Earnings dynamics and uncertainty in Italy: How do they differ between the private and public sectors? ♣

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Abstract
This paper uses Italian panel data from the private and public sectors and analyses earnings dynamics by applying the minimum distance estimator of Chamberlain (1984). We consider two main aspects of earnings careers. First, we estimate a measure of earnings growth heterogeneity, whereby quantifying to what extent the two sectors differ in the ability to differentiate remuneration of time-varying aspects of productivity, such as learning capacity, thence providing different incentives to acquire skills on the job. Second, we estimate the inequality of permanent earnings as opposed to that of transitory earnings, the latter providing a measure of earnings uncertainty in the two sectors. We find that earnings careers markedly differ between public and private sectors. In particular, for private sector workers the life cycle of earnings matters in the formation of earnings differentials, i.e. the data indicate the presence of heterogeneity of earnings growth rates, which may serve as a remuneration of differential learning ability. On the other hand, public sector data indicate that earnings growth is homogeneous over the life-cycle and, as a consequence, initial earnings differences tend to persist over the career. When looking at differences in earnings uncertainty, we find that this is negligible in the public sector, suggesting that the public sector provides more secure jobs.

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Contents

1. Introduction

The 1990s have been an era of profound changes for Italian labour market institutions. Major reforms in the system of wage indexation were implemented at the beginning of the decade, whereby automatic wage growth linked to inflation forecasts has been substituted by ex-post bargained compensations, thus eliminating a main element of earnings equalisation. Also, similarly to other European countries, temporary contracts and measures aimed at cutting hiring and firing costs have been introduced.

The reform of public sector employment is a relevant element of this process. Public sector jobs represent approximately 30% of the employed labour force and have traditionally been characterised by lower exposure to market forces and more compressed pay differentials compared to the private sector. The so-called "privatisation" of the public sector was set out by law at the beginning of the 1990s with the aim of increasing the efficiency of public sector employment and re-establishing economic incentives for public sector employees, for example by introducing performance related pay schemes and output monitoring, first of all at the management level.

Despite the relevance of the reform for the functioning of the Italian labour market, little is known on the features of public sector earnings dynamics and their differences with the private sector besides conventional wisdom.[1] This paper aims at filling in this gap. We use panel data on individual earnings for comparable cohorts of male workers in the two sectors to analyse the earnings covariance structure by applying the minimum distance estimator of Chamberlain (1984). We consider two main aspects of earnings careers. First, we estimate a measure of earnings growth heterogeneity, whereby quantifying to what extent the two sectors differ in the ability to differentiate remuneration of time-varying aspect of productivity, such as learning capacity, and thence to provide incentives to acquire skills on the job. Second, we estimate the dispersion of permanent earnings as opposed to that of transitory earnings, the latter providing a measure of earnings uncertainty due to economic shocks.

The literature on earnings comparisons between private and public sectors has typically focussed on estimating measures of the pay differential between the two sectors. In particular, much effort has been devoted to the control of endogenous selection of workers in the two sectors (see, e.g., Pedersen et al, 1990, and Brunello and Dustmann, 1996, and Bardasi, 2000, for Italy). However, this kind of approach is based on cross-sectional data, thus enabling researchers to assess static differences in earnings between the two sectors, but leaving the dynamic features of earnings careers unexplored. This paper takes a complementary route and provides an empirical characterisation of earnings dynamics in the two sectors.

We find that earnings careers markedly differ between public and private sectors. In particular, for private sector workers the life cycle of earnings matters in the formation of earnings differentials, i.e. the data indicate the presence of heterogeneity of earnings growth rates, which may serve as a remuneration of differential learning ability. On the other hand, public sector data indicate that earnings growth is homogeneous over the life-cycle and, as a consequence, earnings differences at the beginning of the career tend to persist over the career. When looking at differences in earnings volatility, we find shocks persistence to be larger in the private sector, i.e. earnings deviations from the long run component have longer duration, implying higher uncertainty. On the whole, our findings indicate that the share of transitory variability within earnings differential is negligible in the public sector, thus showing that the public sector provides more secure jobs.

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[1] An exception is the study of Lucifora and Vignocchi (1998) who analyse earnings profiles by birth cohort and gender.

The rest of the paper is as follows. In Section two we describe the administrative panel data used in the analysis, while Section 3 provides a statistical description of earnings autocovariances and mobility rates. Section 4 reports the econometric analysis of the earnings covariance structure: empirical models of earnings dynamics are set out and the results discussed. Finally, Section 5 draws some conclusions.

2. The data

The data utilised in this paper originate from administrative longitudinal archives on individual earnings histories. Private sector data have been made available by the National Social Security Institute (INPS) and refer to yearly take home earnings gross of income taxes and net of social security contributions, for employees of the non-agricultural non-self employed sectors over the 1979-95 period. Public sector data on gross yearly take home earnings for the 1981-95 interval are drawn from the Treasury archive: again, figures are net of social security contributions. Information in both archives refers to full-time employment.

The use of administrative data allows us to perform longitudinal comparisons of earnings dynamics between the Italian private and public sectors while ensuring both a large cross-sectional dimension and the coverage of a long time period. Moreover, the administrative nature of the data ensures a good reliability of information on earnings. However, a limited amount of information on personal workers characteristics, such a limitation being particularly relevant in the case of our public sector archive. In particular, information on workers' education, social background and attitudes or preferences is not available. Such a limitation implies that these data are not well suited for analyses in which one looks for the (possibly causal) effect of individual attributes on earnings levels or dynamics. More specific to our analysis is the inability of estimating endogenous selection equations (for the sectoral assignment) due to lack of instruments for the selectivity process. These data limitations justify our analytical approach, which will consist of a characterisation of the dynamic earnings process and of its consequences in terms of earnings differentials within each sector, assuming exogenous sectoral assignment.

We restrict our attention to male data, in order to avoid issues of endogenous labour market participation inherent to the study of women's earnings, which may well be complicated by exits and re-entries over the life-cycle. Secondly, we concentrate on white collar workers. As pointed out by previous studies on Italian sectoral wage differentials (see e.g. Bardasi, 2000), manual occupations are rare in the public sector and hardly comparable to blue collar jobs in the private sector. In particular, we select public sector white collars employed in the Ministries, while excluding occupations such as school teacher or magistrate, for which a private sector counterpart does not exist. A third criterion we impose on our sample is dictated by the scarcity of information on working time. Public sector earnings are recorded on a yearly basis, with no indication on the amount of time actually worked during the year. This generates a problem for individuals who work only part of the year, say because their employment relationship starts or terminates within the year. In this cases, lower labour supply translates into lower earnings, which are not comparable with those of year-round employees. To cope with this issue, we include in our sample individual earnings of a given year only if the individual is observed in sample also in the preceding and following years, thus ensuring that the earnings observation does not refer to a within year start or end of an employment spell. Consequently, we restrict the time window to 1982-1994. Information for the private sector also includes the number of weeks worked, so that year-round earnings can be recovered by multiplying reported figures by $52/n$, n being the number of weeks actually worked. However, given that selecting earnings from continuous employment spells, as we do in the public sector, is likely to reduce earnings volatility, we also apply the same selection criterion to private sector data, in order to preserve comparability. We also restrict the time windows to 1982-1994. Finally, in order to study earnings profiles at comparable phases of the life cycle, we select individuals according to their birth cohort, namely the 1936-1959 interval. In this way we can observe earnings dynamics over a relevant portion of the life-cycle (individuals born in 1959 are 23 in 1982, while workers born in 1936 are 58 in 1994) but not at its extremes, where earnings volatility may be inherent to the life cycle and interfere with structural labour market instability.

[TABLE 1]

Samples used for the analysis are described in Table 1. Private sector data refer to 18540 individuals and 182402 person-year observations. Corresponding figures for the public sector are 60137 and 644027. We use the whole unbalanced panel. While not formally controlling for attrition bias, this strategy enables us to maximize cell size and avoid the likely overstatement of earnings persistence induced by the use of balanced panels. The top part of the table refers to the birth cohort structure of the data and shows that public sector workers tend to belong to older cohorts compared to individuals in the private sector. Also, cohorts' turnover is more evident in the private sector, where younger cohorts increase their relative weight during the final years of the sample period much faster than they do in the public sector. These differences in the cohort structure of the workforce in the two sectors might reflect institutional differences in the hiring process, namely the presence exam based public competitions (often nation-wide) for accessing public sector white collar jobs, which can slow down the entry of young cohorts.

The bottom part of the table reports some summary statistics of the distribution of real earnings (1990 prices). A first remarkable difference between the two sectors can be observed by considering mean and median earnings. A slight differential in favour of private sector employees characterises the first year of data. This gap widens enormously during the following years: while private sector real median earnings grew by 25% between 1982 and 1989, public sector figures only grew by 5% over the same interval. Part of the huge differential produced by these differences in median earnings growth is eliminated during the early 1990s, when a remarkable 18% increase characterise public sector earnings between 1989 and 1990. Again, the highly institutionalised nature of public sector employment, this time in its pay setting framework, can account for differences between the two sectors. In particular, the development of public sector earnings is strongly dependent on bargaining rounds, and the earnings stagnation of the 1980s reflects the absence of contract renewals for this particular public sector workforce. Only in the late 1980s new contracts were signed and the huge increase of 1990 was meant to compensate for the lack of real earnings growth of the preceding years.

Differences between the earnings distributions of the two sectors can also be observed by considering dispersion indicators, showing that the distribution is much more compressed in the public sector compared to the private one. In both cases dispersion grows over the period and, again, while such growth appears to be continuous in private sector data, public sector figures indicate that increasing earnings inequality is concentrated in the late 1980s- early 1990s. Log percentiles ratios computed for the top and bottom halves of the earnings distribution indicate that earning levels are more dispersed at the top in both sectors, suggesting that the distribution is characterised by positive asymmetry. However, the differential dispersion between the two halves is more pronounced in the public sector compared to private sector data.

[FIGURE 1]

An overview of the evolution of the distribution of earnings over the life cycle is provided by Figure 1, which plots the 1st and 9th decile of earnings by birth cohort against age. In particular, we use the 8 3-years birth cohorts described in Table 1 and impute them the central age cohort. Thus, individuals from the oldest cohort, 1936-1938, are imputed ages 45 (in 1982) through 57 (in 1994), while workers in the youngest cohort, 1957-1959, are imputed ages 24 (in 1982) through 36 (in 1994). By considering private sector data first, it can be observed that earnings growth is larger at the top than at the bottom of the distribution for each birth cohort, turning into a widening of earnings dispersion over the period. Also the level of earnings dispersion is larger the older the birth cohort analysed, suggesting the presence of growth rate heterogeneity over individual working lives. Another relevant evidence emerging from the graph is the presence of birth cohort effects in earnings levels: at each age younger cohorts appear to earn more compared their older counterparts, as can be consistent with the existence of secular growth of productivity. Finally the graph shows quite clearly the importance of using longitudinal data organised by birth cohort when inspecting the evolution of earnings over the working life. In particular, earnings growth with age appears to be much steeper if one considers each cohort's profile rather then the cross-sectional profiles of each year.[2]

When moving to consider public sector evidence in Figure 1, the same features singled out for the private sector can –roughly- still be observed. However, for public sector workers life cycle earnings dynamics display much stronger calendar time effects.

[2] This is an old idea in the literature on panel data on incomes, see Shorrocks (1975). Cross-sectional profiles can be recovered by ideally connecting earnings points across

For all cohorts earnings growth presents an initial phase of stagnation, in correspondence of the 1982-87 interval, followed by acceleration. As noted above, these patterns closely follow the evolution of bargaining rounds in the public sector during the period investigated.

3. The autocovariance structure and mobility of earnings

In this Section we begin our characterisation of earnings dynamics in the private and public sectors by summarising patterns of the earnings autocovariance structure and of transitions through the quantiles of the distribution, while deferring a more formal assessment of individual earnings dynamics is to the next Section.

We conduct our analysis in terms of "adjusted earnings", i.e. residuals from first stage OLS regressions in which some structural effects are removed from raw log-earnings. In particular, controls in first stage regressions include year dummies and a quadratic in age, fully interacted with birth cohort dummies.[3] In this way the estimated autocovariance structure and mobility rates will not reflect earnings variation due to the business cycle, the life-cycle and secular growth, respectively.

As a first step, we describe earnings persistence by estimating the earnings autocovariance structure of adjusted log-earnings. For each sector we estimate earnings covariances between each pair of years available in our panels, separately by birth cohort.[4] We next pool estimated autocovariances across birth cohorts and regress them on a set of

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cohorts. For example, by connecting the first point of each profile across cohorts the 1982 cross-sectional profile can be reconstructed.

[3] We also experimented including industry specific age profiles in private sector first stage regressions but found no relevant difference with respect to the results discussed in the text.

[4] To assess their statistical significance, we also estimate fourth moments of earnings using deviations of individual cross-products from their sample average, and find that all variances and covariances are statistically significant. Seconds and fourth moments matrices are available on request.

dummies for lag width, calendar time and birth cohort.[5,6] The first set of dummies is meant at capturing the likely increase in the chance of changing oneself position within the earnings distribution which should be observed as pairs of years further apart are taken into account. More in detail, if the earnings process is serially correlated, we should expect such an increase to take place at decreasing rates and the earnings autocovariance function to present a negative exponential shape. The set of calendar time dummies is aimed at controlling for shifts of the earnings distribution over the sample period, while birth cohort dummies control for heterogeneity of earnings persistence across different stages of the working life.[7]

[TABLE 2]

Results from such non-parametric analysis of the earnings covariance structure are given in Table 2. By considering private sector estimates first we can see that the earnings process might actually present some form of serial correlation, dummies on lag width dropping more evidently at the first lag compared to longer lags. The variation of earnings covariances over time indicates that both inequality and persistence have been rising during the period considered, especially over the second half of the 1980s and the first half of the 1990s. Finally, birth cohort dummies clearly indicate that earnings persistence is

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[5] For a panel of length T there are *[T(T+1)/2]* pair of years between which covariances can be estimated. In our case T=13, so that the covariance matrix of each cohort has 91 distinct elements, with a total of 728 covariances which can be estimated in each sector.

[6] One should note that OLS provide inefficient estimates in this context given the likely presence of heteroskedasticity and serial correlation in the variable analysed. To account for this, we correct standard errors using the fourth moments matrix of adjusted log-earnings.

[7] Lag and calendar time dummies are specified in an incremental way (i.e. the dummy for lag or year j equals 1 if the lag or year considered is equal or greater than j and 0 otherwise). In this way they can be interpreted as change in covariances with respect to the previous lag or year, rather than with respect to a fixed reference category.

lower for younger cohorts, as could be consistent, for example, with job search models in which the probability of changing job (and of experiencing earnings instability as a result of job changes) decreases with labour market experience. Moving to results for the public sector, the first fact to observe is the huge difference in the constant term with respect to the private sector, which indicates a more compressed earnings distribution in the latter case. As for the other features observed in the private sector, these can also be uncovered from public sector's earnings variances and covariances; clearly, variations of the autocovariance structure are smaller in absolute size, given the more compressed earnings range characterising public sector data compared to private sector's ones.

Evidence from the covariance structure analysis reflects differences in the two sectors in both the size of earnings differentials at a point in time and the degree of earnings persistence over time. It may be useful to abstract from differences in the spread of the earnings distribution in the two sectors and focus on the probability of movements within the quantiles of the earnings distribution over time. This exercise will yield an indication of how easy it is to change oneself relative position in the earnings hierarchy through time independently from differences in the width of earnings ranks in the two sectors. With this aim we discretise the earnings distribution of each year using ventiles and summarise transition probabilities using a *quasi-immobility ratio*, i.e. the probability of persisting in the origin ventile or the adjacent one(s) from one year to another. As we did for autocovariances, we estimate the mobility measure for each pair of years and separately by birth cohorts and regress it on lag, year and birth cohort dummies.[8,9]

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[8] Note that the (im-)mobility measure is not computed at lag 0 (the probability of not moving would trivially equal 1). This implies that the sets of dummies on both lags and years lose 1 element, compared to the regression of autocovariances, in order to identify the model. Put another way, this is the loss of information induced by dropping variances from the analysis.

[9] In order to apply OLS regression to the quasi-immobility *ratio* (QIR) we apply a logistic transformation, i.e. log(QIR/(1-QIR)).

Results from the analysis of the mobility indicator are reported in the second part of Table 2 and show that now differences across the two sectors are less evident compared to the analysis of the autocovariance function. First of all, the reference value summarised in the constant is rather homogeneous in the two sectors: the probability of persisting in the origin ventile or the adjacent one(s) for the oldest cohort between 1982 and 1983 is 0.698 in the private sector and 0.704 in the public sector.[10] The behaviour over lags is also more homogeneous across sectors than it was for the autocovariance structure, and the earnings hierarchy appears only slightly more mobile in the private sector compared to the public one: at lag 12 the implied quasi-immobility probability is 0.275 in the private sector and 0.325 in the public sector.[11] An increase in distributional rigidity over time can be observed in both sectors: in particular, such an increase appears to be continuous in the private sector, while public sector data suggest that such an increase is concentrated at the beginning of the 1990s and in the last year observed. Finally, variations of transitions probabilities across birth cohorts indicate that earlier stages of the working life are associated to lower earnings persistence. In this case, differences across sectors are more pronounced compared to lag or year dummies and indicate quite clearly that earnings mobility is more homogeneous across age groups in the public sector compared to private sector employees.

4. GMM analysis of earnings dynamics and uncertainty

In this Section we exploit the longitudinal dimension of the data to distinguish between earnings dynamics and uncertainty. We start by describing the canonical decomposition of

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[10] These figures are computed as exp(constant)/(1+exp(constant)).

[11] For this calculation we use all estimated coefficients on the lag structure, including the ones which are not precisely estimated at conventional levels of significance. Using 10% as the reference level of significance would imply dropping one estimated coefficient in

earnings levels into permanent and volatile components and its implications in terms of the covariance structure of earnings, providing an introduction to the more complex models used in this paper. We next expand the analytical framework to characterise the dynamics of permanent earnings and the process of earnings shocks. Calendar time and birth cohort effects are also modelled.

4.1 Model specification and estimation

The simplest way to characterise the autocovariance function of earnings is to assume that individual adjusted log-earnings levels depend in each time period upon a constant individual-specific component and a white noise term, serially uncorrelated both across individuals and time periods. Let w_{iat} be the adjusted log-earnings of individual i at age a in year t, with, $i = 1,...,N,\quad t = 0,...,T-1,\quad a = 0,...,A$.[12] This simple model postulates that:

$$\begin{aligned} &w_{iat} = \mu_i + v_{it} \\ &\mu_i \sim (0,\sigma_\mu^2) \qquad v_{it} \sim (0,\sigma_v^2) \qquad E(\mu_i v_{it}) = 0. \end{aligned} \tag{1}$$

Here μ_i represents the effect of persistent determinants of earnings capacity (say ability) which can be identified thanks to the longitudinal dimension of the data, whereas v_{it} captures the effect of random deviations from it. We can see μ_i as a the long run expected component of earnings and the random shock v_{it} as the vehicle of year-to-year earnings uncertainty.

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the private sector and two in the public sector, resulting in a widening of the mobility gap between the two sectors reported in the text.

[12] Age is measured in deviations from the minimum observed age in the sample, i.e. 24 years.

It follows from the assumptions on second moments that:

$$E[w_{iat}w_{i(a-k)(t-k)}]=\begin{cases}\sigma_{\mu}^{2}+\sigma_{v}^{2} & if \quad k=0\\ \sigma_{\mu}^{2} & otherwise.\end{cases} \tag{2}$$

Thus, while the permanent earnings component contributes to both variances and covariances, transitory fluctuations only contribute to the variance of earnings. Transitory variation thus measures earnings uncertainty, large values of σ^2_v implying that current earnings are a poor predictor of future earnings.

Several assumptions underlying model (1) should be relaxed in order to obtain a more realistic characterisation of individual earnings dynamics. First of all, the assumption of constancy of the permanent component does not square with human capital theories of earnings dynamics which predict that individual ability might vary over the career thanks to the acquisition of skills and experience.[13] Several studies of the earnings covariance structure have therefore proposed a *random growth* model (RG)[14] in which individual specific components are characterised by an additional parameter measuring earnings growth with age or experience:

$$\begin{aligned} &w_{iat}^{P}=\mu_i+\gamma_i a_{it}\\ &\begin{pmatrix}\mu_i\\ \gamma_i\end{pmatrix}\sim\left[\begin{pmatrix}0\\ 0\end{pmatrix},\begin{pmatrix}\sigma_{\mu}^{2} & \sigma_{\mu\gamma}\\ & \sigma_{\gamma}^{2}\end{pmatrix}\right]\end{aligned} \tag{3}$$

[13] Time varying permanent earnings may be generated also by other theoretical frameworks. For example, matching theories would predict this outcome as a result of ability being revealed over time.
[14] See Lillard and Willis, 1979, Hause, 1980, and, more recently, Baker, 1997, and Baker and Solon, 1998.

where a P superscript denotes permanent earnings.[15] The distributive hypothesis on the vector $(\mu_i, \quad \gamma_i)$ implies that the autocovariance function depends, in its permanent part, on both fixed and time-varying individual heterogeneity, where the latter may, for example, result from differentials in the remuneration of learning ability, measured by the variance of individual growth rates (σ_γ^2). Parameters on the diagonal in (3.a) are variances and thus are always positive, but the sign of the covariance between intercepts and slopes of individual earnings profiles ($\sigma_{\mu\gamma}$) is not determined *a priori*. A negative covariance between fixed and time-varying components of individual heterogeneity is a prediction from models of investment in (general) on the job training (OJT), where trainees bear the cost of investment in terms of lower initial earnings and receive returns in terms of faster growth, compared to those not investing.[16] In this case, the factors generating permanent inequality at the beginning of the career would be offset over the life cycle, so that we should observe the dispersion of permanent earnings to decrease as individuals age and acquire experience in the labour market. On the other hand, a positive covariance could emerge in a schooling-matching framework, as long as "better" workers are endowed with more education which raises their initial earnings and experience faster growth as the quality of the match is revealed to employers. As a consequence, permanent inequality should rise over the life-cycle. The recurrent finding from studies estimating the specification (3) is that the parameter is negative, supporting the OJT explanation of earnings dynamics.[17]

[15] We use age since we do not observe age at labor market entry.

[16] Hause, 1980, proposes a test of the OJT model based on the sign of $\sigma_{\mu\gamma}$.

[17] See Hause (1980), Baker (1997) and Baker and Solon (1998). An exception is the work of Lillard and Weiss (1979), where the parameter was positive after birth cohort effects had been removed from raw earnings.

A second hypothesis underlying equation (1) which could be usefully removed is that of serially uncorrelated transitory earnings. In fact, this assumption would imply that transitory components of the autocovariance structure should entirely disappear after lag 0, so that a drastic drop in the autocovariance function should be observed as we move from variances to covariances. By contrast, the descriptive regressions of the previous Section have shown that the decline of autocovariances with lags is smooth, and that they reach an asymptote (the permanent component) only after few lags. To accommodate these patterns, it is common to assume some low order ARMA process for transitory earnings.[18] In particular, here we will adopt an AR(1) process, i.e.:

$$\begin{aligned} v_{it} &= \rho v_{i(t-1)} + \varepsilon_{it} \\ \varepsilon_{it} &\sim (0,\sigma_{\varepsilon}^2), \qquad v_{i0} \sim (0,\sigma_0^2) \end{aligned} \tag{4}$$

in which the autoregressive parameter (ρ) captures the smooth decline of covariances over lag length.[19, 20] Large values of ρ imply that random fluctuations induce longer durations of current earnings deviations from their long run value, and thus are associated with higher uncertainty.

[18] Clearly, it is not entirely correct to define autoregressive processes as transitory, mean-reverting being a more precise label. However, in the remainder of the paper we will still refer to transitory earnings, both for expositional compactness and for their more intuitive economic interpretation.

[19] We experimented with ARMA(1,1) processes and found difficulties in identifying the MA parameter on public sector data, possibly as a consequence of the low degree of variability characterising the data in this case. In order to maintain comparable specifications across sectors, we proceeded by assuming AR(1) transitory earnings in both sectors.

[20] We treat the variance of initial conditions of the stochastic process as an additional parameter to be estimated rather than assuming, as customary in time series analysis, that the process started in the infinite past. MaCurdy (1982) points out that the application of such time series approach to individual panel data is problematic since the assumption of infinite history is untenable.

The model presented so far implicitly assumes to observe earnings profiles in a "stationary" environment, where no perturbation occur to the earnings distribution. However, Section 3 has shown that there are well-determined calendar time patterns of the autocovariance function which, if not controlled for, might be picked up by RG or AR parameters. To address this problem, we introduce a set of calendar time-specific shifters on each earnings component:

$$w_{iat} = \pi_t w_{iat}^P + \tau_t v_{it} \tag{5}$$

Shifters on the permanent and transitory component (π_t and τ_t, respectively) allow for variations in the relative importance of permanent and transitory earnings over time without altering the earnings hierarchy within the distribution of each component.[21] In this sense, time shifters can be interpreted as "prices" for the two components. It is important to note that in order to separately identify age and calendar time effects observations on autocovariances between the same pairs of years at different points of the earnings life cycle are needed. This is achieved by pooling covariance matrices estimated by cohort.

The descriptive regression of the previous Section also suggests that allowance for cohort-specific shifters should be an useful extension of the analytical framework. In the model discussed so far, the only way by which cohort heterogeneity enters is via age (which in turn allows identification of the RG parameters) but neither permanent nor transitory components parameters explicitly vary by birth cohorts. Such an extension can be achieved by introducing a set of birth cohort shifters on each earnings component, so that a complete model has the following specification:

$$w_{iat} = \kappa_{(a-t)}\pi_t w_{iat}^P + \lambda_{(a-t)}\tau_t v_{it} \quad (6)$$

In this way it is possible to allow earnings components to shift according to the different life-cycle phase in which birth cohorts are observed.[22] In turn, this will account for the fact that life cycle parameters are identified by pooling the histories of different cohorts, rather than by observing a whole life cycle of earnings. Also, birth cohort shifters will accommodate the likely heterogeneous degree of earnings uncertainty characterising the different life cycle phases in which birth cohorts are observed.

To sum up, the model which we estimate on INPS and Treasury data is characterised by dynamic permanent earnings (RG), AR(1) transitory earnings and calendar time and birth cohort shifters on both earnings components. We estimate the parameters of interest applying the minimum distance technique of Chamberlain (1984) (see also Abowd and Card, 1989). See the Appendix for details of the method.

[TABLE 3]

4.2 Results

Results from the estimation of the model in (6) are reported in Table 3. Estimates for the private sector reveal some clear patterns of the dynamics of permanent earnings over the

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[21] This parameterisation has been used by Dickens (2000). Shifters for the first year (1982) are normalised to 1 for identification.

[22] Note that the difference *(a-t)* is constant for each cohort and equal to its age at the beginning of the panel in deviations from that of the younger cohort. Thence the proposed notation allows introduction of cohort specific shifters without requiring additional indices. As explained in Section 3, we construct 3-year birth cohorts and impute them their central age. Thence the *(a-t)* index takes on values {0,3,6,…,18,21} from the youngest (1957-59) to the oldest (1936-38) cohort. Again, identification requires

life-cycle. The variances of intercepts and slopes of individual earnings profiles are well identified, suggesting that both constant and age-related component of individual ability matter in determining the level of permanent earnings dispersion over the working life. In particular, the estimated variance of initial permanent earnings implies that an individual located 1 standard deviation above the mean in the distribution of μ earns some 9% more than the mean level.[23] Moreover, the dispersion of earnings growth rates translates into a 1.4% differential of annual growth in favour of workers 1 standard deviation above the mean in the distribution of γ.[24] On the other hand, there appear to be no evident association between initial earnings and annual growth rates, the covariance between intercepts and slopes of earnings profiles being statistically not different from zero. On the whole, estimated parameters of the covariance structure of permanent earnings imply that after 20 years of working life 9% of permanent dispersion is accounted for by permanent earnings differentials at the start of the working life, while the rest builds up during the career.

These estimates can be compared with those obtained from public sector data. In this case both intecepts and slopes of earnings profiles are much less dispersed than in the private sector, reflecting an earnings distribution which is, on the whole, more compressed, as we saw in Table 1. In particular, the advantage in terms of initial levels is now 6.7% compared to the mean for an individual with initial earnings 1 standard deviation above the mean in the distribution of μ. The difference between the two sectors is much more evident if one considers growth rates. Individual experiencing an earnings growth rate 1 standard deviation above the mean in the distribution of γ see their earnings growing 0.6% faster than the mean. Another difference with respect to the private sector

normalisation of birth cohort shifters on each component, and we set those for the oldest cohort to 1.

[23] This is obtained as $\exp(\sigma\mu)$-1, where $\sigma\mu$ is the standard deviation of μ.

can be observed by inspecting the estimated covariance between intercepts and slopes which is now positive and statistically significant, indicating that high initial earnings are associated to faster growth compared to lower initial earnings. In particular, our estimates indicate that workers 1 standard deviation above the mean in the distribution of μ will find themselves ¼ standard deviation above the mean in the distribution of growth rates.[25] Life-cycle earnings dynamics appear to be a factor favouring permanent earnings dispersion. However the degree of permanent inequality generated over the working life is smaller compared to the private sector: after 20 years of experience 20% of initial permanent dispersion is still present in permanent differentials. Thus, dispersion of permanent earnings at the start of the working life is more relevant in the public sector compared to the private one, as an effect of both the more homogeneous earnings growth and the positive association between starting positions and growth rates found in the former case.

Estimates of AR(1) parameters for transitory earnings reveal some differences in the features of earnings shocks and uncertainty between the two sectors. In particular, the variance of initial conditions is larger in the private than in the public sector, as is consistent with an overall more dispersed distribution. On the other hand, the variance of innovations is approximately the same in the two sectors. Remarkable differences between sectors can be observed from the estimates of the autoregressive coefficient, which is some 60% larger in the private sector. This finding indicates that once shocked, earnings are slower in returning to their expected long run level in the private sector, implying more uncertainty with respect to the public sector. Also, if one sees high serial correlation as a feature of aggregate shocks to the economy, our estimates seem to suggest that public

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[24] This is obtained as $\sigma\gamma$, the standard deviation of γ.

[25] This is obtained as $\sigma\mu\gamma/\sigma\mu\sigma\gamma$, i.e. the linear correlation coefficient between intercepts and slopes.

sector workers are less exposed to economic fluctuations compared to their private sector counterparts.

[FIGURE 2]

The next set of parameter estimates reported in Table 3 refers to calendar time and birth cohort shifters. In order to gain a complete picture of the patterns implied by these estimates Figure 2 graphs out the evolution of predicted permanent, transitory and total variances by birth cohort and sector. By considering results for the private sector first, it can be observe that over the period earnings differentials tend to grow and permanent inequality appears to be the driving force for each birth cohort. Moreover, as we move towards older cohorts the level of earnings differentials increases, as is consistent with the presence of heterogeneity in earnings growth rates. Finally, permanent inequality appears to be more relevant for older cohorts compared to younger groups. Results for the public sector reveal an extremely compressed earnings distribution. However, some of the features observed in private sector data are still evident, such as the tendency for earnings differentials to be wider for older cohorts compared to younger ones and the decrease of the importance of transitory inequality as older cohorts are considered.

5. Concluding remarks

This paper has used administrative panel data on private and public sector employees to characterise earnings dynamics and uncertainty in Italy.

At the descriptive level, we have shown that in the public sector the earnings distribution is characterised not only by lower dispersion, but also by lower chances of moving through the earnings hierarchy through time.

Our econometric analysis has been based on GMM estimation of the earnings covariance structure and, in particular, has been aimed at characterising both the features of permanent earnings profiles and the degree of earnings uncertainty in the two sectors. We find that both earnings uncertainty and growth rates heterogeneity are lower in the public sector compared to private sector data. While the first result confirms that job security is higher in the public sector, the second implies that time varying aspects of skills heterogeneity, such as learning ability, are less remunerated in the public sector than in the private one, so that earnings differentials at the beginning of the career tend to persist in the life cycle.

Our results suggest that public sector employees experience less earnings fluctuations compared to their private sector counterparts, but also face lower opportunities to improve their position in the earnings ladder over time via learning on the job, a fact which could turn into a disincentive towards the acquisition of such skills.

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Appendix: Minimum distance estimation

Parameters of the model outlined in section 5.1 can be estimated by minimum distance (see Chamberlain, 1984, and Abowd and Card, 1989).

Let $M_{(a-t)}$ be an estimate of the $T \times T$ autocovariance matrix of birth cohort $(a-t)$ (T is the number of panel waves), $m_{(a-t)} = vech(M_{(a-t)})$, a *(T(T+1)/2)* vector, and m the *C(T(T+1)/2)* vector obtained by stacking vectors of autocovariances of each cohort, where C is the number of birth cohorts. Let $f(\vartheta)$ be the theoretical autocovariance function implied by the earnings model, a non linear function of parameters of interest, ϑ. A consistent estimator of ϑ is obtained by minimising the squared distance between the theoretical covariance structure $f(\vartheta)$ and its empirical counterpart m:

$$\vartheta = \arg\min((m - f(\vartheta))' A(m - f(\vartheta)) \qquad \text{(A.1)}$$

where A is some suitable weighting matrix.

The choice of A generates a class of minimum distance estimators. In particular, Chamberlain shows that setting $A = V^{-1}$, where V is an estimate of earnings fourth moments, yields asymptotic efficiency (optimal minimum distance, OMD). However, Altonji and Segall (1996) provide Monte Carlo evidence indicating that correlation in sampling errors between second and fourth moments could lead to biased parameter estimates. To cope with this shortcoming of OMD, an equally-weighted minimum distance estimator (EWMD), which uses the identity matrix for weighting, has been widely adopted by the literature on earnings covariance structures. In this case, the problem in (7) can be solved using a non-linear least squares estimator .This is the estimator used in this paper. Note that the estimated covariance matrix of ϑ produced by non-linear least squares routines will be biased by the presence of heteroskedasticity and autocorrelation in m. We derive standard errors that are robust to these problems, i.e. adjusted using the empirical covariance matrix of m:

$$\widehat{\mathrm{var}}(\hat{\vartheta}) = (G'G)^{-1} G'VG(G'G)^{-1} \qquad \text{(A.2)}$$

where $G = \partial f(\vartheta)/\partial\vartheta\,|_{\vartheta*}$ is the gradient matrix evaluated at the solution of (A.1).

The theoretical covariance structure $f(\vartheta)$ can be derived by working out second moments from the specified model of earnings levels. For example, for model (1) theoretical moments are given by (2) and their parameters can be estimated by regressing vector m on a constant (for σ_{μ}^{2}) and a dummy for variances (which identifies σ_{v}^{2}). For a more complicated model like the one resulting from (3), (4) and (6) (i.e. RG permanent component, AR(1) transitory one, calendar time and birth cohort shifters on both components), theoretical second moments are given by:

$$f(\vartheta)=\sum_{(a-t)=0}^{(A-T+1)} c_{(a-t)}\kappa_{(a-t)}^{2}\left\{\sum_{t=0}^{T-1}\sum_{k=t}^{T-1} p_t\pi_t p_{(t-k)}\pi_{(t-k)}E[w_{iat}^{P}w_{i(a-k)(t-k)}^{P}]\right\}+$$

$$\sum_{(a-t)=0}^{(A-T+1)} c_{(a-t)}\lambda_{(a-t)}^{2}\left\{\sum_{t=0}^{T-1}\sum_{k=t}^{T-1} p_t\tau_t p_{(t-k)}\tau_{(t-k)}E[v_{it}v_{i(t-k)}]\right\} \tag{A.3}$$

where

$$E[w_{iat}^{P}w_{i(a-k)(t-k)}^{P}]=\sigma_{\mu}^{2}+\bar{a}_t\bar{a}_{(t-k)}\sigma_{\gamma}^{2}+(\bar{a}_t+\bar{a}_{(t-k)})\sigma_{\mu\gamma},$$

$$E[v_{it}v_{i(t-k)}]=\begin{cases}\sigma_0^2 & if \quad k=0,t=0\\ \sigma_{\varepsilon}^{2}+E[v_{i(t-1)}v_{i(t-1)}]\rho^2 & if \quad k=0,t>0\\ E[v_{i(t-1)}v_{i(t-k)}]\rho & else\end{cases}$$

the c' s are birth cohort dummies and the p' s are calendar time dummies, $\lambda_{21}=\kappa_{21}=\pi_0=\tau_0=1$ for identification, and bars indicate sample averages.

Under the null of correct model specification (against an alternative of unrestricted covariance structure) the quadratic form $(m-f(\hat{\vartheta}))'(WVW')^{-1}(m-f(\hat{\vartheta}))$ (W is the projection matrix of the minimisation problem) is distributed as a $\chi 2$ with *C(T(T+1)/2)*-P degrees of freedom. However, the null has typically been rejected in previous studies of the earnings covariance structure (e.g. in Dickens, 2000) and the statistic is used to measure fitting performance. This is what we also do in the paper.

Table 1: Sample description

a) Private sector, INPS data

	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Birth cohort composition													
1936-38	0.10	0.10	0.10	0.10	0.10	0.10	0.09	0.09	0.08	0.08	0.07	0.06	0.04
1939-41	0.13	0.13	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.11	0.10	0.09	0.08
1942-44	0.13	0.13	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.11
1945-47	0.16	0.16	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.16	0.16	0.17
1948-50	0.16	0.16	0.16	0.16	0.16	0.15	0.15	0.15	0.16	0.16	0.16	0.17	0.17
1951-53	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.15	0.15	0.16
1954-56	0.11	0.11	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.13	0.13	0.13	0.14
1957-59	0.07	0.08	0.09	0.10	0.10	0.10	0.10	0.11	0.11	0.11	0.12	0.12	0.13
Earnings distribution [(a),(b)]													
Mean	32102.10	33302.52	34072.38	35318.70	35852.27	38943.79	39853.26	41258.94	42851.33	44830.93	45493.92	45537.43	47455.13
Median	30317.40	31197.66	31606.54	32844.02	33250.56	35859.22	36905.19	38072.49	39408.84	41064.00	41796.40	41781.86	43642.18
St. deviation	10903.22	11948.63	14197.63	15264.55	13976.59	21969.04	15711.67	16471.46	37763.41	18011.72	18370.99	20443.03	20837.01
p90_10	0.68	0.71	0.71	0.73	0.76	0.80	0.80	0.81	0.83	0.82	0.85	0.84	0.86
p50_10	0.32	0.33	0.33	0.34	0.35	0.37	0.37	0.38	0.40	0.37	0.39	0.39	0.41
p90_50	0.36	0.38	0.38	0.39	0.41	0.43	0.43	0.43	0.44	0.45	0.45	0.45	0.45
observations	13957	14246	14485	14795	14883	14976	14788	14586	14527	14163	13008	12396	11592

Notes:

a) Thousands of lire 1990

b) Px_y is the log of the ratio between percentile x and percentile y

Table 1: Sample description

b)Public sector, Treasury data

	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Birth cohort composition													
1936-38	0.13	0.13	0.13	0.12	0.11	0.10	0.09	0.09	0.09	0.09	0.09	0.09	0.08
1939-41	0.17	0.17	0.17	0.15	0.14	0.13	0.12	0.12	0.12	0.12	0.12	0.12	0.12
1942-44	0.16	0.16	0.16	0.14	0.14	0.13	0.11	0.12	0.12	0.12	0.12	0.12	0.11
1945-47	0.16	0.16	0.15	0.15	0.14	0.13	0.12	0.12	0.12	0.12	0.12	0.12	0.12
1948-50	0.16	0.16	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
1951-53	0.12	0.12	0.12	0.13	0.14	0.15	0.17	0.16	0.16	0.16	0.16	0.16	0.16
1954-56	0.07	0.07	0.08	0.10	0.11	0.13	0.15	0.14	0.14	0.14	0.14	0.14	0.15
1957-59	0.03	0.03	0.04	0.06	0.07	0.08	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Earnings distribution (a),(b)													
Mean	29073.15	29593.95	29373.40	28992.40	28667.80	29529.22	31302.29	31468.48	37097.78	37691.12	36350.92	35636.38	34563.61
Median	28262.01	28664.20	28297.78	27966.86	27541.30	28255.24	29384.27	29672.68	35027.04	35170.92	33944.43	33209.79	32124.84
St. deviation	4743.16	4841.21	5197.10	5007.89	5181.55	5535.86	7364.81	7279.64	8777.92	9704.21	9564.08	9694.92	9544.32
p90_10	0.40	0.40	0.42	0.41	0.42	0.44	0.50	0.51	0.55	0.57	0.59	0.59	0.59
p50_10	0.17	0.16	0.16	0.16	0.16	0.17	0.18	0.19	0.22	0.22	0.23	0.23	0.23
p90_50	0.24	0.24	0.25	0.25	0.26	0.27	0.32	0.31	0.32	0.35	0.35	0.36	0.36
observations	31324	33226	37875	41056	45763	54194	60137	58663	57815	56927	56679	55814	54554

Notes:

a) Thousands of lire 1990

b) Px_y is the log of the ratio between percentile x and percentile y

Table 2

a) OLS analysis of the earnings autocovariance structure (t-ratios [a])

	Private sector		Public Sector	
Lag width[b]				
1	-0.013	(16.35)	-0.005	(45.86)
2	-0.006	(34.48)	-0.003	(45.91)
3	-0.005	(26.55)	-0.003	(62.25)
4	-0.005	(21.24)	-0.003	(81.05)
5	-0.005	(27.42)	-0.003	(85.72)
6	-0.005	(19.48)	-0.003	(66.40)
7	-0.004	(18.24)	-0.003	(68.60)
8	-0.005	(14.97)	-0.002	(49.61)
9	-0.005	(15.37)	-0.002	(41.61)
10	-0.005	(13.30)	-0.002	(25.33)
11	-0.004	(8.68)	-0.002	(35.68)
12	-0.006	(10.56)	-0.002	(20.17)
Year [b]				
1983	0.003	(1.43)	0.001	(1.49)
1984	0.005	(5.26)	0.003	(11.72)
1985	0.004	(2.26)	0.001	(6.39)
1986	-0.001	(0.37)	0.002	(13.77)
1987	0.008	(7.00)	0.003	(24.17)
1988	-0.001	(0.45)	0.008	(67.54)
1989	0.003	(2.86)	0.002	(16.13)
1990	0.003	(1.96)	0.003	(23.60)
1991	0.003	(4.36)	0.004	(41.47)
1992	0.006	(7.10)	0.003	(20.66)
1993	0.002	(3.06)	0.003	(24.88)
1994	0.005	(5.37)	0.003	(21.47)
Birth cohort				
1939-41	-0.006	(0.76)	-0.003	(2.65)
1942-44	-0.028	(3.62)	-0.006	(5.23)
1945-47	-0.036	(5.04)	-0.015	(13.02)
1948-50	-0.048	(6.89)	-0.020	(18.56)
1951-53	-0.052	(7.55)	-0.022	(20.93)
1954-56	-0.060	(8.75)	-0.025	(22.95)
1957-59	-0.070	(10.36)	-0.026	(21.93)
constant	0.127	(19.21)	0.035	(30.93)
Adj R-squared	0.996		0.993	
Observations [c]	N=18540	T×N=182402	N=60137	T×N=644027

Notes:

a) Heteroskedasticity and autocorrelation robust t-ratios obtained using empirical fourth moments of earnings
b) Estimated coefficients refer to variations with respect to the preceding category
c) Regressions use 728 earnings variances and autocovariances

Table 2

b) OLS analysis of quasi-immobility ratios [a] (t-ratios)

	Private Sector		Public Sector	
Lag width [b]				
2	-0.409	(28.36)	-0.435	(15.28)
3	-0.294	(19.67)	-0.202	(6.84)
4	-0.195	(12.45)	-0.125	(4.04)
5	-0.174	(10.51)	-0.180	(5.50)
6	-0.158	(8.94)	-0.086	(2.47)
7	-0.099	(5.21)	-0.089	(2.39)
8	-0.111	(5.36)	-0.095	(2.34)
9	-0.122	(5.33)	-0.135	(3.00)
10	-0.102	(3.93)	-0.062	(1.20)
11	-0.098	(3.14)	-0.100	(1.63)
12	-0.046	(1.10)	-0.087	(1.05)
Year [b]				
1984	0.363	(8.63)	-0.074	(0.89)
1985	0.094	(3.01)	0.192	(3.13)
1986	-0.091	(3.50)	-0.138	(2.68)
1987	0.092	(4.03)	0.212	(4.70)
1988	0.010	(0.49)	-0.007	(0.17)
1989	-0.030	(1.56)	-0.004	(0.11)
1990	0.114	(6.47)	-0.077	(2.22)
1991	0.022	(1.31)	0.150	(4.60)
1992	0.118	(7.51)	0.105	(3.38)
1993	0.070	(4.70)	0.026	(0.88)
1994	0.057	(3.96)	0.185	(6.50)
Birth cohort				
1939-41	-0.111	(7.21)	-0.042	(1.37)
1942-44	-0.317	(20.65)	-0.111	(3.66)
1945-47	-0.290	(18.89)	-0.256	(8.45)
1948-50	-0.419	(27.31)	-0.327	(10.82)
1951-53	-0.480	(31.33)	-0.401	(13.28)
1954-56	-0.620	(40.42)	-0.476	(15.74)
1957-59	-0.717	(46.76)	-0.600	(19.86)
constant	0.840	(23.77)	0.867	(12.44)
Adj R-squared	0.969		0.850	
n.osservazioni[c]	N=18540	T×N=182402	N=60137	T×N=644027

Notes:

a) The measure used is log(QIR/(1-QIR)) where QIR is the quasi-immobility ratio
b) Estimated coefficients refer to variations with respect to the preceding category
c) Regressions use 624 quasi-immobility ratios

Table 3: EWMD[a] estimates of earnings processes (standard errors[b])

a) Private Sector

	Permanent component			Transitory component	
$\sigma^2\mu$	0.0078	(0.0019)	$\sigma^2\varepsilon$	0.0107	(0.0032)
$\sigma^2\gamma$	0.0002	(0.00002)	$\sigma^2 0$	0.0284	(0.0056)
$\sigma\mu\gamma$	0.0001	(0.0002)	ρ	0.8412	(0.0254)
Year					
1983	1.0612	(0.0127)		0.8935	(0.0554)
1984	0.9855	(0.0157)		0.9488	(0.0817)
1985	0.9599	(0.0229)		0.9716	(0.1097)
1986	0.9502	(0.0220)		0.8628	(0.1003)
1987	0.9383	(0.0273)		0.9703	(0.1317)
1988	0.9104	(0.0278)		0.8490	(0.1012)
1989	0.8785	(0.0335)		0.9081	(0.1661)
1990	0.8922	(0.0318)		0.7756	(0.0870)
1991	0.9067	(0.0347)		0.6788	(0.0755)
1992	0.8928	(0.0404)		0.7202	(0.0883)
1993	0.8890	(0.0435)		0.6010	(0.0967)
1994	0.9171	(0.0545)		0.4275	(0.1525)
Birth cohort					
1939-41	0.9835	(0.0480)		1.5515	(0.1813)
1942-44	0.9905	(0.0479)		1.4606	(0.1534)
1945-47	1.1325	(0.0500)		1.2513	(0.1367)
1948-50	1.1909	(0.0571)		1.2810	(0.1328)
1951-53	1.9740	(0.1971)		1.3563	(0.2839)
1954-56	1.5760	(0.0861)		1.1821	(0.1222)
1957-59	1.7929	(0.1034)		1.0711	(0.1170)
SSR[c]	0.0148			2551.6323	
Observations [d]	N=18540			T×N=182402	

Notes:

a) Random growth permanent component, AR(1) transitory component, year and birth cohort shifters on both components.
b) Heteroskedasticity and autocorrelation robust standard errors obtained using empirical fourth moments of earnings.
c) Reported statistics are the sum of squared residuals (left) and the sum of squared residuals weighted by the inverse of estimated covariance matrix of residuals.
d) Regression uses 728 earnings variances and autocovariances

Table 3: EWMD[a] estimates of earnings processes (standard errors[b])

b) Public Sector

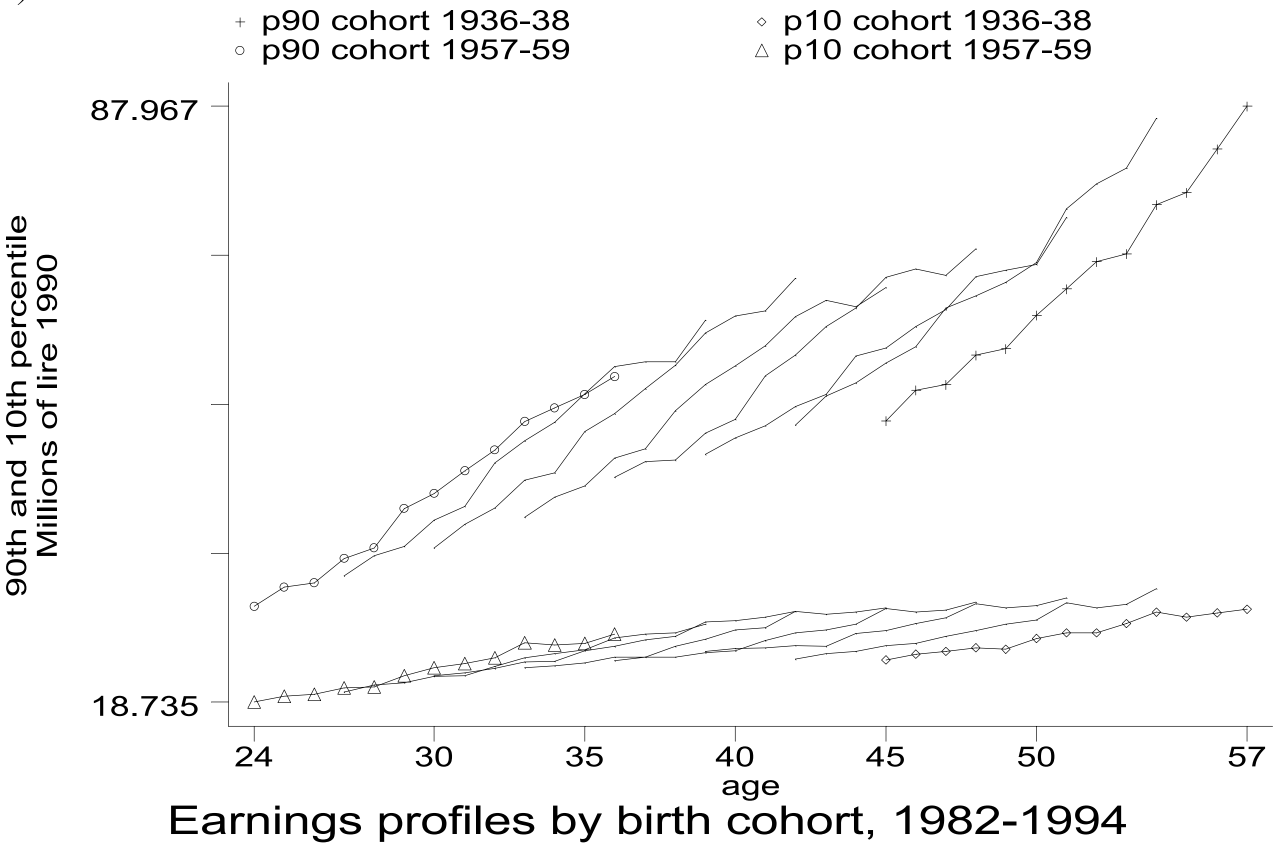
	Permanent component			Transitory component	
$\sigma^2\mu$	0.0046	(0.0004)	$\sigma^2\varepsilon$	0.0136	(0.0063)
$\sigma^2\gamma$	0.00004	(0.000004)	$\sigma^2 0$	0.0042	(0.0007)
$\sigma\mu\gamma$	0.0001	(0.00004)	ρ	0.5358	(0.0225)
Year					
1983	0.9981	(0.0044)		0.4237	(0.1036)
1984	1.0563	(0.0068)		0.3616	(0.0893)
1985	0.9799	(0.0084)		0.4416	(0.1097)
1986	0.9901	(0.0092)		0.4173	(0.0986)
1987	1.0154	(0.0105)		0.3822	(0.0920)
1988	1.1845	(0.0141)		0.4302	(0.0996)
1989	1.1320	(0.0150)		0.5353	(0.1226)
1990	1.1529	(0.0165)		0.5735	(0.1317)
1991	1.1999	(0.0185)		0.5633	(0.1285)
1992	1.1853	(0.0193)		0.5747	(0.1319)
1993	1.1830	(0.0207)		0.5708	(0.1304)
1994	1.1680	(0.0219)		0.5714	(0.1316)
Birth cohort					
1939-41	1.0556	(0.0160)		0.9952	(0.0511)
1942-44	1.1183	(0.0191)		1.0246	(0.0670)
1945-47	1.1018	(0.0215)		1.0830	(0.0484)
1948-50	1.1258	(0.0259)		1.1227	(0.0500)
1951-53	1.4468	(0.0791)		1.3163	(0.2485)
1954-56	1.2989	(0.0417)		1.1224	(0.0572)
1957-59	1.4237	(0.0570)		1.3509	(0.0727)
SSR[c]	0.0008			9573.8195	
Observations [d]	N=60137			T×N=644027	

Notes:

a) Random growth permanent component, AR(1) transitory component, year and birth cohort shifters on both components.
b) Heteroskedasticity and autocorrelation robust standard errors obtained using empirical fourth moments of earnings.
c) Reported statistics are the sum of squared residuals (left) and the sum of squared residuals weighted by the inverse of estimated covariance matrix of residuals.
d) Regression uses 728 earnings variances and autocovariances

Figure 1

a) Private Sector



b) Public Sector

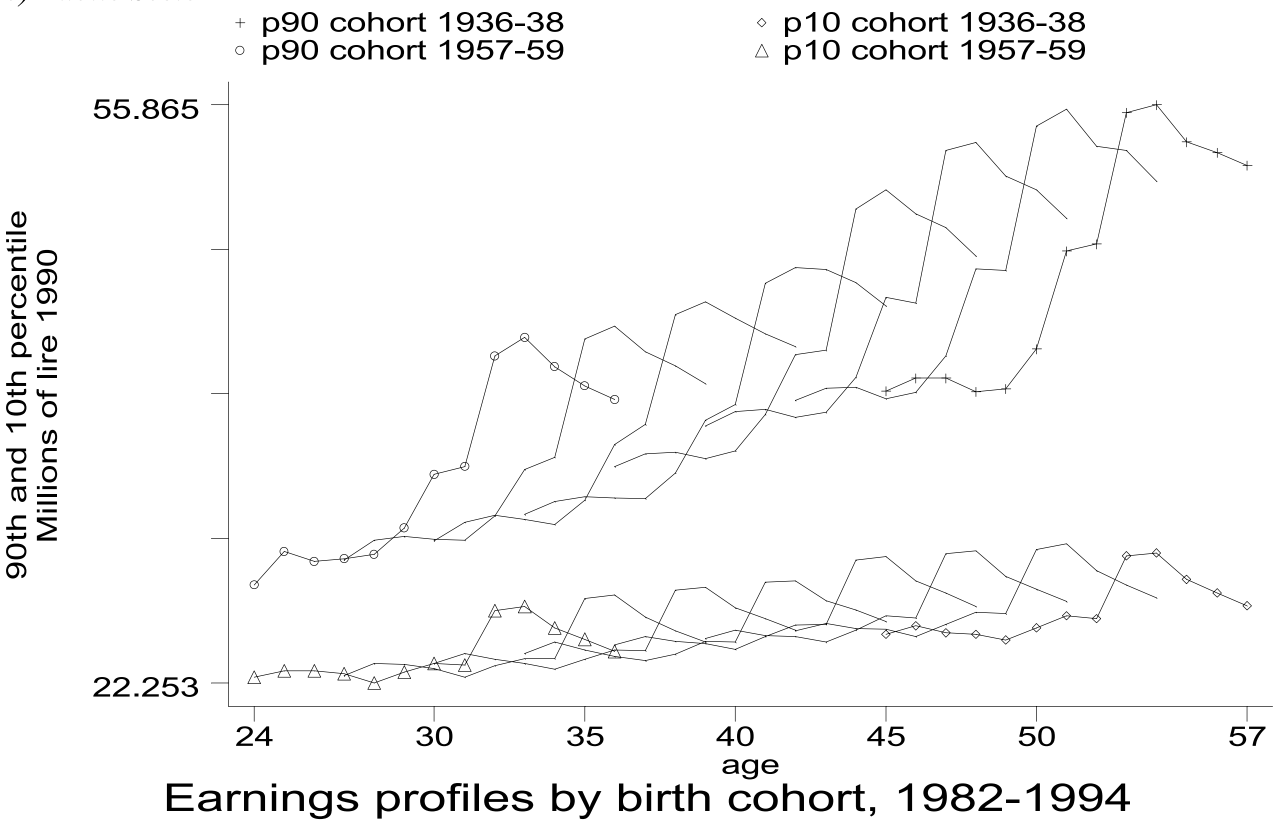
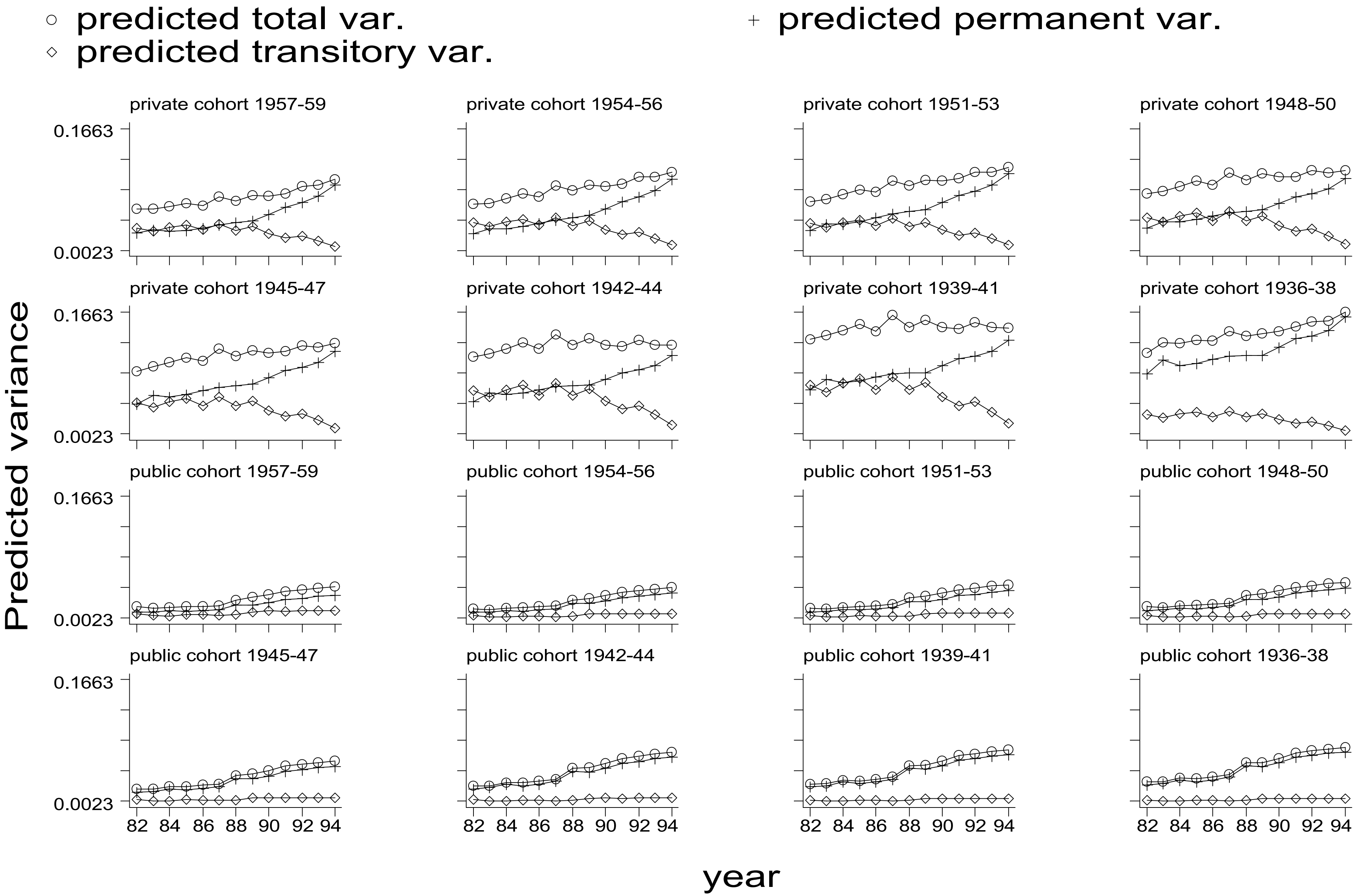


Figure 2



Variance decomposition by sector and birth cohort