observed earnings dynamics. The purpose of this section is to outline some parsimonious error component models that will characterise the dynamic structure of individual earnings and will help us assessing the relative importance of earnings persistence and earnings volatility over the sample period.

I begin with the simplest model of all which, despite its simplicity, provides a very intuitive insight into the matters of concern. However, since this first model overlooks several important features of the earnings dynamics that have been documented in the previous section, then I discuss a more general model that will be used for estimation.

The most rudimentary error component model is the canonical permanent-transitory model with white noise transitory component,

(1) $$y_{iat} = \mu_i + v_{it}, \qquad \mu_i \sim iid(\bar{\mu}_i, \sigma^2_\mu),\ v_{it} \sim iid(0, \sigma^2_v)$$

(2) $$Cov(y_{it}, y_{is}) = \begin{cases} \sigma^2_\mu + \sigma^2_v, & t = s \\ \sigma^2_\mu, & t \neq s \end{cases}$$

where μ_i is a time-invariant individual component with mean $\bar{\mu}_i$ and variance σ^2_μ and v_{it} is a serially uncorrelated transitory component with zero mean and variance σ^2_v.

The simplicity of this model greatly facilitates its interpretation in terms of permanent and transitory components. The variance of the permanent component, σ^2_μ, (which fully determines the covariances) represents the persistent dispersion of earnings and the individual component μ_i is seen as representing the effects of (unmeasured) characteristics such as ability and work related tastes which are assumed to persist throughout the sample period. As the covariance structure imposed by the ECM grows in complexity its interpretation becomes less clear.

Notwithstanding this, the canonical model in (1) imposes very rigid restrictions on the dynamic structure of our data that render it inappropriate. Regarding the permanent component, some empirical studies have found evidence, which support labour market theories, such as human capital o matching theories, which in turn postulate persistent heterogeneity across individuals in their growth rates.[11] Additionally, some earnings shocks may have permanent effects which can be modelled with a random walk specification of the permanent component.[12] The unit root hypothesis has also been previously justified in terms of low rates of depreciation on human capital investments or the effects of labour market conditions through implicit contracts (Baker, 1997). As far as the transitory component is concerned, previous inspection of our data suggests that transitory earnings may be serially correlated.

These considerations (and extensions) to the canonical model still assume a 'stationary' behaviour of individual earnings dynamics. However, the descriptive analysis of our data shows certain time patterns for the variances and covariances which are not stationary and differences across cohorts. To take due account of these time and cohort effects I will also consider time- and cohort-specific loading factors or shifters on both components.

The following specification extents the simple model in (1) and encompasses all the relevant aspects of earnings dynamics considered above

(3) $$y_{icat} = \gamma_c \alpha_t [\mu_i + \eta_i a_{it} + u_{iat}] + \zeta_c v_{it} ,$$

$$\mu_i \sim (\bar{\mu}_i, \sigma^2_\mu), \quad \eta_i \sim (\bar{\eta}_i, \sigma^2_\eta) \ , \ E(\mu_i, \eta_i) = \sigma_{\mu\eta}$$

where

(4) $$u_{iat} = u_{i(a-1)(t-1)} + \pi_{iat} \ , \quad \pi_{iat} \sim (\bar{\pi}_i, \sigma^2_\pi) \ , \quad E(u_{i(a-1)(t-1)}, \pi_{iat}) = 0$$

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

In equation (3) μ_i and η_i are time-invariant individual intercepts and slopes, with variance σ^2_μ and σ^2_η; and a_{it} denotes age of individual i at time t.[13] These parameters model an individual profile heterogeneity as a function of age. A negative covariance between μ_i and η_i is consistent with the on-the-job training hypothesis (Mincer, 1974). In this case, this source of permanent earnings inequality will first decrease and then increase over the life cycle. Alternatively, a positive $\sigma_{\mu\eta}$ implies rising permanent inequality over the life cycle. Such a case is consistent with schooling-matching models where more educated workers have higher initial earnings and these also grow faster as the quality of the match is revealed to employers.

Equation (4) specifies a random walk model. The random-walk innovation π_{iat}, unlike the transitory innovation ε_{it} in equation (5), accommodates any permanent reranking of individuals in the distribution of earnings.

Though, on theoretical grounds these two specifications of the permanent component could be complementary, previous studies treat them as alternative. I model the random growth and random walk specifications jointly and thus employ a specification that generalises that of most earlier studies.[14]

Equation (5) allows the transitory component to follow a first-order autoregressive process, where the serial correlation parameter ρ captures the smooth decline of covariances as the lag length increases, and ε_{it} is a non-mean-reverting white noise innovation.

As mentioned above, the non-stationary pattern of earnings is accommodated using permanent and transitory time-specific shifters α_t, λ_t. Note that the incidence of these two loading factors on cross-section inequality and earnings mobility differs in a relevant way. An increase in permanent time-specific loading factors preserves the order of individuals in the earnings distribution, but increases their earnings differences, whereas an increase in transitory time-specific loading factors leads to more reranking within the earnings distribution.

Finally, cohort shifters γ_c and ζ_c, allow earnings and its components to vary according to the different life cycle stage in which they are observed. Additionally, cohort shifters also help estimating life cycle parameters such as ρ or σ^2_μ for the latter are identified by pooling different cohorts, rather than by observing complete life cycles.

4. Error Component Estimates

This section presents the results of fitting the general error component models outlined in the previous section to the unique elements of the covariance matrix for all four cohorts pooled together (*i.e.* 180 autocovariances), and analyses the changes in the permanent and transitory components over the sample period.

The parameters of the error component models are estimated using minimum distance techniques. The parameters chosen are those which minimise the (weighted) sum of the squared distance between the covariance structure implied by the error component model and the actual covariances.[15] Goodness of fit is assessed and nested models are tested using the sum of squared residuals (henceforth SSR) weighted by the inverse of an estimate of the variance of residuals.[16] Under the null of correct specification the SSR statistic is distributed as a χ^2 with $[4(t(t+1)/2)-p]$, where p is the number of parameters. However, a recurrent result in the literature is that the null is always rejected at conventional levels. Therefore, I employ the SSR as a measure of fit.

It is important to account for the initial conditions of a stochastic process when working with parameterisations for the covariance matrix which require information on variables for periods previous to the starting year of the panel, and thus not observed by the researcher (see MaCurdy, 1982, and Anderson and Hsiao, 1982). I take due account of initial conditions and adopt the method suggested by MaCurdy (1982) which involves the estimation of an 'initial' transitory variance σ^2_0. Although the previous literature has usually restricted the σ^2_0 to be the same for individuals of different ages, I allow the 'initial' variance to vary across cohorts since it is likely that the accumulated autoregression of transitory shocks up to the period of the first observation differs at different stages of the life cycle.

The first column in Table 2 shows the resulting estimates of the general model outlined in equations (3)-(5) where the permanent component is specified as a random growth in age plus a random walk, and the transitory component follows an AR(1) process with cohort-based heteroskedastic initial variances, and time- and cohort-specific loading factors on both components.

The estimates of σ^2_μ and σ^2_η in the first two rows capture the individual heterogeneity in the intercept and slope of the age-earnings profile. Our estimate of σ^2_η

implies that a worker with an earnings growth rate one standard deviation above the mean accumulates a 19% earnings advantage in ten years. The negative estimate of $\sigma_{\mu\eta}$ indicates a trade-off between initial earnings and subsequent earnings growth. That is, consistent with the on-the-job-training hypothesis, individual age-earnings profiles seem to cross at relatively early stages of the working career. This is also the evidence found in several previous studies.[17]

The relatively small estimate of σ^2_π implies that after the first 32 years of the working career, permanent earnings inequality would be 50% larger than at the beginning.

The estimates of the time-specific loading factors on this persistent component, α_t, are typically larger than one and increase sharply in the recovery of the British economy until 1996.[18] Note also that they follow rather closely the trend foreshadowed by the time pattern in the empirical autocovariance matrices captured by the time dummies in the descriptive regression of section 2. This suggests that the persistent component plays an important rôle in the increase of earnings inequality over the sample period. The estimated cohort-specific loading factors, γ_c, indicate that the persistent component increases over the life cycle up until the oldest cohort.

In the next section of the table, I report the estimated parameters for the transitory component. The estimates of the 'initial' variances, which capture the accumulation of the transitory process up to the start of the sample period for each cohort, show that these are most important for the older cohort. Even though *t*-statistics seem to indicate that these variances are not statistically significant, it will be shown below that they do contribute in explaining the cohort-related heteroskedasticity in the transitory component. The rather small serial correlation parameter estimate (ρ = 0.3) implies that the effect of random shocks dies out rather quickly —becoming negligible after five years. Not surprisingly, the time-specific loading factors on the transitory innovation display a much higher variation than the corresponding loading factors for the persistent component. However, it is interesting to note that the relative decline of the former for 1995 and 1998 closely follow the trend of the observed variance. Thus, these parameters help accommodating the 'jerkiness' observed in actual variances over the second half of the Nineties. Finally, the estimated cohort-specific loading factors on the transitory component are larger than one and they rise very rapidly as older cohorts are considered. These cohort-specific parameters are mostly picking up the larger observed variances displayed, on average, by older cohorts.

Using the parameter estimates of this model to predict total variances, Figure 2 shows that our preferred model is able to reproduce quite closely the evolution of the observed variance for each cohort over the sample period. In order to gain a better understanding of the relative contributions of the persistent and transitory components to the evolution of earnings inequality I use the parameter estimates to decompose the predicted variance into its two components for each cohort over the sample period. These correspond to the dotted lines in Figure 2. Clearly, Britain's increase in earnings inequality has stemmed from increases in both the persistent and the transitory components of earnings variation.

Notwithstanding that, the rôle played by both components is not stable over the sample period. As Table 3 shows, relative to the overall variance, the permanent (transitory) component falls (increases) over the whole decade with the marked exception of 1995 —which represents the turning point in terms of economic growth. Thence, the overall rising earnings dispersion becomes less persistent over the course of the decade. By the end of the Nineties, the (growing) earnings differences are mostly accounted for by (increasing) dispersion in the transitory earnings component.

Additionally, as the model implies —through the cohort-specific shifters—, this pattern differs across cohorts mostly in the relative magnitudes of the components. At any point in time, the permanent component (as a proportion of the overall predicted variance) is larger for younger than for older cohorts. Trends of the relative permanent and transitory variances are similar for all the cohorts but for the oldest that shows rather flat trends.

Although cross-studies comparisons should be done with a great deal of caution due to differences in the definition of earnings and in sample selection criteria, my results above differ in many ways from previous findings both for Britain and other countries. For Britain between 1975 and 1995, Dickens (2000a) finds an equal contribution of the two earnings components to rising overall inequality, the transitory component being larger for younger cohorts. For the first half of the Nineties, however, he also finds a sharp increase in the transitory variance. Other studies for the US and Canada reach similar conclusions,[19] while for Italy between 1979 and 1995 Cappellari (2000) finds a rising permanent component over time.

Our preferred model extends most of the specifications used in the previous literature. Perhaps the most notable extensions are (i) considering both the random growth and the random walk specifications in the permanent component and (ii) allowing for cohort-based heteroskedastic initial conditions. Given the low *t*-statistics of the relevant parameters for these restrictions (*i.e.* σ^2_η, $\sigma_{\mu\eta}$, σ^2_π, and the σ^2_{0c} 's), next we test whether the restrictions imposed by previous studies are statistically defensible with our British data, and analyse their implications for the earnings components. Columns 2 to 4 of Table 2 present the results of applying the above restrictions to our preferred model and show that they are all rejected by our data.

In the second column of Table 2 I examine the implications of assuming away permanent shocks by estimating a model with no random walk process (*i.e.* $\sigma^2_\pi = 0$). A Wald test on this restriction clearly rejects the null of no random walk (χ^2 = 28.05, df = 1). However, parameter estimates and, most importantly, the decomposition of earnings inequality do not change substantially. Imposing the restriction leads to a slightly larger estimate of the autorregressive parameter ρ and to a slightly smaller estimate of σ^2_μ . In terms of the decomposition, these minor changes in the estimates result into a tiny decrease in the permanent component.

The third column of Table 2 shows the implications of assuming away individual age-earnings profile heterogeneity (*i.e.* $\sigma^2_\eta = 0$ and $\sigma^2_{\mu\eta} = 0$). Again, a Wald test on this restriction clearly rejects the null of no random walk (χ^2 = 156.96, df = 2). Comparing the parameter estimates for this restricted specification to those for the preferred model reveals that the restriction of no heterogeneity of earnings growth rates imply a larger degree of mobility (smaller estimate of σ^2_μ) and longer persistence of the transitory shocks (larger estimate of ρ). Additionally, cohort-specific initial variances are relatively larger and more statistically significant for the restricted model. These changes in the parameter estimates lead to a much flatter trend of both components for the first four years of the Nineties and a smaller permanent component for most cohorts (compare Figures 3 and 4).

The fourth column of Table 2 shows the results of assuming homoskedastic initial conditions (*i.e.* $\sigma^2_{0,(>61)} = \sigma^2_{0,(51\text{-}61)} = \sigma^2_{0,(41\text{-}51)} = \sigma^2_{0,(<41)} = \sigma^2_0$) —while keeping the random growth plus random walk specification of the permanent component. As for the other restricted models, a Wald test on this restriction resoundingly rejects the null that initial variances are all the same (χ^2 = 152.47, df = 3). Relative to the preferred model, the most noticeable change is the decline in the cohort-specific loading factors, which in turn imply a much smoother trend in the permanent and transitory components over the first four years of the decade and an overall slight increase in the permanent component, that is, a bit less mobility over the whole period.

Finally, a plausible extension of our model is to supplement the autoregressive process already incorporated into the transitory component with a low degree moving average process. This extension could help accommodating the rapid decline in the first lag found in the observed autocovariances, and it has been fitted by few previous researchers —the most notable case for our study for Britain being Dickens (2000a). In terms of our estimated model, this implies replacing the AR(1) specification of equation (5) for the following ARMA(1,1) one

$$(6) \qquad \begin{aligned} &v_{it} = \rho v_{it-1} + \theta\varepsilon_{it-1} + \lambda_t \varepsilon_{it}\,, \\ &\varepsilon_{it} \sim (0, \sigma_\varepsilon^2) \qquad v_{i0} \sim (0, \sigma_{0,c}^2) \end{aligned}$$

The estimates of this full extended model suffered from some identification problems.[20] Consequently, I have restricted the initial conditions to be equal across cohorts. The results of this model are provided in the last column of Table 2.[21] The first thing to note is that, the data does not reject the null of the $\theta = 0$ (χ^2 = 2.05, df = 1). Despite this, the new ARMA specification has very little effect on the other parameter estimates —with the notable exception of ρ, which increases to 0.38— or on the decomposition of earnings inequality into its persistent and transitory components.

Log-earnings residuals

Next, consider the rôle of observed variables in the earnings components. In the first-stage regression, the covariates $\mathbf{X}_{it}$ explain some 45 per cent of total earnings variation for the youngest and oldest cohort and some 30% for the middle ones.

When the effect of several human capital and job related observable characteristics on log earnings are removed through the first-stage earnings regression actual (log-earnings residual) autocovariances are smaller, they do not differ across cohorts as much as those for log-earnings and they exhibit a flatter trend over the sample period.

In accordance to that, I fit a model which incorporates a persistent component, specified as a simple random effect, plus a transitory component following an AR(1) process with cohort-based heteroskedastic initial conditions and time-specific loading factors on both components —see Table 3. Note that this specification of the preferred model is much simpler than that for log earnings. On the one hand, now the data reject individual-specific heterogeneity in the age-earnings profile as well as the random walk specification, and on the other hand, they also reject the cohort-specific shifters.[22] In terms of the decomposition, the inclusion of the covariates changes dramatically the nature of earnings dispersion— compare Figures 3 and 6. Now, earnings differences are mostly transitory and the relative contribution of both components to the overall predicted variance hardly changes over cohorts. The transitory component falls until 1994 and then increases until the end of the decade. This evidence suggests several things. First, earnings differences across cohorts as well as their persistent or transitory nature, are mostly accounted for by the observable variables. Second, the increasing mobility experienced up until 1994 is mostly accounted for by the covariates of the first-stage regression. These covariates have a relatively small effect on the earnings differences decomposition in the course of the second half of the Nineties.

When the previous model is embellished with an ARMA(1,1) specification for the transitory component the autocorrelation parameter estimate becomes very large (ρ = 0.95) and all terms that specify the permanent component are not significant —see column 2 in Table 3. This change in the specification of the transitory component is important because it has a great bearing on the decomposition. As Figure 7 shows, this model suggests that differences in log earning residuals are mostly transitory over the whole sample period but for 1993-1994. In other words, the human capital and job related variables of the first-stage regression account for nearly all persistent differences in log earnings.

Finally, if we restrict all parameters that specify the permanent component to zero, the model fits the data better. Of course, the implications of this model are that the human capital and job related covariates account for all persistent earnings differences and that the transitory term is highly persistent.

5. Conclusions

In this paper I have analysed some dynamic aspects of earnings inequality in Great Britain for the period 1991-1999 by decomposing the earnings covariance structure into its permanent and transitory components. Using information on monthly earnings of male full-time employees from the first nine waves of the British Household Panel Study I find that earnings inequality increases over the Nineties and follow rather closely the business cycle.

The study of the dynamic processes governing such a widening in individual earnings dispersion indicates that both persistent and transitory differences account for increasing earnings inequality. At the beginning of the Nineties, the persistent component plays a somewhat larger rôle. However, in the course of the decade, earnings dispersion becomes more transitory and much less persistent. Thus earnings volatility within the distribution has increased over the Nineties.

Surprisingly, I also find that relative earnings persistence declines over the life cycle, which implies lower mobility for younger cohorts. This evidence contrasts with previous literature on earnings dynamics both for Britain and other OECD countries, which have found the transitory and persistent components to play a very similar rôle in accounting for increasing earnings dispersion, and smaller earnings persistency for younger cohorts.

To start exploring the causes of the increases in long-run inequality and instability I analyse the residuals from a first-stage regression which nets out the effects of human capital and job related characteristics from log earnings. The results suggest that these covariates account most earnings persistency. However, further research is needed to understand which of those factors is the main responsible of permanent earnings differences.

The potential sources of earnings instability are many. Increasing job instability is probably the first one that comes to mind. However, job tenure has not substantially changed, at least, up to the mid 1990s (Burgess and Rees, 1996; Gregg and Wadsworth, 1999), and the proportion of temporary jobs has remained stable over the Nineties (Booth, Francesconi and Frank, 2000). Of course, increasing transitory earnings differences could always stem from unstable earnings dynamics of those who remain in employment over the whole sample period. Evidence drawn on NES data, for example, suggests that the risk of a substantial decline in real hourly pay have increased by 20 to

30 per cent from the early 1980s to the mid 1990s (Nickell, Jones and Quintini, 2000). Notwithstanding this, Dickens (2000b) and Ramos, (1999b,c) provide evidence of stable earnings mobility for the first half of the Nineties.

Another possible source of increased earnings volatility is an increase in earnings losses after an unemployment spell. This is precisely what Nickell *et al*. (2000) find for Britain: a 40 percent increase in hourly earnings from the early 1980s to the mid 1990s. Gregg and Wadsworth (2000) also find that real entry wages (from unemployment) have fallen substantially since the beginning of the Eighties. Additionally, the 'low pay-no pay' cycle found by Stewart and Swaffield (1999) may have got worse, increasing earnings instability at the bottom end of the distribution.

Labour reallocation is another plausible factor. As Burgess, Lane and Stevens (2001) show the continual re-sorting of workers across different firms paying different wage *premia* have a substantial impact on earnings dispersion. Although such a reallocation process may have some permanent effects on earnings (most likely captured by the random walk process) it is also likely to have large transitory effects.

The main focus of this paper has been on modelling the persistency and instability of increasing earnings inequality. I have estimated more general models than most previous studies. For instance, I have successfully specified a permanent component that incorporates a random growth and a random walk process. As Baker and Solon (1999) put it, "this is a reassuring finding because there are good economic reasons to expect both aspects to be present". Another salient feature of my preferred model is the inclusion of initial conditions that differ across cohorts. Again, this is economically very plausible since it is likely that the accumulated autoregression of transitory shocks up to the period of the first observation differs at different stages of the life cycle. Finally, the non-stationary features of the British data are accommodated by year-specific and cohort-specific loading factors on each component. The inclusion of these shifters is important because otherwise we may be falsely attributing some of the nonstationarity apparent in the earnings data to the stationary features included in the model.

References

Abowd, J. and D. Card (1989): "On the covariance structure of earnings and hours changes", *Econometrica*, **57** (2), pp. 411-45.

Altonji, J.G. and L.M. Segal (1996): "Small-sample bias in GMM estimation of covariance structures", *Journal of Business and Economic Statistics*, **14**:353-66.

Anderson, T.W. and C. Hsiao (1982): "Formulation and estimation of dynamic models using panel data", *Journal of Econometrics*, **18**, pp. 47-82.

Baker, M. (1997): "Growth-rate heterogeneity and the covariance structure of life-cycle earnings", *Journal of Labour Economics*, **15** (2), pp. 338-75.

Baker, M. and G. Solon (1999): "Earnings dynamics and inequality among Canadian men, 1976-1992: Evidence from longitudinal income tax records", *NBER Working Paper* 7370.

Booth, A., M. Francesconi and J. Frank (2000): "Temporary jobs: Who gets the, what are they worth, and do they lead anywhere?", *ISER Working papers*. Paper 2000-13 Colchester: University of Essex.

Burgess, S. and H. Rees (1996): "Job tenure in Britain, 1975-1992", *The Economic Journal*, **106**: 334-44.

Burgess, S., J. Lane and D. Stevens (2001): "Jobs, workers and changes in earnings dispersion", Centre for Economic Performance Working Paper No. 491, London School of Economics.

Cappellari, L. (2000): "The dynamics and inequality of Italian male earnings: permanent changes or transitory fluctuations?", *ISER Working papers*. Paper 2000-41 Colchester: University of Essex.

Dickens, R. (2000a): "The evolution of individual male wages in Great Britain: 1975-95", *The Economic Journal*, **110**: 27-49.

Dickens, R. (2000b): "Caught in a Trap? Wage mobility in Great Britain: 1975-1994" *Economica*, **67**: 477-497.

Farber, H.S. and R. Gibbons (1996): "Learning and wage dynamics", *Quarterly Journal of Economics*, **111**:1007-47.

Gottschalk, P. and R. Moffitt (1995): "Trends in the covariance structure of earnings in the US: 1969-1987", *Working Paper*, Brown University.

Gregg, P. and J. Wadsworth (2000): “Mind the gap, please: The changing nature of entry jobs in Britain”, *Economica*, **67**: 499-524.

Gregg, P. and J. Wadsworth (1999): “Job tenure, 1975-1998” in *The State of Working Britain* (eds. P. Gregg and J. Wadsworth), Manchester University Press.

Hause, J. (1977): “The covariance structure of earnings and the on-the-job training hypothesis”, *Annals of Economic and Social Measurement*, **6**, pp. 335-65.

Hause, J. (1980): “The fine structure of earnings and the on-the-job training hypothesis”, *Econometrica*, **48**, pp. 1013-1029.

Jantti, M. (1993): “Earnings dynamics and industrial structure in Finland”, Working Papers of the European Scientific Network on Household Panel Studies. Paper 76. Colchester: University of Essex.

Lillard, L. and R. Willis (1978): “Dynamic aspects of earning mobility”, *Econometrica*, **46** (5), pp. 985-1012.

Lillard, L. and Y. Weiss (1979): “Components of variation in panel earnings data: American scientists, 1960-1970”, *Econometrica*, **47**, pp. 437-54.

MaCurdy, T. (1982): “The use of time series processes to model the error structure of earnings in a longitudinal data analysis”, *Journal of Econometrics*, **18**, pp. 83-114.

Mincer, J. (1974): *Schooling, Experience and Earnings*. New York: NBER.

Nickell, S., T. Jones and G. Quintini (2000): “A Pictureof job insecurity facing British men”, Centre for Economic Performance Working Paper No. 479, London School of Economics.

Ramos, X. (1999a): “The covariance structure of earnings in Great Britain:1991-1995”, *ISER Working Paper 99-4,* Colchester: University of Essex.

Ramos, X. (1999b): “Earnings inequality and earnings mobility in Great Britain: Evidence from the BHPS, 1991-1994”, *ISER Working Paper 99-8*, Colchester: University of Essex.

Ramos, X. (1999c): “Anatomy of earnings mobility in Britain: Evidence from the BHPS, 1991-1995”, *ISER Working Paper 99-11*, Colchester: University of Essex.

Stevens, A.H. (1997): "Persistent effects of job displacement: The importance of multiple job losses", *Journal of Labor Economics*, **15**: 165-188.

Stewart, M. and J.K. Swaffield (1999): "Low pay dynamics and transition probabilities", *Economica*, **66**: 23-42.

Taylor, A. (1994): "Appendix: sample characteristics, attrition and weighting" in *Changing Households: the British Household Panel Study 1990-1992* (eds. N. Buck, J. Gershuny, D. Rose, & J. Scott), Colchester: ESRC Research Centre on Micro-Social Change, University of Essex.

Taylor, M.F. (ed.) (1995a): *British Household Panel Survey User Manual Volume A: Introduction, Technical Report and Appendices*. Colchester: ESRC Research Centre on Micro-Social Change, University of Essex.

Taylor, M.F. (ed.) (1995b): *British Household Panel Survey User Manual Volume B1: Codebook*. Colchester: ESRC Research Centre on Micro-Social Change, University of Essex.

Table 1. Descriptive regression of the earnings covariance matrix

	Coefficient	t-ratio
Lag structure		
Lag1	-0.262	-7.30
Lag2	-0.026	-0.69
Lag3	-0.025	-0.63
Lag4	-0.001	-0.03
Lag5	-0.012	-0.26
Lag6	0.049	0.89
Lag7	0.030	0.45
Lag8	-0.094	-1.04
Year dummies		
1992	0.010	0.29
1993	0.062	1.64
1994	0.056	1.39
1995	-0.047	-1.08
1996	0.117	2.40
1997	0.091	1.64
1998	-0.132	-1.99
1999	0.826	9.19
Cohort dummies		
(51-61)	-0.025	-0.82
(41-51)	0.074	2.46
(<41)	0.182	6.00
constant	0.430	10.46

Table 2. Estimates of Earnings Dynamics Models (Log Earnings, y_{iact})[a]

	(RG+RW) + AR(1)		RG + AR(1)		RW + AR(1)		(RG+RW) + AR(1) $\sigma^2_{0,c} = \sigma^2_0$		(RG+RW) + ARMA(1,1) $\sigma^2_{0,c} = \sigma^2_0$	
					Permanent Component					
σ^2_μ	0.27	(5.41)	0.25	(6.09)	0.19	(8.62)	0.26	(6.23)	0.25	(6.01)
σ^2_η	0.0003	(1.43)	0.0003	(1.54)			0.0003	(1.20)	0.0003	(1.21)
$\sigma_{\mu\eta}$	-0.01	(-1.79)	-0.008	(-2.85)			-0.01	(-1.77)	-0.01	(-1.71)
σ^2_π	0.005	(0.47)			0.005	(0.28)	0.005	(0.56)	0.005	(0.52)
α_{92}	0.92	(10.42)	0.91	(10.53)	0.97	(9.99)	0.94	(11.07)	0.95	(11.29)
α_{93}	1.05	(7.97)	1.06	(8.12)	1.10	(7.52)	1.08	(8.73)	1.09	(8.54)
α_{94}	1.14	(6.62)	1.15	(6.68)	1.22	(7.38)	1.17	(7.03)	1.17	(6.46)
α_{95}	1.18	(7.73)	1.23	(8.47)	1.25	(10.33)	1.22	(8.32)	1.21	(7.72)
α_{96}	1.35	(7.03)	1.40	(6.82)	1.27	(4.81)	1.38	(7.25)	1.38	(7.02)
α_{97}	1.14	(6.00)	1.20	(6.18)	1.04	(7.31)	1.18	(6.79)	1.17	(7.13)
α_{98}	1.05	(8.89)	1.09	(8.71)	0.94	(5.23)	1.07	(9.01)	1.08	(8.13)
α_{99}	1.36	(4.62)	1.37	(4.44)	1.24	(4.72)	1.38	(4.65)	1.39	(4.56)
$\gamma_{(51\text{-}61)}$	1.50	(2.86)	1.54	(2.79)	0.75	(1.92)	1.36	(2.41)	1.37	(2.44)
$\gamma_{(41\text{-}51)}$	2.04	(1.14)	2.24	(1.00)	0.81	(1.36)	1.62	(1.19)	1.64	(1.19)
$\gamma_{(<41)}$	1.30	(1.24)	1.42	(1.16)	0.69	(1.13)	1.09	(1.21)	1.08	(1.24)
					Transitory Component					
$\sigma^2_{0,(>61)}$	0.03	(0.42)	0.05	(0.87)	0.13	(3.53)				
$\sigma^2_{0,(51\text{-}61)}$	0.04	(0.69)	0.06	(0.82)	0.11	(2.23)				
$\sigma^2_{0,(41\text{-}51)}$	0.01	(0.11)	0.03	(0.33)	0.02	(0.85)				
$\sigma^2_{0,(<41)}$	0.14	(1.61)	0.15	(1.73)	0.10	(1.45)				
σ^2_0							0.11	(1.67)	0.11	(1.63)
σ^2_ε	0.10	(1.76)	0.10	(1.93)	0.06	(1.49)	0.09	(1.73)	0.09	(1.74)
ρ	0.30	(2.00)	0.32	(2.51)	0.41	(2.47)	0.29	(1.96)	0.38	(1.19)
θ									-0.09	(-0.34)
λ_{93}	1.21	(3.63)	1.21	(4.12)	1.26	(3.29)	1.21	(3.65)	1.25	(3.46)
λ_{94}	1.39	(3.23)	1.38	(3.70)	1.43	(2.96)	1.38	(3.22)	1.42	(3.20)
λ_{95}	0.79	(3.43)	0.79	(3.86)	0.75	(2.73)	0.78	(3.42)	0.80	(3.30)
λ_{96}	1.31	(2.06)	1.31	(2.25)	1.63	(2.16)	1.30	(2.08)	1.40	(2.37)
λ_{97}	1.83	(3.63)	1.76	(3.90)	2.07	(3.11)	1.82	(3.53)	1.90	(3.45)
λ_{98}	1.34	(4.02)	1.31	(4.50)	1.52	(3.95)	1.35	(4.04)	1.37	(3.92)
λ_{99}	2.38	(3.30)	2.33	(3.80)	2.74	(3.00)	2.38	(3.22)	2.49	(3.02)
$\zeta_{(51\text{-}61)}$	1.15	(5.54)	1.17	(5.97)	1.23	(5.08)	1.15	(5.58)	1.15	(5.60)
$\zeta_{(41\text{-}51)}$	1.30	(6.28)	1.35	(6.98)	1.52	(5.25)	1.33	(6.19)	1.33	(6.27)
$\zeta_{(<41)}$	1.89	(4.49)	1.86	(4.37)	2.12	(3.97)	1.93	(4.46)	1.92	(4.43)
SSR		889.49		917.54		1046.45		1041.96		1039.92

[a]: *t*-ratios in parentheses.

Table 3. Estimates of Earnings Dynamics Models (Log Earnings Residuals, ω_{iact})[a]

	RE + AR(1)		RE + ARMA(1,1)		ARMA(1,1)	
Permanent Component						
σ^2_μ	0.05	(11.50)	0.01	(0.57)		
α_{92}	0.82	(5.84)	0.76	(1.07)		
α_{93}	1.19	(4.11)	2.00	(1.13)		
α_{94}	1.62	(2.81)	2.31	(1.08)		
α_{95}	1.05	(8.41)	-0.26	(-0.28)		
α_{96}	1.01	(5.88)	-0.70	(-0.64)		
α_{97}	0.99	(5.53)	-1.00	(-0.63)		
α_{98}	0.79	(4.54)	-0.80	(-0.64)		
α_{99}	0.81	(5.40)	-1.09	(-0.83)		
Transitory Component						
$\sigma^2_{0,(>61)}$	0.07	(6.63)	0.10	(4.48)	0.13	(11.71)
$\sigma^2_{0,(51-61)}$	0.08	(5.82)	0.12	(3.78)	0.16	(4.01)
$\sigma^2_{0,(41-51)}$	0.07	(5.83)	0.12	(5.46)	0.15	(8.88)
$\sigma^2_{0,(<41)}$	0.05	(3.41)	0.07	(2.91)	0.10	(5.77)
σ^2_ε	0.10	(6.79)	0.14	(5.35)	0.13	(5.41)
ρ	0.41	(4.65)	0.95	(36.54)	0.86	(26.36)
θ			-0.36	(-16.31)	-0.32	(-10.17)
λ_{93}	0.97	(6.18)	0.97	(3.59)	1.14	(6.19)
λ_{94}	0.68	(1.30)	0.67	(1.30)	0.88	(3.21)
λ_{95}	0.84	(5.62)	0.71	(1.60)	0.86	(5.41)
λ_{96}	0.95	(6.68)	1.19	(2.77)	1.01	(6.41)
λ_{97}	1.23	(5.15)	1.36	(3.44)	1.36	(4.90)
λ_{98}	1.22	(7.99)	1.40	(4.20)	1.27	(4.60)
λ_{99}	1.52	(5.43)	1.75	(3.99)	1.71	(3.60)
SSR		1785.86		1510.56		1313.27

[a]: *t*-ratios in parentheses.

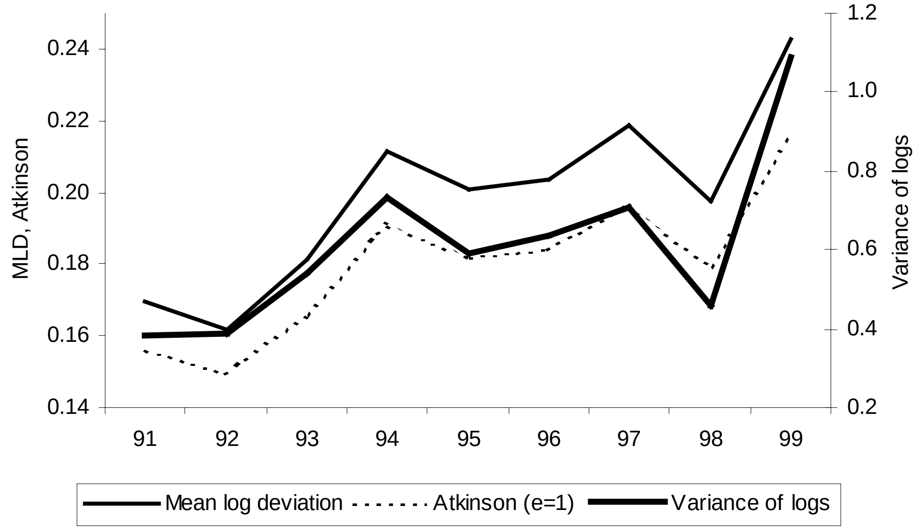

Figure 1. Earnings inequality. Great Britain, 1991-1999.

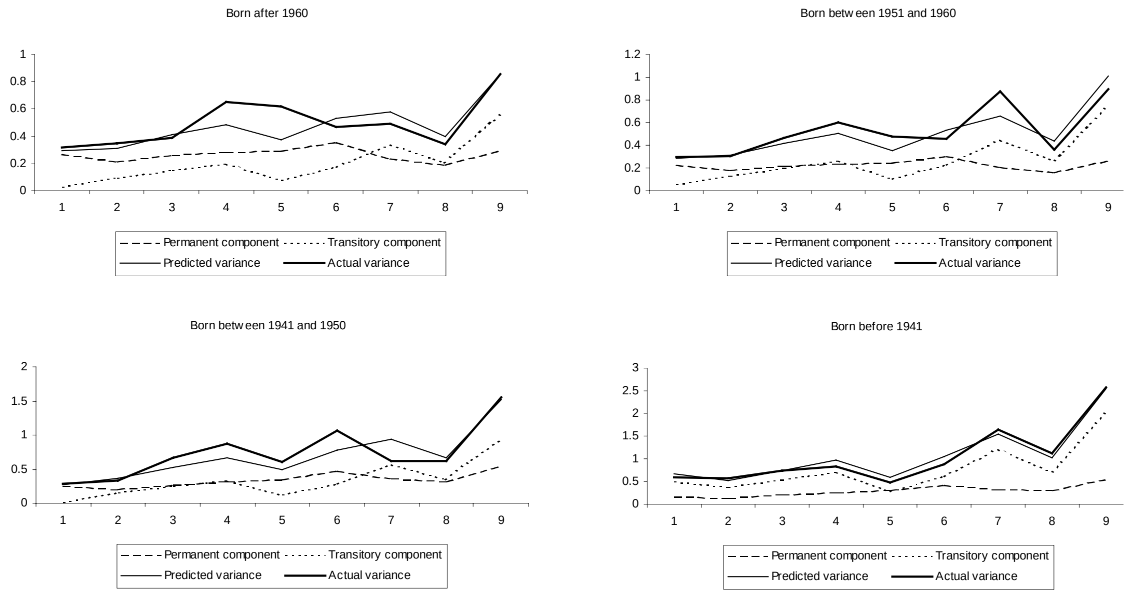

Figure 2. Actual and Predicted variances with permanent and transitory predicted components, by cohort
Log earnings: (Random Growth + Random Walk) + AR(1)

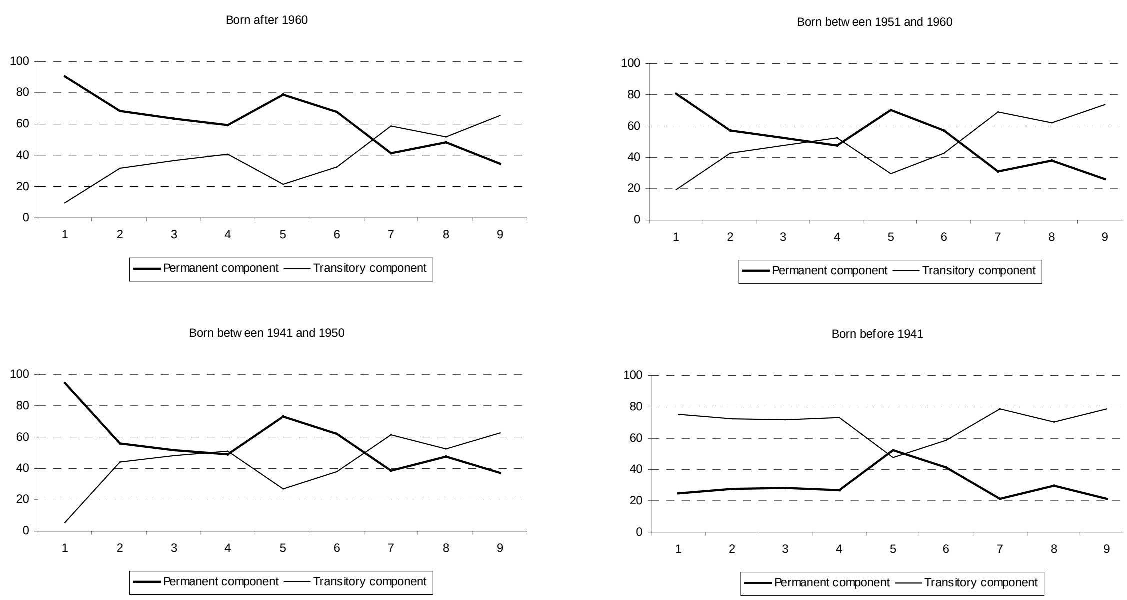

Figure 3. Predicted permanent and transitory components by cohort
(% of predicted overall variance)
Log earnings: (Random Growth + Random Walk) + AR(1)

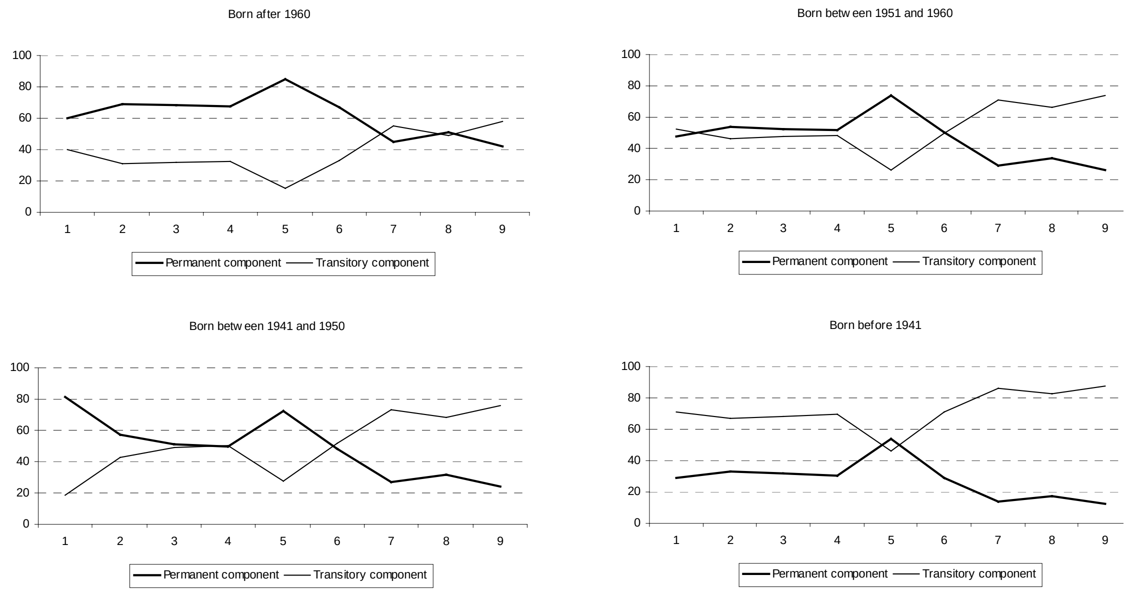

Figure 4. Predicted permanent and transitory components by cohort
(% of predicted overall variance)
Log earnings: Random Walk + AR(1)

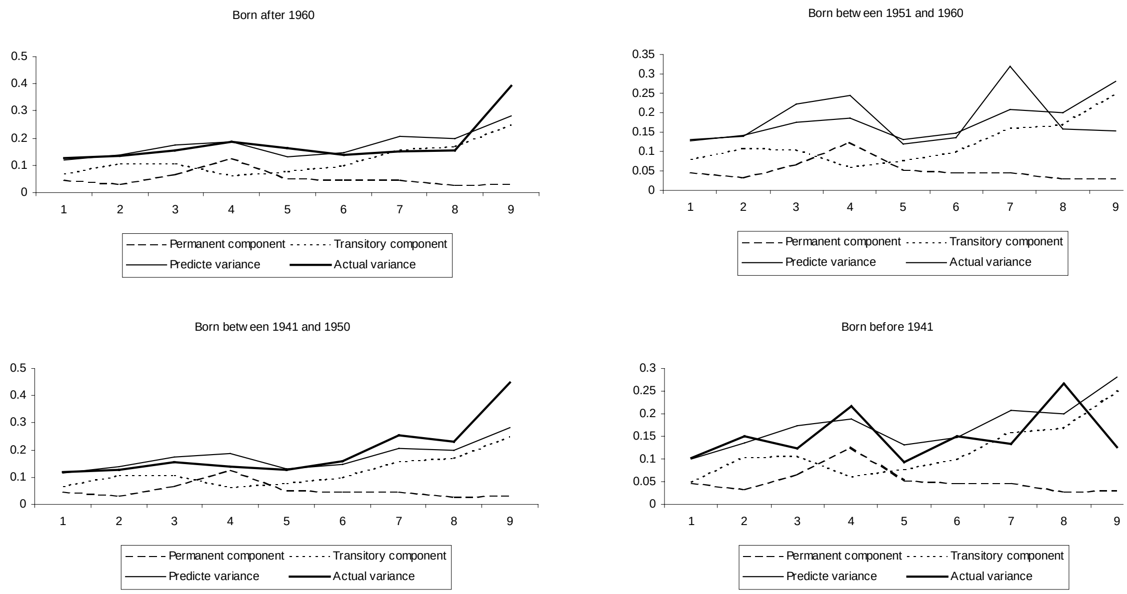

Figure 5. Actual and Predicted variances with permanent and transitory predicted components, by cohort
Log earnings residuals: Random effect + AR(1)

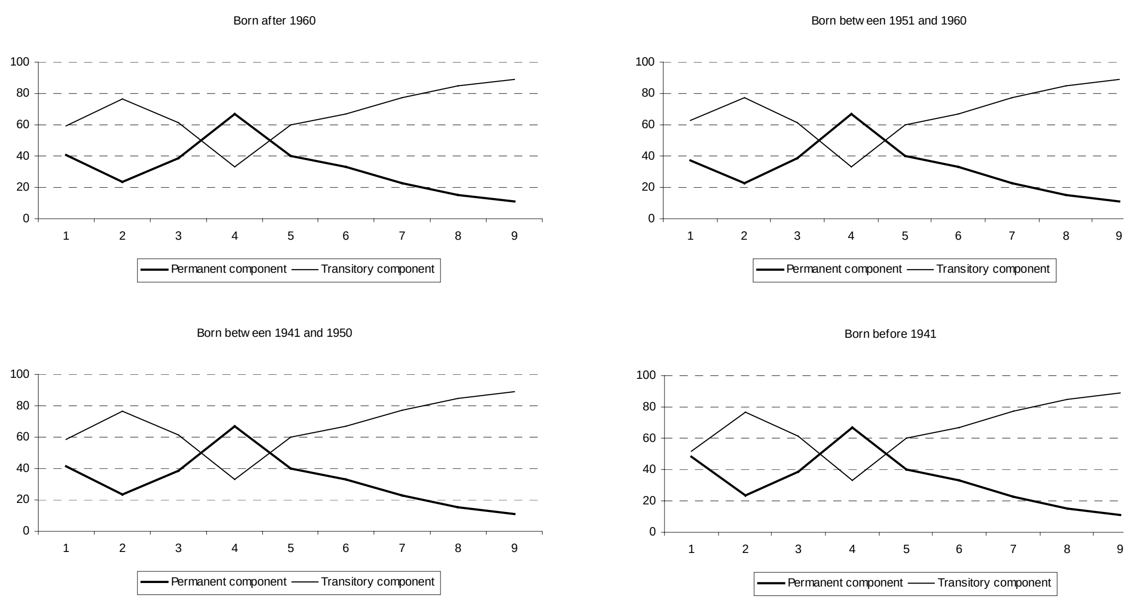

Figure 6. Predicted permanent and transitory components by cohort
(% of predicted overall variance)
Log earnings residuals: Random effect + AR(1)

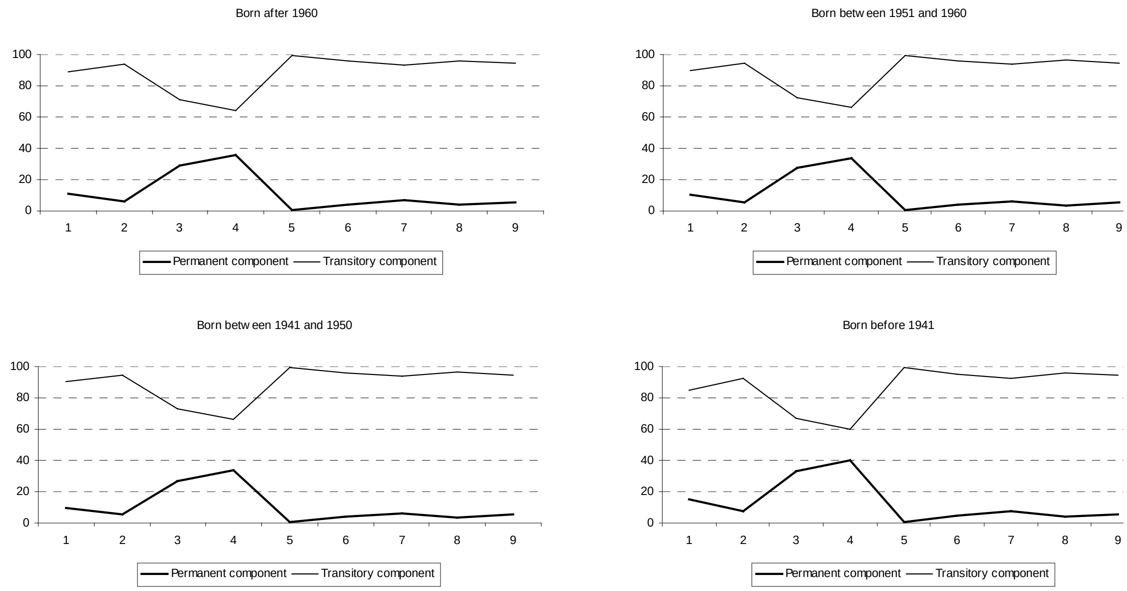

Figure 7. Predicted permanent and transitory components by cohort
(% of predicted overall variance)
Log earnings residuals: Random effect + ARMA(1)

Appendix

Table A1. Log Earnings Regression by Cohort

Explanatory Variable	*Birth Cohort (year of birth)*			
	1961 +	*1951-60*	*1941-50*	*< 1941*
Constant	6.778*	7.273*	7.897*	6.096*
Other Higher Qual. [a]	0.008	-0.228*	-0.778*	-0.011
A Levels	-0.186*	-0.232	-0.295	-0.946
O Levels	-0.373*	-0.487*	-1.128*	-0.897
Other Qualifications	-0.463*	-0.195	-0.572	-1.021
No Qualifications	-0.377*	-0.388*	-1.187*	-1.002
Experience	0.115*	0.019	0.001	0.097*
Experience squared	-0.003*	-0.0003	-0.0003	-0.001*
Other Higher Qual. × Experience	-0.013	0.002	0.022*	-0.010
A Levels × Experience	-0.007*	-0.003	0.007	0.013
O Levels × Experience	0.003	0.009	0.031*	0.012
Other Qualifications × Experience	0.009	-0.004	0.012	0.014
No Qualifications × Experience	-0.009	-0.001	0.028*	0.013
Wave 2	-0.055	-0.021	-0.051	-0.080
Wave 3	-0.074*	-0.115*	-0.001	-0.034
Wave 4	-0.072*	-0.074	-0.131*	-0.170*
Wave 5	-0.092*	-0.019	-0.030	-0.049
Wave 6	-0.109*	-0.003	-0.028	0.012
Wave 7	-0.103*	-0.045	-0.054	-0.079
Wave 8	-0.098*	-0.045	-0.073	-0.105*
Wave 9	-0.094	-0.006	-0.065	-0.005
Occupation: [b]				
Professional	-0.023	-0.129*	-0.196*	-0.144*
Associate profess. & technical	-0.094*	-0.250*	-0.270*	-0.174*
Clerical	-0.322*	-0.506*	-0.514*	-0.593*
Craft & related	-0.217*	-0.402*	-0.481*	-0.426*
Personal & protective services	-0.278*	-0.262*	-0.489*	-0.512*
Sales	-0.241*	-0.350*	-0.425*	-0.611*
Plant & machine operatives	-0.250*	-0.464*	-0.469*	-0.522*
Other	-0.347*	-0.605*	-0.571*	-0.544*
Industry: [c]				
Energy & water supplies	0.401*	0.536*	0.348*	0.534*
Extract minerals & manuf. Chemicals	0.291*	0.481*	0.197*	0.425*
Metal goods, engineering & vehicle	0.280*	0.393*	0.230*	0.237*
Other manufacturing	0.237*	0.344*	0.122	0.197*
Construction	0.233*	0.400*	0.110	0.213*
Distribution, hotels & catering	0.083*	0.228*	-0.076	-0.068
Transport & telecommunication	0.262*	0.386*	0.163	0.282*
Banking & finance	0.295*	0.455*	0.158	0.250*
Other services	0.132*	0.342*	0.007	0.188*
Region: [d]				
South East	-0.092*	0.003	0.006	-0.065
South West	-0.227*	-0.048	-0.076	-0.138*
East Anglia	-0.185*	-0.179*	-0.117*	-0.031
East Midlands	-0.261*	-0.130*	-0.196*	-0.213*
West Midlands	-0.213*	-0.181*	-0.088*	-0.146*
North West	-0.225*	-0.100*	-0.019	-0.080
Yorkshire & Humbershire	-0.293*	-0.188*	-0.100*	-0.165*
North	-0.270*	-0.131*	-0.011	-0.229*
Wales	-0.258*	-0.193*	-0.126*	-0.254*
Scotland	-0.184*	-0.159*	-0.091*	-0.175*
No Union Coverage	-0.085*	-0.086*	-0.078*	-0.062*
Not Married	-0.114*	-0.153*	-0.055*	-0.058
Adj. R^2	0.425	0.340	0.280	0.438

Notes: [*] significant at the 5 percent level;
[a] reference category: Higher Degree; [b] reference category: Managers & administrators;
[c] reference category: Agriculture, forestry & fishing; [d] reference category: Greater London.

Notes

[1] Some recent contributions are Dickens (2000a) for Britain, Gottschalk and Moffitt (1995) and Baker (1997) for the US, Baker and Solon (1999) for Canada, and Cappellari (2000) for Italy. Prior to these studies, and with the exception of Abowd and Card (1989), the literature on the covariance structure of earnings jumps back to the late Seventies/early Eighties: Hause (1977, 1980), Lillard and Willis (1978), Lillard and Weiss (1979), MaCurdy (1982).

[2] The BHPS is a longitudinal panel data set consisting of some 5500 households (approximately 10000 individuals) firs interviewed in the autumn of 1991 (wave 1) followed and re-interviewed every year subsequently. The initial sample represents a response rate of about 69% (proxies included) of the effective sample size. Wave-on-wave attrition rates for the subsequent waves are low. For a detailed discussion of BHPS methodology and representativeness see Taylor, A (1994) and Taylor, M.F. (1995a,b).

[3] These sample selection criteria are the same as in the three most recent studies on the covariance structure of earnings for the US (Gottschalk and Moffitt, 1995, and Baker, 1997) and for the UK (Dickens, 2000a).

[4] Ideally I would like to consider one age cohort per year of birth. However, due to the small sample size, I group individuals born in different years into the same cohort. In other words, I choose this level of disaggregation to ensure that there are sufficient observations in each cohort to make the analysis meaningful.

[5] In the other study on the covariance structure of earnings in GB, Dickens (2000a) employs the log of real hourly earnings which is obtained by dividing weekly earnings by total weekly hours as reported in the NES. Other studies that use US data by Lillard and Willis (1978), Lillard and Weiss (1979), Hause (1980), Gottschalk and Moffitt (1995) and Baker (1997) use the log of real annual earnings.

[6] The earnings measure I use can be interpreted as the average hourly wage times hours worked. Hence the observed earnings variances and covariances are partly determined by the variation and covariation in hours, which, in turn, implies that earnings variances and covariances are expected to be larger than wage variances and covariances unless the covariance of wages and hours is negative and large (see Abowd and Card, 1989).

[7] In particular, the vector of covariates $\mathbf{X}_{it}$ contains: education qualifications as a categorical variable, years of potential labour market experience and experience squared, wave dummies, interaction between educational qualifications and years of experience, occupation as a categorical variable, industry as a categorical variable, union coverage at the work place as a dummy variable, marital status as a dummy variable, regional dummies. Wave dummies (which can be seen as year dummies since in the BHPS most interviews are done in the fourth quarter of the year) capture the combined effect of time-varying macroeconomic variables, such as changes in productivity and other changes in market conditions exogenous to the individual, that are not accounted for by the set of exogenous variables included in the regression. In particular, they may capture the change in business cycle undergone by the British economy during the sample period—for the British economy, the years 1992-93 represent a turning point from recession to recovery. Note that this specification is prone to endogeneity problems, in which case, the log earnings residual estimates, ω_{it}, would be biased.

[8] Such an increasing earnings inequality trend does not change if other relative inequality measures (that satisfy the principle of transfers) are employed.

[9] Covariance matrices for each cohort are available from the author. For a detailed technical description about how to estimate covariance matrices with an unbalanced panel, see the Technical Appendix in Dickens (2000a). The covariance structure of log earnings differ across cohorts. The cohort covariance structure which differs most from the other cohorts is that of the oldest cohort.

[10] Lag and year dummies are specified in an incremental way. That is, they should be interpreted with respect to the previous lag or year rather than with respect to a given reference category. Standard errors are adjusted using the matrix of fourth moments to mitigate the inefficiency of OLS estimates due to the likely presence of heteroskedasticity and serial correlation.

[11] See, among others, Cappellari (2000), Baker (1997), Hause (1980), Lillard and Weiss (1979).

[12] Stevens (1997) finds evidence of persistent effects of job displacement, and Farber and Gibbons (1996) also find that new information on worker's productivity has persistent effects on individual earnings. Previous studies that model the permanent component as a unit root include Dickens (2000a), Gottschalk and Moffitt (1995), Abowd and Card (1989), MaCurdy (1982).

[13] Age is defined in deviations from the minimum observed age in the sample.

[14] See Baker and Solon (1999) for the only study where these two specifications are also modelled jointly.

[15] For a detailed description of the statistical methodology employed to estimate the models, see Ramos (1999a). Minimum distance estimation methods for error component models are also outlined in Dickens (2000a), Gottschalk and Moffitt (1995) and Abowd and Card (1989). Following Altonji and Segal (1996) I use the identity matrix as a weighting matrix.

[16] The weighting matrix is given by $(\vartheta I \vartheta')^{-1}$, where ϑ is the projection matrix of the minimisation problem and I is the identity matrix.

[17] Lillard and Wiess (1979), Hause (1980), Jantti (1993), Baker (1997). In contrast to this evidence, Cappellari (2000) finds a positive covariance.

[18] For identification, α_t for 1991 (wave 1), λ_t for 1991 and 1992, and γ_c and ζ_c for the youngest cohorts are all set to 1.

[19] See, *inter alia*, Gottschalk and Moffitt (1995) and Baker (1997) for the US; and Baker and Solon (1999) for Canada.

[20] In particular, when I estimate the full extended model specified by (3), (4) and (6), *i.e*. an ARMA(1,1) for the transitory component with cohort-based heteroskedasticity for the initial conditions, the estimated initial variance $\sigma^2_{0,(41\text{-}51)}$ is negative and the predicted transitory component for some years and some cohorts is also negative.

[21] This parameter estimates ought to be compared with those in the previous (fourth) column.

[22] Other richer models suffer from convergence problems —*i.e*. either the model does not converge or it converges to a solution with negative estimates of some variance. In particular I have experimented with the following models: (i) the specification fitted for log earnings as defined in equations (3)-(5); (ii) the same specification as in (i) but without cohort-specific loading factors; (iii) the same specification as in (ii) but restricting the permanent component first to a random growth specification, and then to a random walk process. Finally, note that I have also tested the hypothesis of homoskedastic initial conditions but the data rejects it (χ^2 = 14.69, df = 3).