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THE EVOLUTION OF INDIVIDUAL MALE EARNINGS IN GREAT BRITAIN: 1975-94

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ABSTRACT

In this paper I study the changing dynamic structure of male wages in Great Britain using the New Earnings Survey Panel from 1975-94. Computing the covariance structure of individual wages by cohort I find evidence of a substantial permanent component of earnings that increases over the life cycle and a highly persistent, serially correlated transitory component. In addition, the estimated variances of both the permanent and transitory components have risen over this period, each explaining about half the rise in inequality. These results imply that the observed cross sectional rise in inequality is reflective of largely permanent differences between individuals that have grown over the last decade or so.

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Richard Dickens

1. Introduction

Possibly the most striking phenomena in the UK labour market over the last couple of decades has been the massive rise in wage inequality. Wage differentials have risen to a degree that pay inequality is now higher than at any time over the last century. This increase in cross sectional inequality has been widely documented. (For example see: Gosling, Machin and Meghir, 1996; Gregg and Machin, 1994; Schmitt, 1995; Machin, 1996).[1] Dispersion appears to have risen in almost every measurable dimension. Looking at groups of individuals with different observable characteristics (such as education, experience, age, occupation, etc) one finds an increase in dispersion both between and within these groups.

Despite this comprehensive literature on the cross sectional rise in inequality, little attention has been paid to the evolution of individual's earnings through time.[2] Observed differences in a cross section of earnings may reflect long run permanent differences or short run transitory differences between individuals. The relative importance of these two components has implications for the way in which we view the rise in inequality and may throw some light onto the likely causes of increased inequality. From a welfare point of view, if earnings dispersion is composed of largely transitory shocks to individuals then inequality is in some sense being shared amongst individuals. However, if earnings differences are largely permanent then inequality has much more serious implications for individuals' lifetime welfare. From the point of view of explaining the rise in inequality, an analysis of changes in the permanent and transitory components of earnings may shed some light on the various competing hypotheses. For example, a popular view is that inequality is rising due to skill biased technological change resulting in an increase in the demand for skilled relative to unskilled labour. One would expect this to be reflected in a rise in the permanent component of earnings, as skills are probably fairly permanent to the individual.

In this paper I study the pattern of individual male wages over time in Great Britain. In order to assess the relative importance of permanent and transitory components of individual wages I require panel data on individuals with a sufficient time dimension. For this I use the New Earnings Survey Panel Dataset (NESPD) which covers some 180,000 males for the period 1975 to 1994. I divide the data into year of birth cohorts and analyse the auto-covariance structure of hourly earnings for each cohort. The covariances display an increasing pattern over the life cycle and also with time. Defining the permanent element of earnings as a non-mean reverting component and the transitory element as a serially correlated, mean reverting component I estimate error component models decomposing earnings into these two parts and analysing changes in these over time. The earnings process is adequately 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 that vary each year. Nearly half of the rise in inequality can be explained in terms of a rise in the permanent component, with the rest being explained by the persistent transitory effect.

In the next section I present some reasons why it is important to study the dynamic process of earnings and briefly review some of the existing evidence on the dynamics of individual earnings. Section 3 describes the data and the construction of the cohorts. Section 4 presents evidence on the auto-covariance structure of hourly earnings by cohort. Section 5 fits error components models to this covariance structure, decomposing the rise in dispersion into that accounted for by changes in the permanent and transitory components. Section 6 offers some conclusions.

2. Why are Earnings Dynamics Important?

Recent cross section studies of wage inequality have established a widening of the pay distribution throughout the 1980s in the UK.

This is in contrast to the experience of most other developed countries with the exception of the US, which has also experienced a large increase in wage dispersion. (See Katz, Loveman and Blanchflower, 1995, Machin, 1996, for an international comparison and Juhn, Murphy and Pierce, 1993, Levy and Murnane, 1992 for a more detailed account of the US experience.) This increased dispersion has occurred both between and within groups with the same observable characteristics. So wage differentials between different education, experience and skill groups have increased over the last decade as well as wage dispersion within these groups. Whilst this literature has documented the patterns in the structure of earnings and how they have changed, little attention has been paid to the nature of earnings dynamics and how these may have changed over time. This issue has important implications for the welfare consequences of cross section inequality and may shed some light on the possible causes of the rise in inequality.

Atkinson, Bourguingon and Morrisson (1992) provide an excellent survey of the earnings mobility literature and highlight the limitations of cross sectional analysis of inequality. Repeated snapshots of the distribution of earnings tell us little about the extent of movement up and down the distribution each period. If we are interested in lifetime inequality and welfare then it is important to look at the degree of mobility within the distribution. Cross section snapshots of the distribution may appear the same, but they may be concealing a high level of mobility each period. It is important from a welfare point of view to understand if people are persistently low paid or whether this is just a transitory state.

The degree of earnings mobility in the labour market may also have important policy implications. For example, the desirability or otherwise of a minimum wage may depend on the persistence of low pay. Many have argued that a minimum wage is an ineffective tool for tackling inequality since most people it affects are in a transitory state of low pay. In the same way, the success of policies that offer employment subsidies to get the unemployed back to work will depend on the degree of progression up the wage distribution of these low wage entrants. For example, Bingly, Bjorn and Westegard-Nielson (1995) study mobility in Denmark and find a high level of progression out of low wage jobs. They conclude that policy should be designed to get the unemployed into jobs, albeit low paid ones from where they can progress. One should note that this is in the context of an economy with a stable wage distribution over the time period of the study.

Atkinson *et al* (1992) point out that we may be concerned about mobility as a means to some objective, such as equity, or just in its own right. Many people would agree that equality of opportunity is a desirable feature for a society and a more mobile labour market, where jobs and earnings are more evenly shared may be favoured on these grounds. However, as pointed out by Gittleman and Joyce (1994), a high level of mobility may also be seen as creating more instability and a difficulty in retaining one's position in the earnings distribution, thus making mobility less desirable. One person's rise in the distribution is another's fall. So the question of whether more or less mobility is preferred is a normative one with no clear answer.

So far I have been concentrating on intra-generational mobility, and this is what I will study in this paper. However, the related question of inter-generational earnings mobility is also very important. When considering the degree of inter-generational mobility, most people are likely to favour higher mobility on the grounds of equality of opportunity. Somehow, the idea that you will inherit the position that your father had in the earnings distribution seems less deserving than that of you retaining the position you have had in the past. Recent work on the degree of inter-generational mobility of earnings (Dearden, Machin and Reed, 1997) has found a high correlation between the earnings and education of children and their fathers, suggesting quite low levels of inter-generational mobility.

The degree of earnings mobility takes on even more importance in the light of the huge rise in cross sectional earnings dispersion. Given that dispersion in the cross section has risen we may expect there to have been changes in the dynamic structure of earnings. How permanent and transitory components of earnings have changed over time has potentially serious implications for the welfare consequences of the rise in inequality. If the rise in earnings inequality is due to a rise in permanent inequality and mobility has decreased then this can have important implications for individuals' welfare. However, if the rise in earnings inequality is due to an increased dispersion of the transitory component of earnings and mobility has increased then it is not necessarily true that the dispersion of lifetime earnings has increased. Nethertheless, the welfare consequences in this case may be serious if individuals find it difficult to transfer income between periods and smooth short run fluctuations in earnings, due to say imperfect capital markets. A decomposition of the rise in inequality into that due to permanent and transitory components of earnings is essential for gauging the significance of the rise in inequality in welfare terms. Of course, if one believes the permanent income model of consumption then a study of the pattern of consumption inequality should provide some answers to this question.[3]

An analysis of the dynamics of the earnings structure may also shed some light on the possible causes of rising inequality. Juhn, Murphy and Pierce (1993) break down the rise in US wage inequality from 1963-89 into within and between group components. Wages for individual i in time period t are defined as:

$$W_{it} = b_{it} X_{it} + U_{it} \tag{1}$$

The rise in wage inequality is decomposed into that due to changes in the observable characteristics of the workforce X_{it}, that due to changes in the returns to these observable characteristics b_{it}, and that due to changes in the unobservable component of earnings U_{it}. They find that about two thirds of the rise in inequality is due to a rise in the unobserved component of earnings. (Schmitt (1995) carries out a similar analysis for Britain and finds that about 60% of the rise in earnings inequality between 1974 and 1988 occurred within education and experience groups.)

Juhn *et al* (1993) interpret their results as indicative of a rise in the return to unobserved skill brought about by an increase in the demand for skilled relative to unskilled labour. This hypothesis is best presented by further decomposing the unobserved component of wages into unobserved ability, V_{it} and the price of unobserved ability, d_t to give a wage equation of the form:

$$W_{it} = b_{it} X_{it} + d_t V_{it} \qquad \textbf{(2)}$$

They assume that the distribution of unobserved ability, V_{it} is unchanged over the sample period. If their hypothesis is correct then the rise in the unobserved component is driven by a rise in d_t, the price of unobserved skill. Given that unobserved skill is generally a permanent asset, one would expect the rise in inequality to be largely composed of a rise in permanent inequality. In order to test their hypothesis, one needs to be able to take out the individual effect in this equation and identify the relative importance of changes in the permanent and transitory components of earnings.

Of course, even when it is possible to decompose the rise earnings inequality into permanent and transitory components, it is not always clear what interpretation should be given to these. Typically the permanent component is associated with relatively stable individual characteristics such as unobserved education and skill effects. On the other hand the transitory component is identified with what we may believe to be rather more unstable determinants of the rise in earnings dispersion, such as the decline in union power, increased job turnover or the falling value of the minimum wage. However, it is not obvious that this distinction is correct. For example, it is entirely possible that a rise in demand for skilled labour may result in an increase in both the permanent and transitory variances. If skill biased technical change leads to significant changes in the workplace then more workers may behave like workers in new jobs, resulting in greater transitory fluctuations in earnings. (This idea was put forward by Larry Katz in his discussion of Gottschalk and Moffitt (1994).) So although it is interesting to analyse the changes in these components of earnings, the results of such an exercise may throw up many questions of interpretation.

The existing literature on the dynamics of individual wages is predominantly from US data (again see Atkinson *et al*, 1992, for a survey of the literature on earnings dynamics). The few early papers that have been written in this area were generally carried out without any clear reference to the rise in wage inequality. Early work concentrated on fitting statistical models to the earnings process. Lillard and Willis (1978) fit an error components model to male earnings from the Panel Study of Income Dynamics (PSID) and find a substantial permanent element, predicting a low degree of mobility. Similarly, Lillard and Weiss (1979) estimate error components models for American scientists for 1960-70, incorporating some time variation with a random growth rate term.

MaCurdy (1982) estimates models of weekly and hourly earnings growth for prime age males also using the PSID from 1967 to 1976. He finds that a stationary MA(2) process adequately describes the path of wage growth. This is consistent with the presence of a permanent effect in wage levels. Abowd and Card (1989) fit models of the covariance structure of earnings and hours changes for three different US datasets. They find that earnings growth is adequately described by a non-stationary bivariate MA(2) process that is compatible with the presence of a permanent effect, possibly a random walk, in earnings levels. Both these studies are consistent with the presence of a permanent individual component of earnings and a serially correlated transitory effect. However, neither of them estimate the relative importance of these components and, perhaps more significantly, neither model the changing structure of these over time.

More recently, Gottshalk and Moffit (1995) have used PSID data to estimate permanent and transitory components of earnings for white male household heads aged 22 to 59 and study how these have changed over time. Splitting their data into ten year birth cohorts they model the permanent component of earnings as an individual effect (a random walk in age) and the transitory component as a low order serially correlated effect (an ARMA(1,1). The parameters of these are allowed to vary over time. They find that the permanent component of earnings explains about 40% of the rise in inequality between 1967 and 1987, the rest being explained by a rise in transitory inequality. In a separate piece of work Gottschalk and Moffitt (1994) use a simpler procedure to estimate the rise in the components of earnings. They split their sample into two periods, defining permanent earnings as an individual's average earnings in each period and transitory earnings as deviations from permanent earnings in each year. They find that the variance of the permanent and transitory components rise by similar proportions. Given the permanent component is the largest, this implies that about two thirds of the rise in earnings dispersion is due to a rise in the permanent component of earnings and one third is due to the transitory component. If one thinks of unobserved ability as being a relatively permanent effect then their results suggest that Juhn *et al*'s hypothesis is important but may not be the whole story. They argue that the literature on earnings inequality has overlooked an important aspect, namely the rise in the instability of earnings. Possible explanations they put forward for this are a rise in job shopping, part time work or the decline in union power.

Gittleman and Joyce (1994) use matched cross sections from the Current Population Survey from 1967-91 to estimate patterns of earnings mobility in the US. They find differences across demographic groups in terms of mobility. In particular, the less educated and blacks appear to have less stable earnings. Looking at changes over time, they find little evidence of a changing short run mobility structure. This is consistent with Gottschalk and Moffitt's findings of proportional increases in permanent and transitory components.

Buchinsky and Hunt (1996) analyse wage mobility using the National Longitudinal Survey of Youth from 1979 to 1991. This data is a sample of individuals aged 14-24 in 1979. They use summary inequality measures and study how these change when computed over different time horizons. Their results suggest that when dispersion is measured over a four year period, wage inequality is reduced by 12-26% in comparison to the one year cross section figure due to the mobility of individuals in the wage distribution each year. Nethertheless, they also report falling mobility over the sample period, implying that the sharp rise in inequality observed is actually larger than it appears. However, since the NLSY is a cohort with no new entry it is quite possible they are confounding life cycle effects with time effects. This last result may be indicative of falling mobility within a cohort as it ages, something which is implied by my results below.

The evidence from the US is indicative of a rise in earnings inequality driven by substantial increases in both permanent and transitory earnings. As a consequence, mobility rates within the distribution are fairly stable or may actually be falling for younger workers. This is very worrying from a welfare point of view as the increasing differences between individuals appear to be largely permanent.

Early work from the UK (Creedy and Hart, 1979; Hart, 1976; Department of Employment, 1973, 1977) established a high degree of correlation between individuals' earnings in different time periods. This correlation declines at longer lags but is still indicative of a strong permanent component of earnings. For example, the Department of Employment study reports a correlation coefficient of 0.65 between weekly earnings of manual males in 1970 and 1971. This declines to 0.52 when comparing 1970 with 1974. More recently, Gregory and Elias (1994) use the New Earnings Survey Panel to study transition rates out of the bottom earnings quintile. They find that young males in the bottom quintile in 1976 face a low probability of remaining there by 1984 and 1990. However, exit rates are lower for older males and for females in general. They conclude that the experience of low pay is closely linked to life cycle patterns of pay, but that for some low pay is a persistent phenomena.

Stewart and Swaffield (1996) use the British Household Panel Survey to study transitions into and out of various low pay thresholds. They report a high degree of persistence of low pay for certain individuals. For example, 75% of those low paid in both 1991 and 1992 remain low paid in 1993. They also emphasise that the low paid are more likely to move into non-employment than those further up the distribution. As a consequence, restricting attention to those in employment will overstate the probability of moving up the distribution.

A drawback with much of the UK analysis is that it has not addressed the question of whether there have been changes in the dynamics of the earnings process. However, in an ingenious piece of work, Blundell and Preston (1995a, 1995b) develop an intertemporal model of consumption expenditure. They show that permanent and transitory income inequality can be identified from cross section data on consumption and income inequality. The results of their analysis of Family Expenditure Survey Data from 1970-92 suggest a steady increase in permanent inequality over this period coupled with a sharp rise in transitory inequality in the later part of the 1980s.

The purpose of this paper is to extend the UK work on the dynamics of the earnings process. Before going on to look at these issues I will first provide an outline of the data that I will use for this analysis.

3. Data Description

The New Earnings Survey is an annual survey, conducted in April, of roughly 1% of employees in employment in Great Britain.[4] The sample frame is derived from those with a National Insurance number ending with two particular digits. Employees' workplaces are obtained through the Inland Revenue tax register using current PAYE records and the survey is sent for completion by the employer. About 75% of the responses are collected in this way. The remainder are obtained directly from large public and private organisations who supply details of all employees with the selected National Insurance numbers. Employers are required by law to respond to the survey under the Statistics of Trade Act 1947. Individuals can be matched across years by their National Insurance number to form a panel of employees in employment. The panel is characterised by a constant churning of the sample as new individuals enter the labour market and older ones exit, maintaining the sample size each year. A clear benefit of the NES panel is that if individuals do go missing in a given year they still have the potential of re-entering in later years. I have access to the data for the years 1975 to 1994.

Details on individual characteristics are limited[5], but there is a wealth of detailed information on earnings, hours, industry, occupation, sector and region. Individuals may be missing from the panel for a number of reasons. They may leave the stock of employees for retirement, unemployment, inactivity or self employment. Alternatively, their weekly pay may fall below that required to pay income tax, in which case they will not appear on Inland Revenue records. They may also be untraced because they have left the employer they worked for when the tax records were collected.[6]

Because of this, the NES is likely to under sample individuals with weekly earnings which fall below the income tax threshold. This is predominantly a problem for part time workers, most of whom are women. In the empirical work here I restrict the sample to full time males between the ages of 22 and 59 who are unlikely to be seriously affected by the PAYE cut off. However, the NES is also likely to under sample employees in small organisations and those who experience high rates of job turnover. This is a potential problem for the sample that I am using here.

Attempting to resolve these attrition problems in the NES is difficult since there is no information on why an individual may have been absent in any given year or any good instruments to model this with. Therefore, it is not possible to estimate a structural model of presence or absence in the panel. However, it is likely that the panel will contain those with more stable employment histories and as a consequence may overstate the permanent element of earnings.

For the empirical analysis, I categorise individuals into age cohorts and follow them through time. This allows an analysis of the covariance structure of individuals' earnings at the same age but at different points in time, forming the basis for an examination of whether the covariance structure has changed over time.[7] The cohorts are arranged by each year of birth and are tracked over the period 1975 to 1994. So the youngest cohort is aged 22 in 1994 (born in 1972), the next youngest is 22 in 1993 (born in 1971) and so on down to the oldest cohort, aged 59 in 1975 (born in 1916). The cohorts can be present for between 1 and 20 years depending on their date of birth. This gives a total of 57 cohorts.

The earnings measure is the log of real hourly earnings, defined as gross weekly earnings/total weekly hours, deflated by the consumer price index. I exclude individuals whose real hourly earnings are below £0.50/hour or above £100/hour at 1994 prices to reduce the noise in the data. In order to maximise the sample utilised I include every wage observation for each individual over the time period 1975-1994, allowing individuals to re-enter the panel if they do exit. This gives an unbalanced panel since many individuals are not present for the full 20 years. The final sample consists of 182,344 men with a total of 1,298,849 individual-year observations.

The structure of the panel sample is presented in Table 1 for selected cohorts and years. The table presents the sample size for a cohort in a given year and the percentage of these that are still in the panel after a given number of years. Taking the cohort born in 1953 as an example; 1679 individuals from this cohort are present in 1975. 68% of these individuals are still in the panel in 1976, falling to 51% in 1994. A large proportion of the attrition appears to occur in the first year. Notice that the percentage present may rise again at longer lags since individuals may re-enter the panel after exit. So although some 56% of this cohort are present after 10 years, this number rises to 57% after 15 years. Also, the size of the cohort may rise over time as new individuals enter the panel. For example, by 1980 there are 1955 individuals in this cohort.

The attrition rate is similar for the other age cohorts. However, when a cohort approaches retirement age the percentage present falls more steeply. For example, for the cohort born in 1933 only 44% of those present in 1975 are there 15 years later (i.e. at age 57) compared to 57% and 59% for the cohorts born in 1953 and 1943 respectively. Attrition rates for other starting years exhibit a similar pattern to that described above, easing fears that attrition rates may have changed over time.

Table 2 presents descriptive statistics on the earnings measure for each year for the full sample. Real average hourly earnings have risen by about 31% between 1975 and 1994. However, this wage growth has not been uniform across the distribution of wages. Table 2 also includes the 10th, 50th and 90th percentiles of the distribution. We can see that whilst the 10th percentile has risen by some 13% over the period, the median has risen by 31% and the 90th percentile by nearly 50%. It is clear from these figures that there has been a large increase in dispersion since the late 1970s (see Gosling, Machin and Meghir, 1995 or Gregg and Machin, 1994). However, they tell us nothing about the relative importance of permanent and transitory components of earnings and which is driving the increase in dispersion. We turn to this now.

4. The Covariance Structure of Earnings

To begin with, it is informative to have a description of the dynamic nature of individual earnings. For this purpose, I compute the covariance structure of hourly wages for each cohort described above. Taking each cohort separately I compute the variance and covariances, at differing lag lengths, following the cohort through time. The methodology used to compute these covariances and their corresponding standard errors is similar to that employed by Abowd and Card (1989) and is presented in the technical appendix.

Computing covariance matrices for each cohort gives some 6650 variance and covariance elements so in order to present the patterns in the data clearly I have taken selected cohorts and auto-covariances.[8] Figure 1 presents the variances and covariances of lags 1, 5, 10 and 15 years for selected cohorts born in 1923, 1933, 1943, 1953 and 1963. The first point to notice is that the auto-covariances display different patterns across cohorts. The younger the cohort the faster the rise in the variance and covariances, even over the same time period. In fact, the cohort born in 1923 shows no significant rise in dispersion between 1975 and 1982.

For all cohorts the covariances are all positive and quite large in magnitude relative to the variances. They fall quite sharply for the first couple of lags and then appear to asymptote to a long run level at longer lags. This is consistent with the presence of a permanent individual component of earnings and a transitory component that is serially correlated. However, the relative magnitudes of the covariances differ across cohorts. For the younger cohorts the ratio of the longer lag covariances to the variances is greater than that for the older cohorts. While the variances will reflect both permanent and transitory components of earnings, the longer lag covariances will largely reflect the permanent component of earnings. As such, Figure 1 indicates that the proportion of earnings that is accounted for by the permanent component is larger for older cohorts.

It appears that the covariance structure of earnings is changing over the life cycle. There are a number of theoretical reasons that can explain why this may be the case. For example, matching models where information about the individual's ability is revealed on the job imply that wage dispersion within a cohort will rise as the cohort ages and more information is revealed (See Jovanovic, 1979)[9].

To look at these life cycle effects more clearly we need to strip out the time effects that are present in these within cohort covariances. Figure 2 presents the auto-covariances by age for the years 1975, 1980, 1985, 1990 and 1994. Each panel of the Figure is now taking out time effects and we are left with life cycle and cohort effects. The variance and covariances of hourly wages rise quite sharply over the life cycle up until about age 40 after which they are fairly stable. Notice also that the variances and covariances of different lags appear to rise at similar rates over the life cycle. This is consistent with the presence of a permanent component that rises with age until an individual reaches their 40s. Looking across the different panels we can see that the variances and covariances are larger in later years. It is also interesting to note that the life cycle profile appears to be steeper in later years. This is compatible with increasing returns to the permanent component over time, resulting in a faster rise in dispersion of wages for younger cohorts. It is also apparent that the difference between the variance and longer covariances has increased with time. This is an indication that the transitory component of earnings may also have risen over time.

5. Variance Components Models

Having presented some of the trends in the data the aim in this section is to fit a parsimonious model to the auto-covariance structure of earnings for all cohorts. We have seen that there is evidence of a strong permanent component of earnings and also a transitory component that may exhibit some degree of serial correlation. Both of these components are likely to have changed in magnitude over the sample period. In addition there appears to be important differences in the covariance structure over the life cycle. The error components model has to be general enough to allow for these patterns in the data. At the same time our interest lies in modelling how the components of earnings have changed over time. The following model of earnings provides a general equation which encompasses many of the features in the data:

$$w_{iat} \ ' \ a_t \mu_{iat} \ \% \ d_t ?_{iat} \qquad \textbf{(3)}$$

Here w_{iat} are log real hourly earnings for individual i, at age a and time t. The first term, $a_t \mu_{iat}$, is the permanent component of earnings. I will estimate models where the μ_{iat} is a random individual effect, i.e. μ_{iat} = μ_i where μ_i is independently distributed across individuals μ_i ~ (0,s $_\mu^2$).

Alternatively, μ_{iat} may be a random walk term; μ_{iat} = $\mu_{ia-1t-1}$ + p_{iat} where p_{iat} ~ iid (0,s $_{pa}^2$) and the variance s $_{pa}^2$ may differ with age. a_t is a parameter that allows the permanent effect to vary over time. This may seem a little odd but I use the term permanent here to signify non-mean reverting effects. One could think of the term μ_{iat} as a proxy for ability (or revealed ability) and the term a_t as the return on this ability. In the same way the transitory effect, $d_t?_{iat}$, may exhibit persistence through some serial correlation structure, but this effect is mean reverting. So $?_{iat}$ may be some ARMA process, where the parameters of this process may vary with time. An alternative way of allowing time variation of this effect is to let d_t to vary with time. We may think of measurement error in this model as coming through the transitory component.

The parameters of these models are fit to the covariance structure for each cohort using minimum distance methods of estimation. For estimation I have dropped those cohorts that are in the sample for less than five periods. This leaves us with 49 cohorts and a total of 6610 variances and covariances. More details of this estimation procedure are presented in the technical appendix, along with the inference procedures. Essentially, the covariance structure implied by each model is mapped to the observed covariance structure. The sum of the squared distance between these is minimised, weighted by an appropriate weighting matrix. The optimal choice for this weighting matrix is the inverse of the covariance matrix of these covariance elements, i.e. the inverse of the matrix of fourth moments. However, Altonji and Segal (1994) show that this can seriously bias the estimates due to correlation between measurement error in the second and fourth moments. They recommend the use of equally weighted minimum distance, i.e. using an identity matrix as the weighting matrix. I follow their procedure here and weight using an identity matrix.[10]

Before presenting the results I should like to make a point about the expected fit of such error components models when such large samples are used to compute the covariance elements. When computing inference statistics of the models fit with these large samples, any small deviation from the expected distribution will be multiplied up, resulting in rejection of the model at conventional critical values. For this reason, I do not expect to find a model that will not be rejected by standard significance levels. My aim is to find the best fitting of a number of models. Table 3 presents the results of fitting assorted estimates of equation (3) to the 6610 covariance elements, with different restrictions applied to the parameters. Column 1 presents an estimate of the simple canonical permanent-transitory model of earnings, whereby earnings consist of a stationary individual effect and a white noise transitory effect. In terms of equation (3) we have:

$$w_{iat} \text{ ' } \mu_i \text{ \% } e_{it} \qquad \textbf{(4)}$$

where μ_i is a stationary random effect, $\mu_i \sim (0, s_{\mu}^{2})$ and e_{it} is a white noise error term, $e_{it} \sim (0, s_{e}^{2})$. This model implies that the variances and covariances are constant over time and age and that all the covariances are the same at all lags. This simple model is clearly rejected by the large chi-square value in column 1. Nethertheless, the estimated parameters provide some evidence of a permanent individual component of earnings.

Casual observation of the covariances presented in Figures 1 and 2 suggests three reasons why the simple canonical permanent-transitory model is not a good approximation to the earnings process. Firstly, the covariance elements are not all the same at all lags, secondly the variances and covariances are not stationary through our sample period and thirdly they are not stationary over the life cycle. Column 2 attempts to deal with the first of these problems. We have seen that the covariances appear to diminish as the lag length increases, sharply for the first couple of lags and then more smoothly at longer lags. This is consistent with some serial correlation in the transitory error term. Therefore, column 2 presents a model with an individual random effect plus an ARMA(1,1) transitory effect.

$$w_{iat} \text{ ' } \mu_i \text{ \% } ?_{it} \qquad \textbf{(5)}$$

where:

$$?_{it} \;\; ' \;\; ??_{it\&1} \;\; \% \;\; f_{\,it} \;\; \% \;\; ?f_{\,it\&1} \qquad \textbf{(6)}$$

and f $_{it}$ ~ (0,s $_{f}^{\,2}$) is a white noise error term. The model fit is somewhat improved with this extension but the chi-square statistic is still way above conventional levels. There is evidence of a strong permanent individual component of earnings as well as a serially correlated transitory component that exhibits a high degree of persistence.

In the next column, I present the model of column 2 but allow the weighting parameters on the permanent and transitory effects to vary each time period in an attempt to fit the non-stationarity in the auto-covariances. (The a and the d are free to vary each year, normalised to one in 1975.) Permitting time variation helps to provide a better fit of the data, however the chi-square statistic is still way above conventional critical values.

Column 4 replaces the Random Effects term with a Random Walk in age. This implies increasing dispersion over the life cycle as observed in Figure 2. The weighting parameters are permitted to vary over time to capture the changing patterns of the permanent and transitory components.

$$w_{iat} \;\; ' \;\; a_t\mu_{iat} \;\; \% \;\; d_t?_{it} \qquad \textbf{(7)}$$

where μ_{iat} = $\mu_{ia\text{-}1t\text{-}1}$ + p$_{iat}$ is the random walk term with initial variance s $^{2}_{\mu}$ at age 22 and p$_{iat}$ ~ iid (0,s $^{2}_{p}$) is the innovation each period. ?$_{it}$ is an ARMA(1,1) as in equation (6), and the a and the d are allowed to vary freely each year. The random walk in age provides a significant improvement over the random effects model. The variance of the initial shock is estimated to be zero, implying that all the dispersion at age 22 is transitory. As each cohort ages the permanent variance increases by the innovation variance, s $^{2}_{p}$ each year. Notice that the weights of both the permanent and transitory components have risen over the sample period, the transitory weights rising substantially more. Most of the increase in the permanent component occurs in the early 1980s whereas the transitory component increases sharply in the late 1980s. The persistence parameter ? is very high, implying that over 65% of a shock today will be present in 10 years time.

This random walk model with a constant innovation variance implies that the life cycle profile of the variance of permanent earnings is linear over the whole life cycle. In fact Figure 2 displayed a concave profile with the variance rising up until the early 40s after which it remained quite stable. Given this, I experimented with a specification which allowed the innovation variance to be different at each age. The results implied that the variances decreased over the life cycle and after age 41 were zero. Column 5 of the table reports such a specification also setting the initial variance to zero, as estimated in column 4. The models fit is greatly improved by this generalisation and the chi-squared value of 11539 (df = 6550) isn't too bad given the large sample sizes being dealt with.

The innovation variance s^2_{pa} is largest at the younger ages and declines with age. This pattern indicates that the permanent component of earnings becomes increasingly important over the life cycle, but at a diminishing rate. So the proportion of earnings variation within a cohort accounted for by the permanent component of earnings rises with age up until the early 40s, after which it remains at it's current level. The model is effectively a random walk in age up to age 41 and after that is a random effects model with the distribution of the effects fixed at that implied by the random walk. This model is consistent with many matching or human capital models whereby human capital is acquired, or revealed, for the first 20 or so years of labour market experience, after which time differences between individuals stop growing.

The a_t 'price' term on the permanent component also increases over the sample period, indicating a rise in the permanent variance of earnings. Most of this rise occurs in the early 1980s, after which it rises slightly up until 1994. The weights on the transitory component also rise, by a little more than those on the permanent. Notice also that they are quite stable until the mid 1980s, at which point they rise sharply for the rest of the sample period. The persistence parameter remains high in this specification implying 40% of a shock today will remain after 10 years. As such, the transitory component estimated here is behaving very much like a permanent component itself.

The specification estimated here seems to explain the auto-covariance structure of wages within and between cohorts well.[11] However, one may be concerned that the specification should allow for separate cohort effects. It is informative to think about the impact cohort effects may have on the patterns in the covariance structures presented above. If we believe that rising dispersion is a result of younger cohorts being more heterogeneous then this would serve to flatten the age profiles in Figure 2 in any given year, since younger cohorts would enter the labour market with a greater degree of dispersion. In fact the age profiles become steeper over time. This could only happen if the age and time effects were outstripping this rise in cohort dispersion. Alternatively, we might believe that successive cohorts are becoming more homogeneous. This would explain the steepness of the lifecycle profile of the auto-covariances but seems rather unlikely given the large rise in dispersion over the sample period.

Figure 3 plots the actual and predicted variances from the preferred specification for the cohorts in Figure 1. It is clear that this model works pretty well in capturing the age and time profile of the variance structure for these cohorts. The random walk in age gives the rising life cycle dispersion for the first 20 or so years. The increasing weights on this term explain why dispersion within a cohort continues to rise at all ages and also why younger cohorts display a faster rise in dispersion than older ones, over the same age range. Therefore, this estimated specification appears to adequately model the dynamic structure of earnings for these cohorts.

Having estimated a suitable error components models for the earnings process we now want to assess the relative importance of the permanent and transitory components of this process and analyse their contribution to the rise in the total variance over the sample period. To

do this I have computed the predicted variances for each year, holding fixed the transitory and permanent weighting parameters in turn to estimate their impact on the total variance. Figure 4 presents four different predicted variances for selected cohorts. The first is the predicted variance allowing all the parameters to vary. The second restricts both the permanent (a_t) and transitory weights (d_t) to their 1975
values, so the only rise in the variance is that which occurs due to the random walk term. The third restricts the permanent weights (a_t) to their 1975 values, giving the transitory effect, and the fourth restricts the transitory weights (d_t) to their 1975 values, giving the permanent effect.

Looking at the cohort born in 1953 first we can see that from 1975 to about 1984 all of the rise in the variance is explained by a rise in the permanent variance, after which time its effect is very small. In 1985 the transitory component begins to rise sharply and by 1989 has become slightly more important than the permanent variance. Taking the whole period 1975 to 1994, about 60% of the rise in the variance is explained by a rise in the transitory component, the rest being accounted for by the permanent component. The older cohorts portray a similar pattern, with the rise in the variance from 1975-1994 accounted for by similar increases in the permanent and transitory components. For the youngest cohort (born in 1963), the effect of the transitory component is greater, explaining about 75-80% of the rise in the variance between 1985 and 1994. This is because the proportion of the variance that is permanent is lower for this younger group.

6. Summary and Conclusions

In this paper I have used the New Earnings Survey Panel Dataset to analyse the covariance structure of individual earnings by cohort over the period 1975 to 1994. The results of this analysis of the earnings process imply that an individuals earnings contain a highly permanent element, modelled by a random walk in age. As such, the proportion of earnings variation accounted for by this permanent element increases with age within a cohort. In addition, the rise in earnings inequality since the late 1970s appears to be driven by similar increases in both the permanent and transitory elements of earnings, the transitory component explaining slightly more. It is interesting to note that although the variance of earnings rises smoothly over the 1980s, the components of variance display different trends. The permanent component increases in the most part in the early 1980s, whereas the rise in the transitory element occurs later in the decade. This finding is consistent with the results of Blundell and Preston (1995a, 1995b) who use a different methodology based on cross sectional differences in consumption and income inequality described above.

Trying to draw any implications from these results regarding possible causes of the rise in inequality is difficult. The substantial rise in the permanent component is consistent with increasing returns to skill. Interpretation of the rise in the transitory component is less clear. Because of the persistence this exhibits, it is not obvious what this term is picking up. It could be some combination of rising skill demand, decentralisation of bargaining, the decline in the value of the minimum wage or the end of the social contract.

However, these results do imply that from a welfare point of view we should be worried about both the level of earnings inequality in the UK and the increase this has displayed over the last decade or so. The observed cross sectional dispersion in earnings reflects largely persistent differences between individuals. Against the backdrop of rising inequality these permanent differences have become greater over the last decade or so.

ENDNOTES

1. There is also a large literature on the rise in wage inequality in the US. See Levy and Murnane (1992) for a survey of that literature.

2. This is largely due to limitations in data availability. However, see Atkinson, Bourguignon and Morrisson (1992) for a cross country survey of the earnings dynamics literature to that date. More recent work on US data which links the changing cross sectional distribution of earnings with changes in dynamics can be found in Gottschalk and Moffitt (1994, 1995), Gittleman and Joyce (1994) and Buchinsky and Hunt (1996).

3. See Cutler and Katz (1992) for this type of analysis on US data and Blundell and Preston (1995a, 1995b) for the UK.

4. As such, the sample frame covers about 220,000 individuals.

5. In particular, the NES does not contain data on individuals' education. However, because my sample is of males aged 22 to 59 their level of education is unlikely to change much once they are in the sample. Therefore, education effects will emerge as a part of the estimated fixed effect in earnings.

6. In addition, the NES does not cover those in private domestic service, occupational pensioners, non-salaried directors, those working outside Great Britain, people working for spouses or clergymen. As a consequence, anyone moving into these categories will also exit from the panel.

7. The aim is to separate out life cycle effects from time effects and this requires a cohort analysis. Of course, it is impossible to separately identify age, time and cohort effects (See Gosling, Machin and Meghir, 1996) and some assumption has to be made about one of these.

8. Information on all cohorts is available on request.

9. Of course, there are other models that predict increasing life cycle covariances within a cohort. For example, a model whereby human

capital is acquired with age at different rates across individuals will lead to increasing wage dispersion with age.

10. I also experimented with a weighting matrix that contained in each cell the corresponding number of observations used to compute each autocovariance, as such, giving less weight to covariances of greater distance apart. The results obtained from such an exercise were not unduly different from the equally weighted estimates.

11. All the analysis presented here is in terms of the autocovariance structure of wage levels. One might believe that constructing the autocovariance structure of first differenced wages would simplify the analysis and provide a clearer split between the permanent and transitory components. However, the levels model I have presented here with changing "price" terms on the permanent and transitory components has some intuitive appeal. First differencing this model would not remove the permanent effect because of the changing "price" term and would actually complicate the model further.

TABLE 1

Structure of the Panel by Cohort - Per cent of cohort present after given number of years

Cohort born 1963							
Year	Sample size	% of these present after 1 year	% of these present after 3 years	% of these present after 5 years	% of these present after 10 years	% of these present after 15 years	% of these present after 19 years
1985	1754	72	64	60	-	-	-
1990	2087	75	68	-	-	-	-

Cohort born 1953							
Year	Sample size	% of these present after 1 year	% of these present after 3 years	% of these present after 5 years	% of these present after 10 years	% of these present after 15 years	% of these present after 19 years
1975	1679	68	65	61	56	57	51
1980	1955	69	67	61	59	-	-
1985	1761	76	72	67	-	-	-
1990	1827	81	71	-	-	-	-

Cohort born 1943							
Year	Sample size	% of these present after 1 year	% of these present after 3 years	% of these present after 5 years	% of these present after 10 years	% of these present after 15 years	% of these present after 19 years
1975	1625	71	68	62	57	59	47
1980	1718	70	67	62	61	-	-
1985	1579	78	73	70	-	-	-
1990	1613	79	66	-	-	-	-

TABLE 1 continued

Structure of the Panel by Cohort - Per cent of cohort present after given number of years

Cohort born 1933							
Year	Sample size	% of these present after 1 year	% of these present after 3 years	% of these present after 5 years	% of these present after 10 years	% of these present after 15 years	% of these present after 19 years
1975	1628	72	68	64	55	44	-
1980	1693	70	65	59	46	-	-
1985	1421	77	67	58	-	-	-
1990	1165	75	-	-	-	-	-

Cohort born 1923							
Year	Sample size	% of these present after 1 year	% of these present after 3 years	% of these present after 5 years	% of these present after 10 years	% of these present after 15 years	% of these present after 19 years
1975	1779	71	68	63	-	-	-
1980	1724	68	-	-	-	-	-

Source: New Earnings Survey Micro Data.

TABLE 2

Descriptive Statistics of Log Hourly Earnings each Year

Year	Average Log Real Hourly Wage	10th Percentile Log Real Hourly Wage	50th Percentile Log Real Hourly Wage	90th Percentile Log Real Hourly Wage	Standard Deviation Log Real Hourly Earnings	Sample Size
1975	1.760	1.363	1.716	2.225	0.356	65224
1976	1.787	1.383	1.738	2.272	0.365	69406
1977	1.711	1.321	1.662	2.182	0.355	69475
1978	1.759	1.353	1.711	2.244	0.362	68862
1979	1.787	1.374	1.746	2.268	0.364	68492
1980	1.794	1.370	1.749	2.286	0.372	68474
1981	1.821	1.376	1.769	2.350	0.393	66736
1982	1.827	1.369	1.780	2.364	0.401	66227
1983	1.872	1.407	1.824	2.426	0.408	65060
1984	1.892	1.412	1.847	2.451	0.415	63862
1985	1.890	1.403	1.846	2.449	0.418	61277
1986	1.938	1.443	1.894	2.507	0.427	63059
1987	1.967	1.453	1.920	2.549	0.442	62536
1988	2.006	1.480	1.959	2.604	0.453	64954
1989	2.011	1.477	1.962	2.621	0.463	64837
1990	2.010	1.467	1.959	2.626	0.466	64801
1991	2.040	1.482	1.993	2.667	0.475	64049
1992	2.060	1.495	2.015	2.702	0.480	61375
1993	2.083	1.504	2.040	2.723	0.490	59751
1994	2.073	1.489	2.030	2.723	0.497	60392

Source: New Earnings Survey Micro Data.

TABLE 3

Error Components Models for Log Real Hourly Earnings

	Random Effect + White Noise	Random Effect + ARMA(1,1)	a_t (Random Effect) + d_t ARMA(1,1)	a_t (Random Walk) + d_t ARMA(1,1)	a_t (Random Walk to 41) + d_t ARMA(1,1)
s^2_μ	.1295 (.0008)	.0666 (.0056)	.0124 (.0032)	6.6E-10 (.0037)	
$a_{75} = 1$					
a_{76}			1.0987 (.0707)	1.0133 (.0219)	1.0666 (.0248)
a_{77}			1.0796 (.0742)	1.0087 (.0229)	1.0670 (.0269)
a_{78}			0.9281 (.0731)	0.9874 (.0230)	1.0787 (.0279)
a_{79}			0.6862 (.0879)	0.9604 (.0236)	1.0468 (.0291)
a_{80}			0.9052 (.0812)	0.9934 (.0253)	1.1031 (.0320)
a_{81}			1.3060 (.0943)	1.0690 (.0265)	1.2237 (.0342)
a_{82}			1.3429 (.1028)	1.1121 (.0280)	1.2448 (.0357)
a_{83}			1.3313 (.1047)	1.1069 (.0290)	1.2503 (.0377)
a_{84}			1.5323 (.1251)	1.1220 (.0306)	1.2658 (.0384)
a_{85}			1.6139 (.1379)	1.1147 (.0314)	1.2553 (.0393)
a_{86}			1.6369 (.1380)	1.1166 (.0324)	1.2560 (.0398)
a_{87}			1.7531 (.1504)	1.1349 (.0345)	1.2827 (.0412)
a_{88}			1.5157 (.1342)	1.1174 (.0359)	1.2726 (.0415)
a_{89}			1.2688 (.1188)	1.1080 (.0371)	1.2723 (.0417)
a_{90}			1.1851 (.1149)	1.1136 (.0382)	1.2700 (.0420)
a_{91}			1.0742 (.1148)	1.1082 (.0412)	1.2906 (.0436)
a_{92}			1.0138 (.1167)	1.1415 (.0453)	1.3116 (.0453)
a_{93}			0.9664 (.1217)	1.1846 (.0509)	1.3339 (.0483)
a_{94}			0.8495 (.1278)	1.1799 (.0543)	1.3041 (.0497)
?		.9441 (.0047)	.9721 (.0012)	.9794 (.0013)	.9567 (.0012)
?		-.4762 (.0071)	-.5327 (.0057)	-.6367 (.0074)	-.5693 (.0068)
s^2_f		.0351 (.0003)	.0240 (.0005)	.0199 (.0006)	.0242 (.0011)
s^2_e	.0429 (.0003)				
$d_{75} = 1$					
d_{76}			1.0283 (.0084)	1.0470 (.0138)	0.9957 (.0194)
d_{77}			0.9981 (.0089)	0.9979 (.0143)	0.9263 (.0211)
d_{78}			1.0393 (.0086)	1.0292 (.0151)	0.9446 (.0216)
d_{79}			1.0552 (.0095)	1.0124 (.0158)	0.9465 (.0239)
d_{80}			1.0585 (.0098)	1.0403 (.0164)	0.9425 (.0251)
d_{81}			1.0983 (.0122)	1.1306 (.0171)	0.9813 (.0247)
d_{82}			1.1125 (.0132)	1.1301 (.0173)	0.9937 (.0257)
d_{83}			1.1291 (.0135)	1.1534 (.0181)	1.0162 (.0275)
d_{84}			1.1125 (.0164)	1.1629 (.0185)	1.0240 (.0276)
d_{85}			1.1061 (.0191)	1.1757 (.0192)	1.0488 (.0288)
d_{86}			1.1355 (.0201)	1.2197 (.0204)	1.1102 (.0296)
d_{87}			1.1669 (.0224)	1.2761 (.0221)	1.1702 (.0312)
d_{88}			1.2307 (.0172)	1.3260 (.0239)	1.2353 (.0322)
d_{89}			1.3032 (.0144)	1.3839 (.0257)	1.3055 (.0332)
d_{90}			1.3227 (.0136)	1.3938 (.0263)	1.3244 (.0333)
d_{91}			1.3756 (.0136)	1.4440 (.0284)	1.3584 (.0348)
d_{92}			1.4084 (.0139)	1.4551 (.0294)	1.3706 (.0360)
d_{93}			1.4462 (.0146)	1.4700 (.0310)	1.3963 (.0385)
d_{94}			1.4787 (.0152)	1.4932 (.0337)	1.4573 (.0405)
s^2_p				.0025 (.0001)	

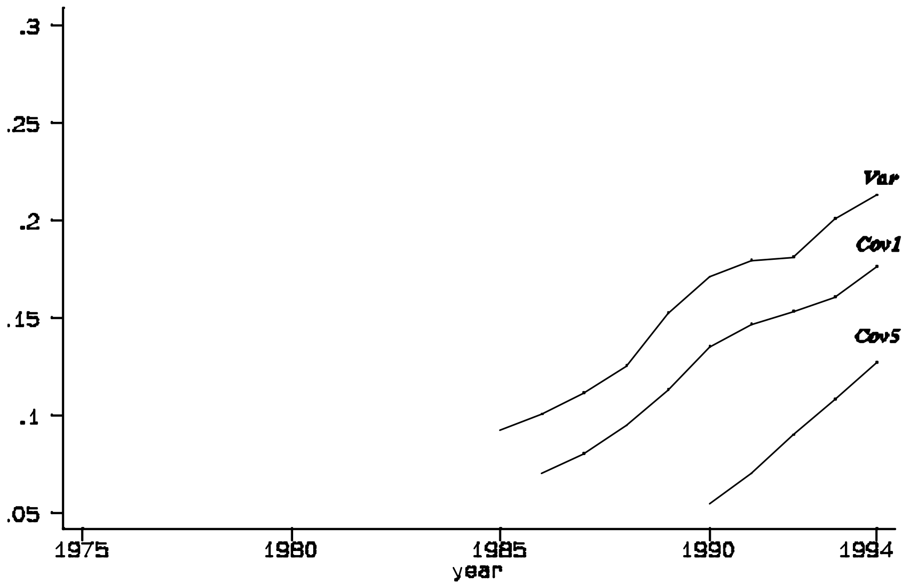
TABLE 3 continued

$s^2_{p\,23}$ $s^2_{p\,24}$ $s^2_{p\,25}$ $s^2_{p\,26}$ $s^2_{p\,27}$ $s^2_{p\,28}$ $s^2_{p\,29}$ $s^2_{p\,30}$ $s^2_{p\,31}$ $s^2_{p\,32}$ $s^2_{p\,33}$ $s^2_{p\,34}$ $s^2_{p\,35}$ $s^2_{p\,36}$ $s^2_{p\,37}$ $s^2_{p\,38}$ $s^2_{p\,39}$ $s^2_{p\,40}$ $s^2_{p\,41}$					.0054 (.0005) .0057 (.0006) .0070 (.0006) .0046 (.0006) .0052 (.0006) .0053 (.0006) .0044 (.0006) .0039 (.0006) .0040 (.0006) .0043 (.0007) .0037 (.0007) .0032 (.0007) .0030 (.0008) .0033 (.0008) .0021 (.0008) .0013 (.0008) .0010 (.0008) .0006 (.0008) .0035 (.0012)
?2 (DF)	127780 (6608)	84484 (6606)	41959 (6568)	19248 (6567)	11539 (6550)

FIGURE 1

Auto-Covariances for Selected Cohorts: 1975-94

Cohort born 1963



Cohort born 1953

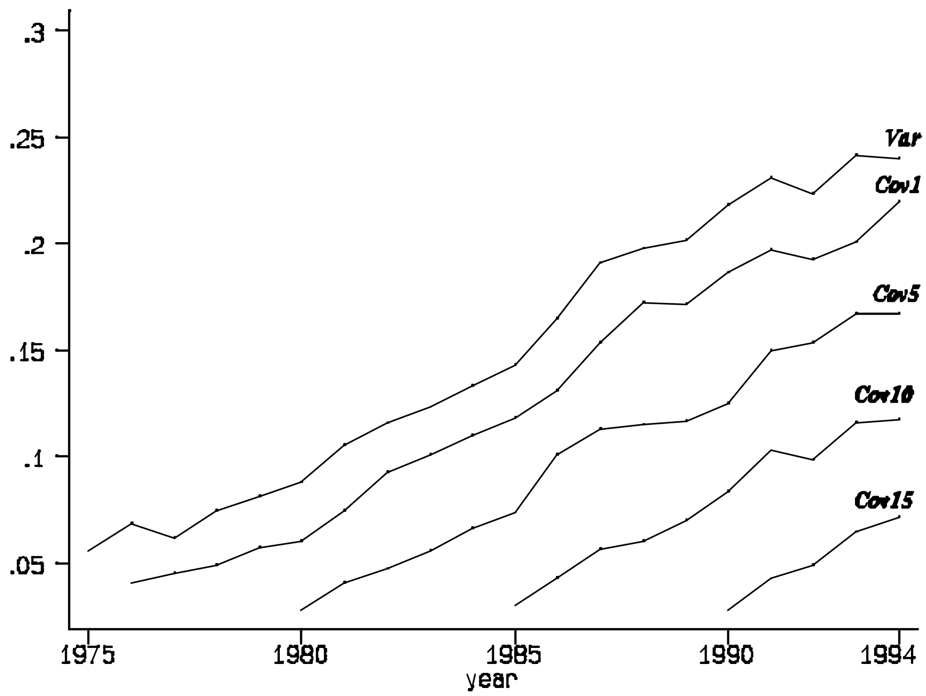
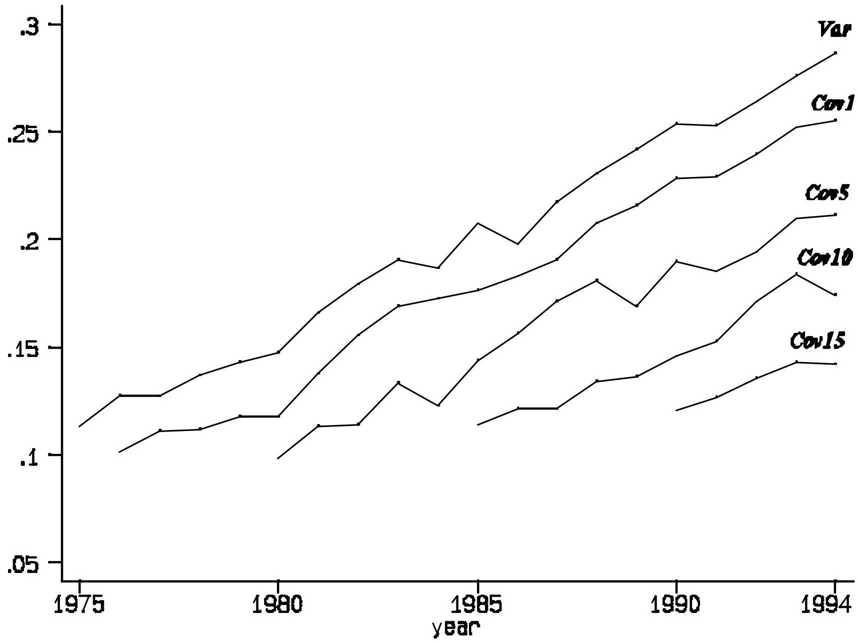


FIGURE 1 continued

Auto-Covariances for Selected Cohorts: 1975-94

Cohort born 1943



Cohort born 1933

FIGURE 1 continued

Auto-Covariances for Selected Cohorts: 1975-94

Cohort born 1923

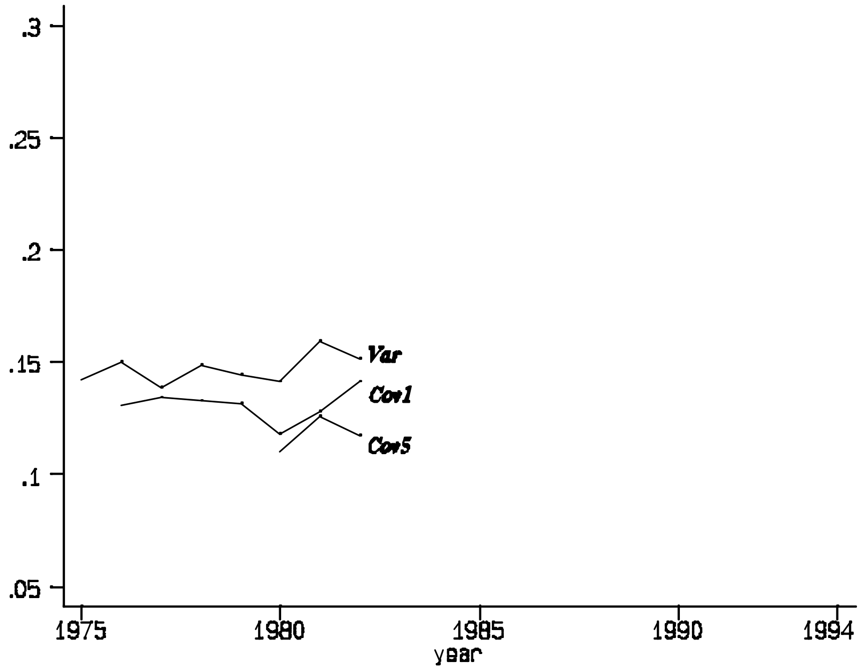
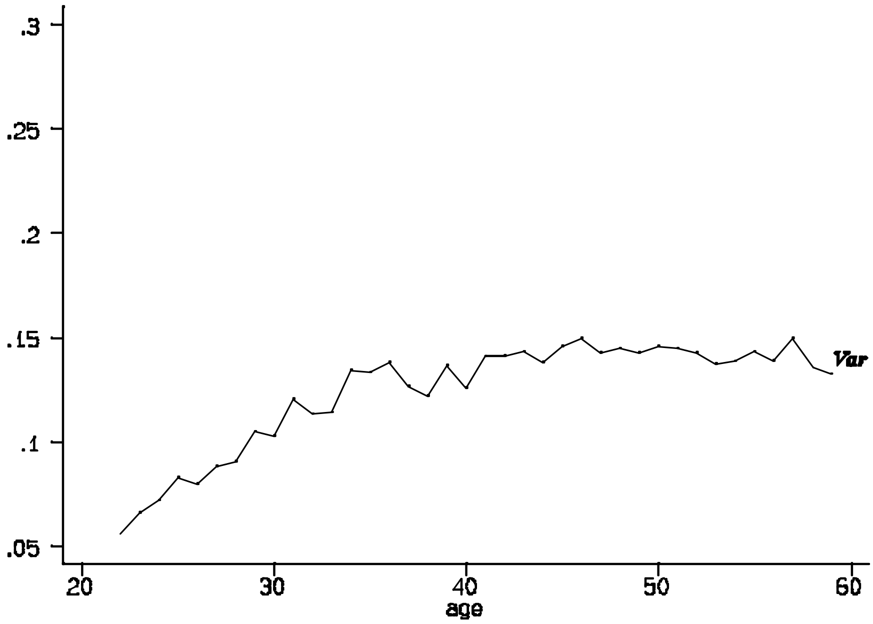


FIGURE 2

The Life Cycle Profile of Variances and Covariances: 1975-94

1975



1980

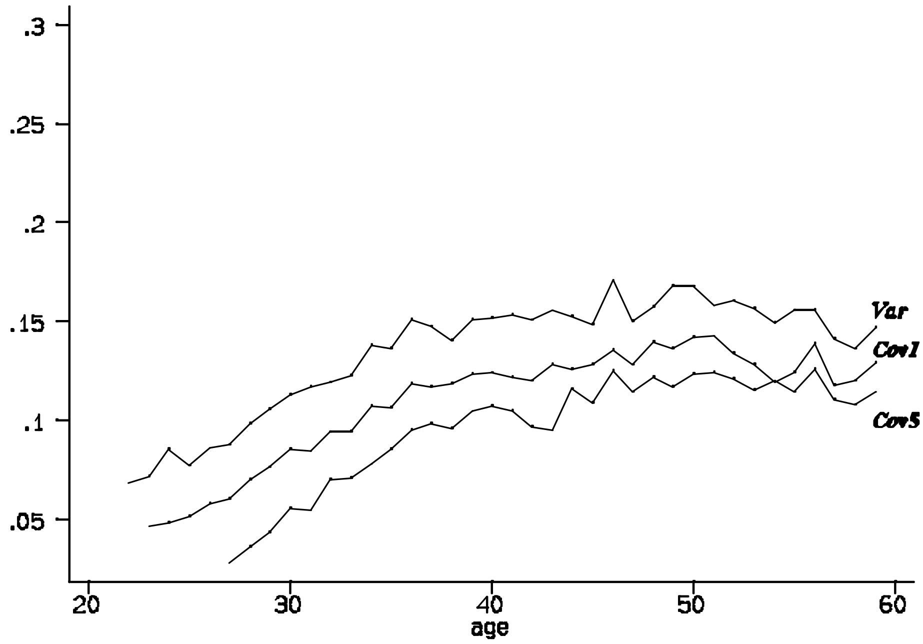
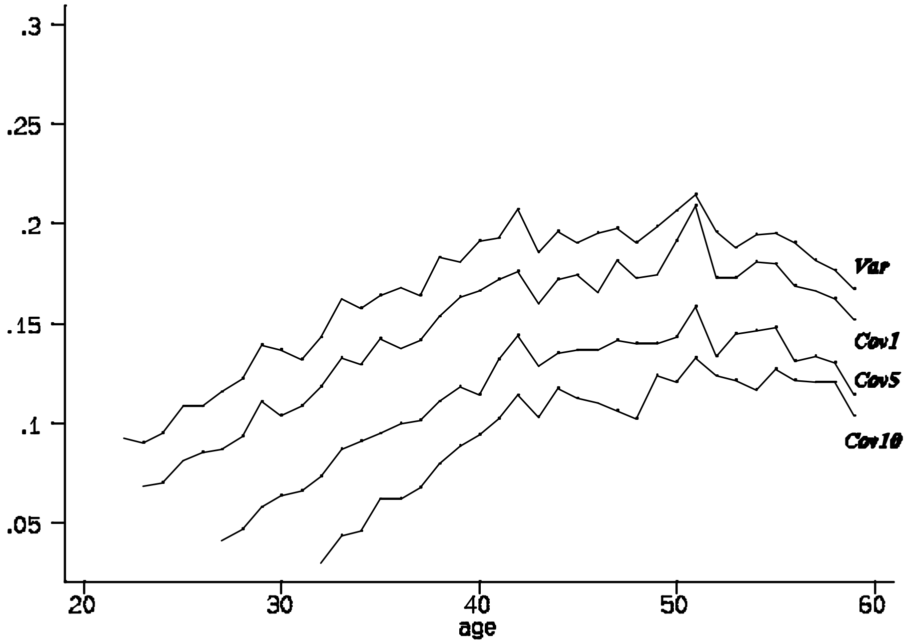


FIGURE 2 continued

The Life Cycle Profile of Variances and Covariances: 1975-94

1985



1990

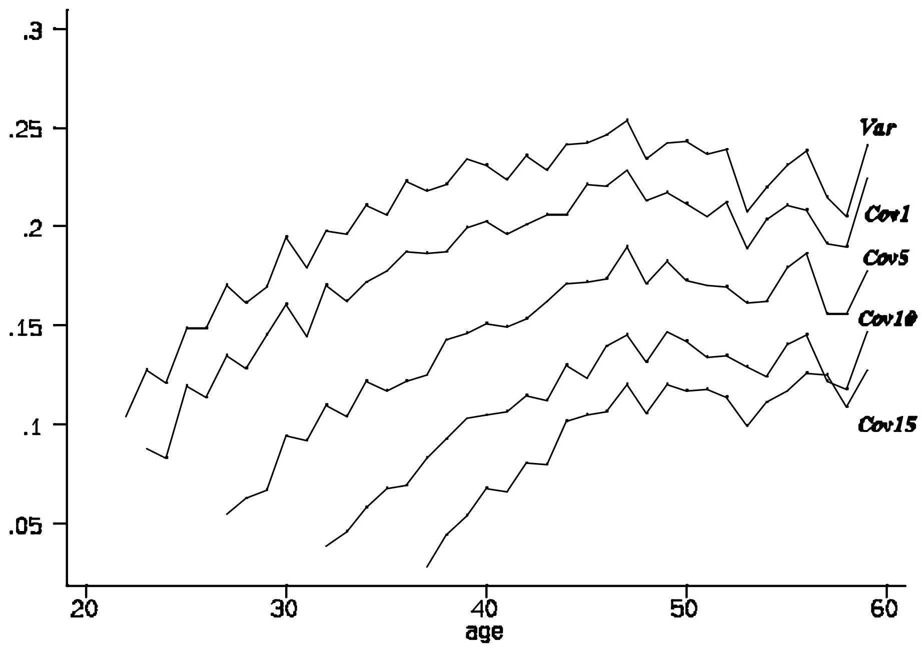


FIGURE 2 continued

The Life Cycle Profile of Variances and Covariances: 1975-94

1994

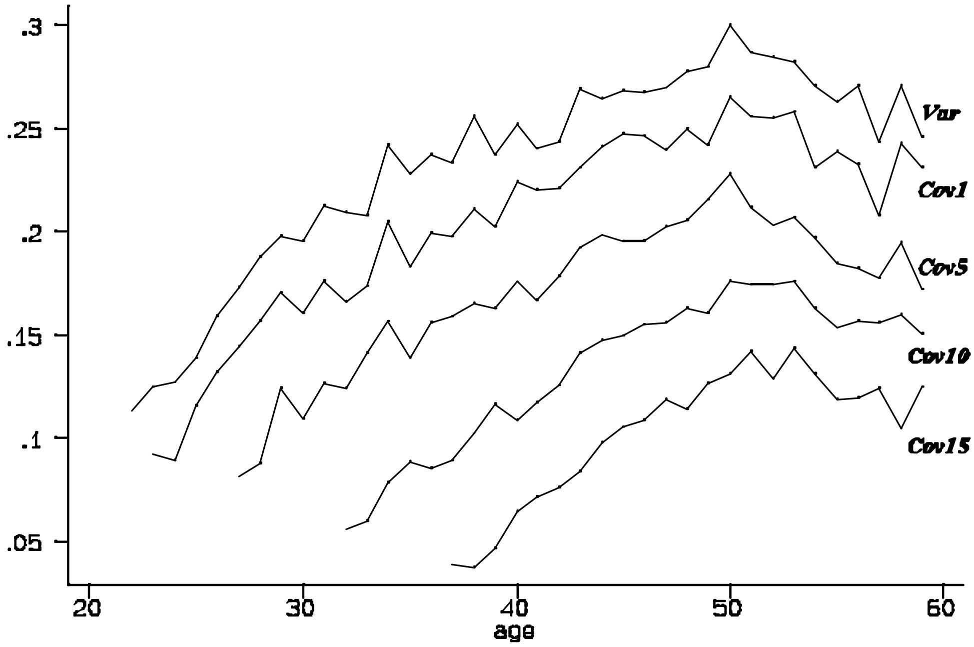
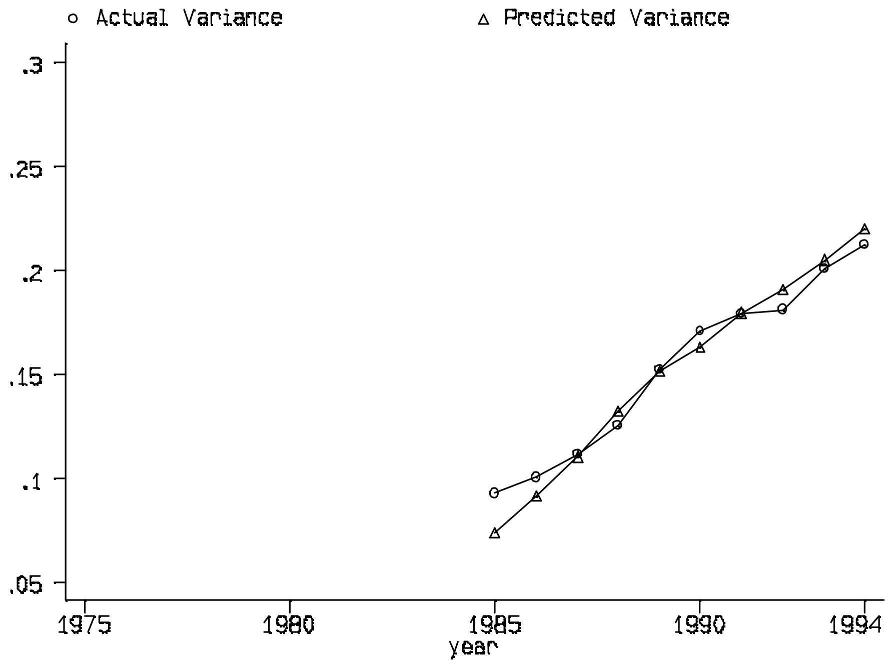


FIGURE 3

Actual and Predicted Variances for Selected Cohorts: 1975-94

Cohort born 1963



Cohort born 1953

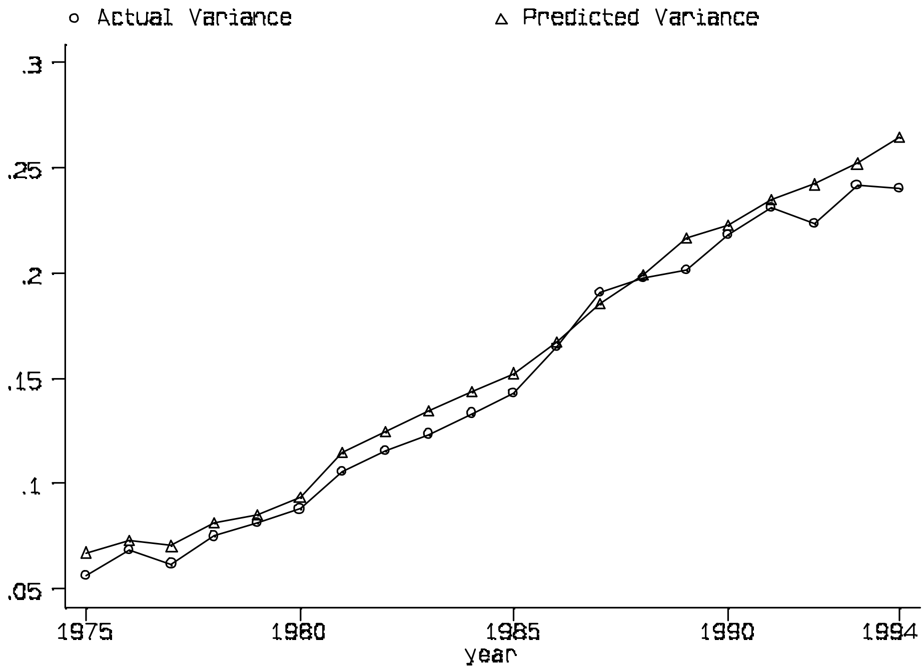
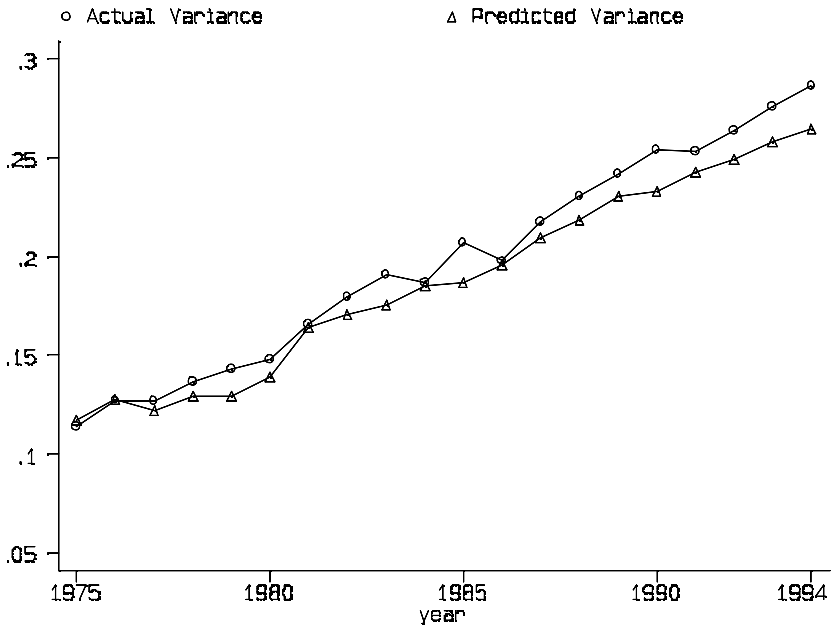


FIGURE 3 continued

Actual and Predicted Variances for Selected Cohorts: 1975-94

Cohort born 1943



Cohort born 1933

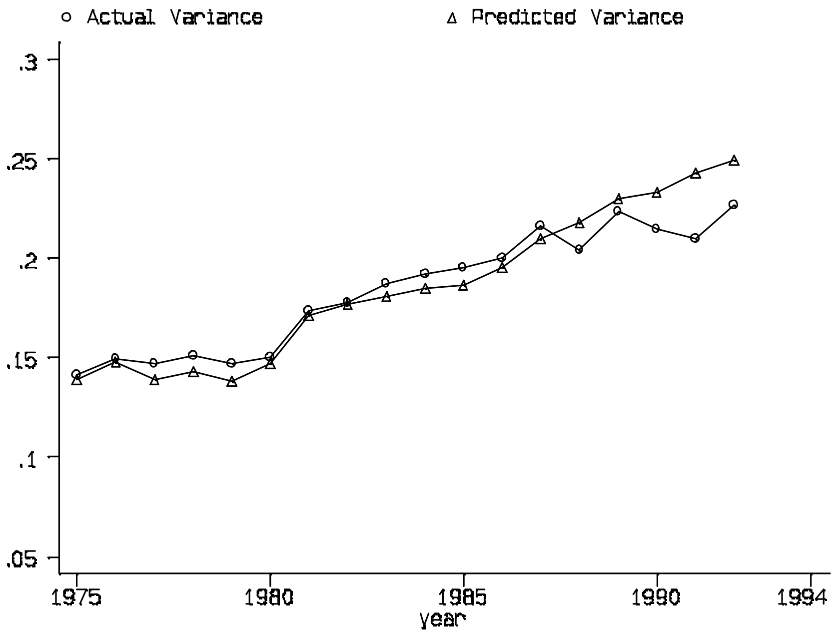


FIGURE 3 continued

Actual and Predicted Variances for Selected Cohorts: 1975-94

Cohort born 1923

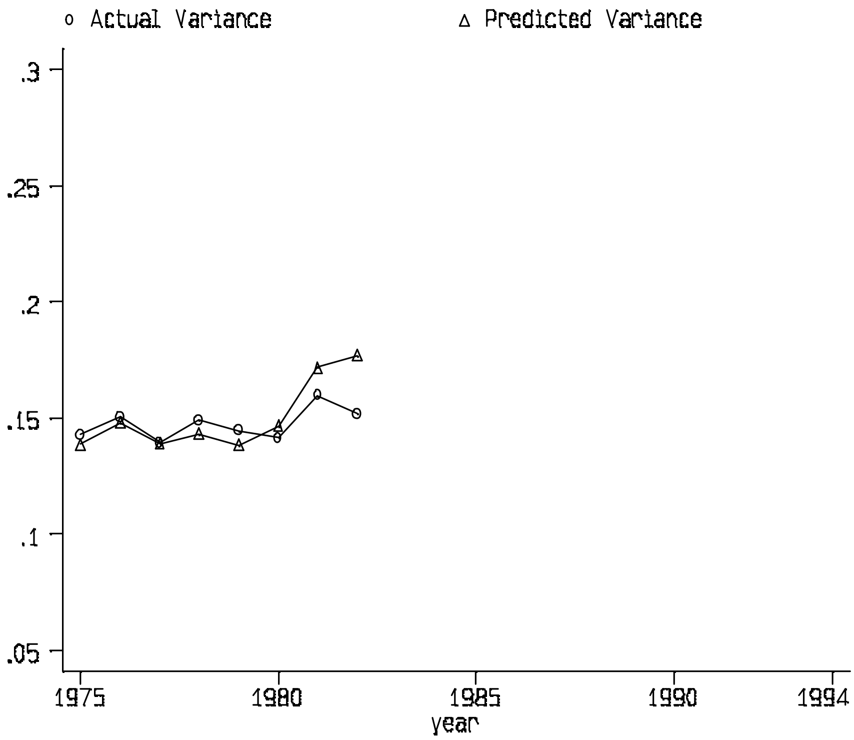
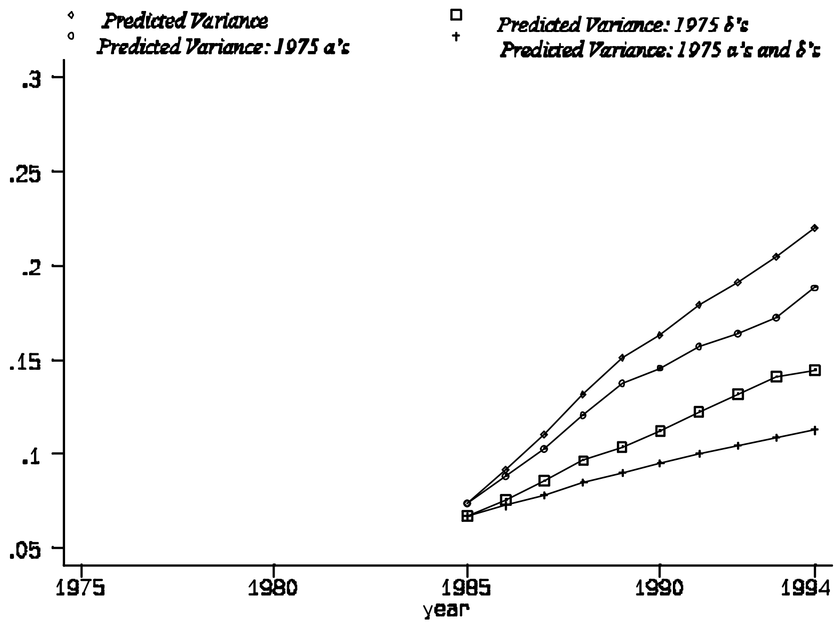


FIGURE 4

Permanent and Transitory Effects on the Predicted Variances for Selected Cohorts: 1975-94

Cohort born 1963



Cohort born 1953

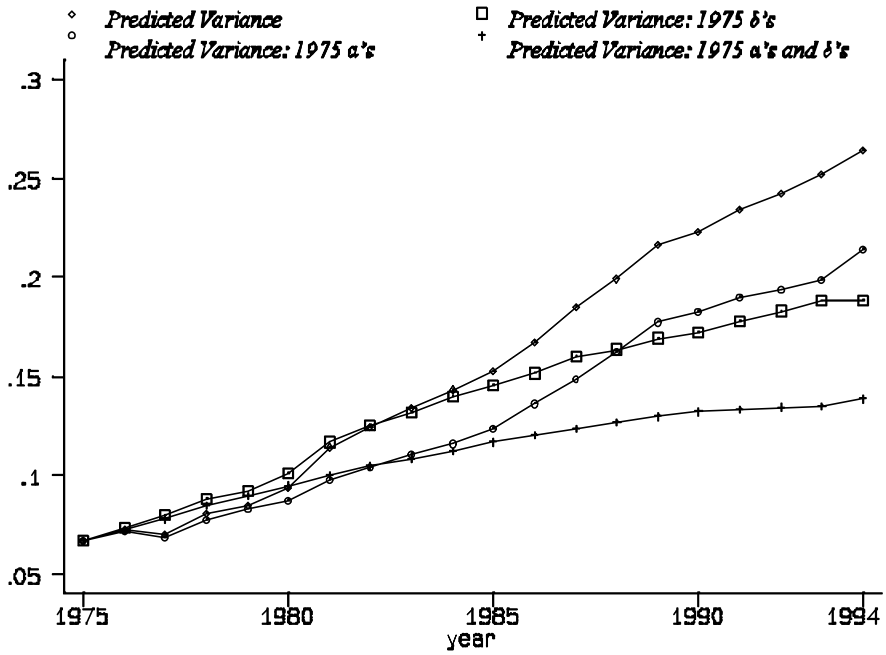
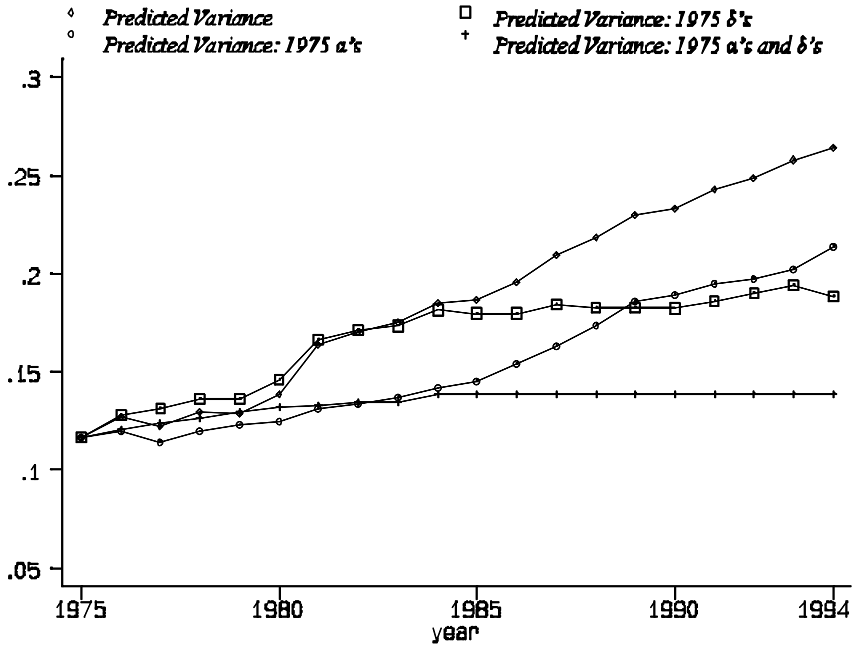


FIGURE 4 continued

Permanent and Transitory Effects on the Predicted Variances for

Selected Cohorts: 1975-94

Coho rt born 1943



Coho rt born 1933

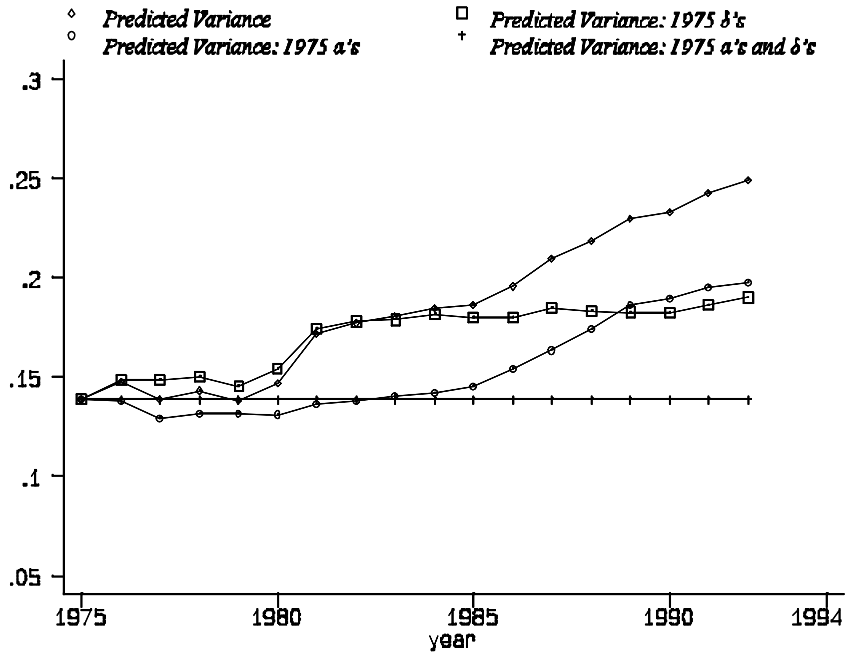
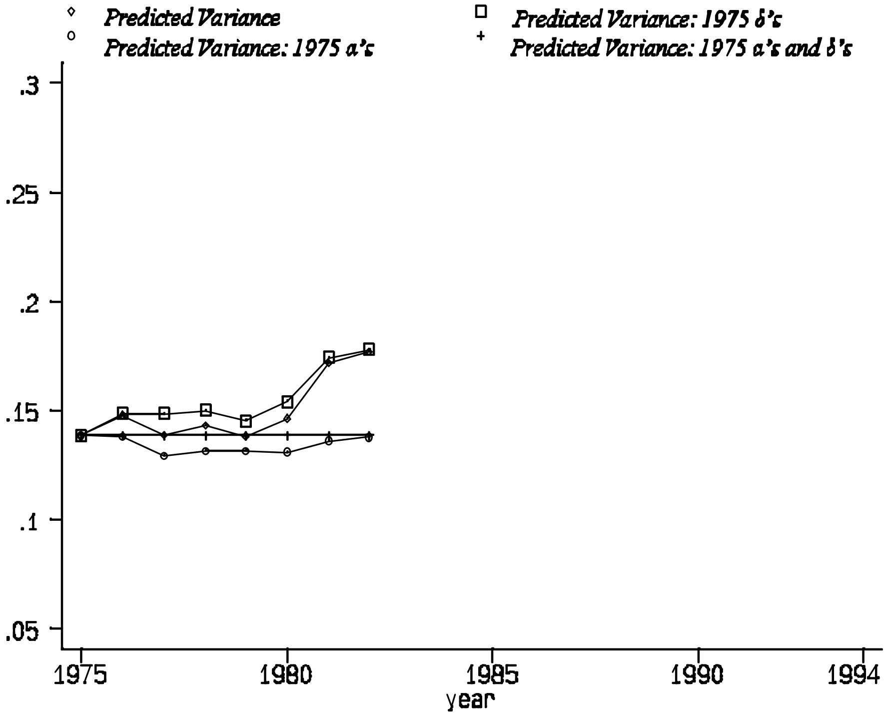


FIGURE 4 continued

Permanent and Transitory Effects on the Predicted Variances for

Selected Cohorts: 1975-94

Cohort born 1923



TECHNICAL APPENDIX

In this appendix I present the statistical methods employed in this paper for computing the covariances of earnings for each cohort and for estimating error component models for individual earnings. The methodology used is the same as that utilised by Abowd and Card (1989), except that here I have an unbalanced panel of individuals. For each cohort c and individual i, define a vector:

$$d_{ci} = \begin{pmatrix} d_{ci1} \\ . \\ . \\ . \\ d_{ciT_c} \end{pmatrix}$$

where d_{cit} is an indicator variable such that:

$d_{cit} = 1$ if the individual is present in year t of the panel.

$d_{cit} = 0$ otherwise.

and T_c is the total length of the panel for each cohort (between 1 and 20 years).

Analogously to d_{ci} , define a vector:

$$w_{ci} = \begin{pmatrix} w_{ci1} \\ . \\ . \\ . \\ w_{ciT_c} \end{pmatrix}$$

where w_{cit} are log hourly earnings for cohort c and individual i in year t, in mean deviation form for each cohort and year. Since the panel is unbalanced the elements of w_{ci} corresponding to missing years of data will be set to zero.

The covariance matrix of log hourly earnings for each cohort is then computed as:

$$C_c = \frac{\sum_{i=1}^{N_c} w_{ci}\, w_{ci}'}{D_c}$$

where N_c is the total number of individuals in the cohort and

$$D_c = \sum_{i=1}^{N_c} d_{ci}\, d_{ci}'$$

Define m_c to be a vector of the distinct elements of the covariance matrix C_c, m_c = vech(C_c). Since C_c is symmetric there are T_c (T_c +1)/2 elements in m_c. Conformably with m_c, define m_{ci} to be the distinct elements of the individual cross product matrix $w_{ci}\, w_{ci}'$. Similarly, let p_c be a vector of the distinct elements of D_c. Chamberlain (1984) proves
that, under some fairly general conditions, independence of the w_{ci} implies that m_c has an asymptotic normal distribution $m_c \sim N(m_c, V_c)$. Where V_c can be estimated by:

$$V_c = \frac{\sum_{i=1}^{N_c} (m_c - m_{ci})\,(m_c - m_{ci})'}{p_c\, p_c'}$$

Now define the vector m to be the vertical concatenation of all the m_c vectors. To estimate the error components models of Section 5 we want to fit the elements of m to a parameter vector b, so that m =

f(b). Minimum distance estimation involves minimising the following quadratic form: $(m - \mathrm{f}(b))\ A\ (m - \mathrm{f}(b))'$ where A is an appropriate weighting matrix.

Chamberlain (1984) shows that the optimal choice for A is V^{-1}, where V is a block diagonal matrix which is constructed from all the V_c matrices. However, Altonji and Segal (1994) provide Monte Carlo evidence that optimal minimum distance (OMD) is seriously biased in small samples. This bias arises from the correlation between sampling errors in the second moments, m, and the weighting matrix of fourth moments, V^{-1}. They present an alternative estimator, the independently weighted optimal minimum distance estimator (IWOMD) but conclude that equally weighted estimation (where A is an identity matrix) is often preferable. I follow their procedure and use equally weighted minimum distance estimation.

Following Chamberlain (1984), the standard errors of the estimated parameters are obtained from the following formula:

$$(G'AG)^{-1}\ G'AVAG\ (G'AG)^{-1}$$

where G is the $T*P$ gradient matrix $\mathrm{df}(b)/\mathrm{d}b$ evaluated at $b*$, the estimated value of b, where T is the sum across cohorts of $T_c(T_c+1)/2$ and P is the number of parameters.

Under the hypothesis of a correct specification the minimised quadratic form:

$$(m - \mathrm{f}(b*))\ V^{-1}\ (m - \mathrm{f}(b*))'$$

has a chi-squared distribution with degrees of freedom equal to the dimension of m (=T) minus the number of parameters P. This is the test statistic presented in Table 3.

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