The Dynamics and Inequality of Italian Male Earnings: Permanent Changes or Transitory Fluctuations?

Lorenzo Cappellari[#]
Institute for Social and Economic Research
University of Essex
CO4 3SQ Colchester UK
lorenzo@essex.ac.uk

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Abstract

This paper looks at longitudinal aspects of changes in Italian male earnings inequality since the late 1970s by decomposing the earnings autocovariance structure into its persistent and transitory parts. Cross-sectional earnings differentials are found to grow over the period. The longitudinal analysis shows that such growth is determined by the permanent earnings component and is due both to a divergence of earnings profiles over the working career and an increase in overall persistence during the first half of the 1990s. Moreover, when allowing for occupation-specific components in the parameters of interest, the bulk of growing permanent differentials arises from the earnings distribution of non-manual workers. This evidence indicates that labor market changes in favour of more skilled workers drove observed aggregate patterns.

Keywords: Earnings Inequality, Earnings Dynamics, Minimum Distance Estimation

JEL-code: C23, D31, J31

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A vast body of economic research has been devoted to the analysis of changes in earnings inequality over the past decade. Increasing differences between earnings at the top and the bottom of the pay hierarchy have been observed in several industrialised Countries. Various explanations have been put forward to account for this stylised fact, emphasising the introduction of technical innovations which increased the demand of skilled workers in the labour market, the effects of globalisation or the decline of labour market institutions. However, relatively few studies have looked at changing inequality using longitudinal data on individuals' earnings histories. This paper performs such an exercise using Italian panel data from the National Social Security Institute (*Istituto Nazionale di Previdenza Sociale*, INPS) between 1979 and 1995.

The use of longitudinal data can yield useful indications for the understanding of earnings inequality. Panel data allow researchers to observe earnings for the same individual at different dates and, thence, to split earnings at each point in time into a part that is stable over time (the so called *permanent component*) and a part representing short term deviations from it (the *transitory component*). As a consequence, the contributions of the two components to overall earnings inequality can be identified, providing insights on the nature of changing inequality. Inequality of permanent earnings is consistent with those explanations highlighting the role of skills' demand, as long as skills are permanent to individuals. Transitory inequality, on the other hand, has more to do with economic instability, as could result from declining labour market institutions. Moreover, permanent earnings inequality is more likely to impact on the personal income distribution and on households' poverty than transitory earnings fluctuations whose effect vanish after few years.

Several changes, typically oriented at enhancing "flexibility", occurred in the Italian system of wage determination since the mid-1980s. Previous research has shown that these changes were followed by a widening of the gap between the top and the bottom of the earnings distribution. This paper exploits the longitudinal dimension of the INPS data to unravel the contributions of the permanent and transitory earnings components to overall inequality.

Results show that overall earnings inequality increased since the first half of the 1980s and that these changes were predominantly driven by the permanent earnings component.

A first source of permanent inequality has been identified in the characteristics of earnings dynamics over the working career. In particular, the data indicate that those workers who had an advantage in terms of earnings at the beginning of the career also experienced faster earnings growth over the period. Several mechanisms could produce such an outcome: for example, individuals with good educational background (which raises earnings at the start of the career) can acquire remunerative skills on-the-job faster than workers with worse schooling endowment. This result contrasts with what has been found in other Countries, for example the US, where individual earnings appear to converge over the working career.

Permanent inequality has also been found to stem from a general increase in earnings persistence over the early 1990s. This finding is consistent with aggregate shifts of labour demand against the unskilled. On the other hand, the analysis of earnings components across different birth cohorts revealed that younger workers –who are observed at earlier stages of the earnings career- experience larger earnings fluctuations from one year to the next compared to their older counterparts.

The analysis has been extended to assess the effect of observable workers attributes on the relative importance of the two earnings components. Workers' occupation appeared to be the most important personal characteristic associated with the inequality of permanent earnings. In particular, the growth of permanent inequality arose from the earnings distribution of non-manual workers, while no change could be detected for manual workers earnings. This finding indicates that the higher flexibility in pay setting characterising the second half of the 1980s and the early 1990s was paralleled by persistently larger earnings differentials in favour of more skilled non-manual workers.

1 Introduction

The analysis of earnings inequality has become a major topic in economics during the past decade. The observation of widening earnings differentials in many industrialised economies – most notably the US – over the last 30 years has stimulated a large body of research.[1] Interpretations of stylised facts recurrent in this literature range from structural changes in the relative demand and supply of workers skills (driven by "skill-biased" technical change, international trade or, in the case of supply, changes in labor force composition) to arguments emphasising the increased competition and instability of the economic environment brought about by the decline in labor market institutions. Some authors, moreover, have stressed that rising earnings inequality may exacerbate households' poverty and that, consequently, attention should be devoted to the design of policies aimed at alleviating such welfare worsening effects (see Gottschalk and Smeeding, 1997, among others).

This paper analyses the evolution of Italian earnings inequality from 1979 to 1995 from a longitudinal perspective. Using panel data on individual male earnings, I apply Chamberlain's (1984) minimum distance method[2] to analyse earnings dynamics and estimate the extent with which the development of aggregate earnings differentials reflects changes in long-run inequality or an increase in short term earnings volatility. Both the adoption of a longitudinal perspective and the focus on the Italian labor market between the late 1970s and the mid-1990s are important features of this study.

Longitudinal investigations of earnings dynamics are useful to understand the causes of inequality and, consequently, to design policy measures to cope with it. Panel micro-data allow observation of individual earnings profiles over time and, thus, estimation of the earnings distribution not only at a point in time (or a sequence of them), but also between different time periods. Thence, evidence on the size of cross-sectional earnings differentials can be extended by an indication of their persistence over time. Put differently, by enabling researchers to observe long-run earnings, panel data makes it possible to identify a permanent earnings component and to measure its dispersion, distinguishing it from transitory fluctuations, for any given level of aggregate cross-sectional inequality. The larger the share of permanent dispersion, the more point in time earnings differences will persist over individual life-cycles. On the other hand, transitory variability implies that there is a lot of "churning" within the earnings distribution and that

[1] See Levy and Murnane (1992), Gottschalk and Smeeding (1997) and the contributions of Fortin and Lemieux, Gottschalk, and Johnson to the 1997 Symposium hosted by Journal of Economic Perspectives for surveys of the earnings inequality debate.
[2] This is an application of Generalised Method of Moments (GMM). Details on minimum distance estimation are given in Section 4 of the paper.

individuals observed in low earnings in a given period will abandon the bottom of the distribution after few years.

The distinction between permanent and transitory components of earnings differentials has important implications for the understanding of changing inequality (Gottschalk, 1997). Widening differentials driven by the permanent earnings component could arise from variations in the remuneration of persistent workers attributes, say individual ability, and be consistent with those explanations stressing the impact of skill biased changes on the labor market. On the other hand, earnings volatility could be produced by labor market instability resulting from declining institutional protections and, more generally, from increased competition in the economic environment. The relevance of this distinction for policy design follows from observing that while transitory differentials vanish within few years, persistent earnings inequality is an ingredient for a more segmented distribution of households income and welfare, thus calling for interventions.[3]

Given the relevance of the issue for the debate on earnings inequality, it is rather surprising that relatively few studies have been devoted to the decomposition of earnings dispersion into its permanent and transitory components. Only recently researchers have begun to look at these longitudinal aspects of inequality applying the minimum distance technique of Chamberlain (1984).[4] Moffitt and Gottschalk (1995) use a sample of male heads from the Panel Study on Income Dynamics (PSID). They fit stochastic earnings processes to the empirical covariance structure and decompose it into its permanent and transitory parts, in order to understand which is the driving force behind trends in the US widening earnings distribution. They find that the two earnings components equally contributed to the growth of earnings inequality during the 1970s and 1980s.[5] Baker and Solon (1998) apply minimum distance techniques to longitudinal tax records on Canadian men and look at the implied decomposition of trends in inequality into permanent and transitory components. Similarly to the US study, they find that the two earnings component play an equal role in determining changes in inequality. Evidence for the UK is reported by Dickens (2000). He uses panel data from the New Earnings Survey (NES) to assess the contribution of the two earnings components to upward trends in British

[3] Blundell and Preston (1998) note that in the presence of risk aversion also earnings volatility could produce welfare worsening effects by inducing households to deviate from optimal intertemporal consumption plans.

[4] Studies of earnings dynamics unravelling the relative importance of permanent and transitory components of earnings from panel data have a well-established tradition. Early contributions to this literature are focused on characterising the earnings process using maximum likelihood methods (see Lillard and Willis, 1978, Lillard and Weiss, 1979, Hause, 1980, and MaCurdy, 1982). More recently Abowd and Card (1989) pioneered the application of the Chamberlain method to the covariance structure of earnings and use the PSID to estimate stochastic processes of earnings and hours. Another study of earnings dynamics applying the Chamberlain method to the PSID is Baker (1997). These studies, however, do not analyse the role played by earnings components in explaining changing inequality.

[5] In a related work (Gottschalk and Moffitt, 1994) the authors estimate the extent of changes in earnings instability, defined as the variance of deviations from medium term individual earnings, and find that their measure of volatility accounts for one third of growing US earnings dispersion.

earnings dispersion from the mid-1970s to the mid-1980s. His findings suggest that the rise of earnings inequality was mainly driven by permanent earnings differentials during the first half of the 1980s, while, on the other hand, trends over the late 1980s and early 1990s appear to be the outcome of earnings volatility.

This paper looks at earnings dynamics and inequality in Italy. Major changes in the wage setting framework and bargaining practices occurred in Italy throughout the period investigated (Baccaro, 2000). During the late 1970s, the system of wage indexation to the cost of living (the *scala mobile*) was based on compensations uniform – in absolute terms - over the wage distribution. Reforms of this system towards proportionality took place since the first half of the 1980s, while any form of automatic indexation was abolished by the income policies round of 1992. Also, since the mid-1980s the relevance of firm level bargaining increased and individual wage premia were used as a mean of counteracting the compression of differentials induced at the central level by the egalitarian indexation system.

Previous research on the Italian earnings distribution predominantly used cross-sectional micro-data to estimate the size and evolution of earnings differentials.[6] Ericksson and Ichino (1995) show that earnings inequality decreased over the late 1970s and the first part of the 1980s, while a re-opening of differentials is apparent thereafter. They stress that while the compression of differentials was induced by the egalitarian nature of wage indexation, opposite trends were imparted at the firm level (the so-called *wage drift*) since the mid-1980s. Dell'Aringa and Lucifora (1994) reach similar conclusions. Using firm level data they observe wage inequality to start rising since the first half of the 1980s, and point towards the relevance of individual productivity premia paid at the firm level to skilled non-manual workers to explain these trends. Manacorda (1997) also produces evidence of u-shaped inequality trends between the late 1970s and the early 1990s and shows that the recent reforms of wage indexation determined real wage losses for workers in the bottom end of the earnings distribution.

The results of this paper reproduce, to some extent, these patterns of aggregate inequality and add longitudinal insights to the existing evidence on the Italian distribution of earnings. I find that aggregate inequality rises since the early 1980s up until the mid-1990s, the end of the period observed. For all birth cohorts analysed, growing differentials are driven by the permanent earnings component, especially over the first half of the 1990s, while younger cohorts are characterised by larger levels of transitory variations. Estimated models of permanent earnings dynamics allow for individual specific

[6] An exception is the work of Bigard et al. (1998) in which earnings mobility indicators are used to compare earnings transitions between Italy and France, showing that the Italian distribution is characterised by more rigidity, especially at the bottom.

earnings profiles, similarly previous studies of individual earnings dynamics (see Lillard and Weiss, 1979, Hause, 1980, Baker, 1997, and Baker and Solon, 1998). Differently from these studies, however, I find earnings profiles to diverge with age, implying a widening of permanent differentials over the working career. Also, models of this paper allow for shifts in the relative importance of earnings components over time, showing that permanent differentials have become predominant in recent years. Finally, I explicitly allow for occupational effects within covariance structure parameters, finding that permanent earnings growth arose within the earnings distribution for white collar workers, while no clear variation can be detected from manual workers data. This evidence suggests that changes in labor market structure in favour of more skilled non-manual workers have occurred, and their timing parallels the diffusion of new, less rigid, compensation schemes.

The rest of the paper is structured as follows. In Section 2 I present the longitudinal administrative records used for the empirical analysis, while Section 3 reports a descriptive statistical analysis of both static and dynamic aspects of earnings inequality. Section 4 lays out the analytical framework. Models of earnings dynamics of interest are discussed and the minimum distance method outlined. Results from this analysis are presented in Section 5, while section 6 concludes.

2 The data

The data set utilised in this study is a panel on individual earnings drawn over the 1979-95 interval, made available by the Italian National Social Security Institute (*Istituto Nazionale di Previdenza Sociale*, INPS). The data come as a by-product of administrative activity; its administrative origin implies a good reliability of the information provided but, on the other hand, the range of available information is relatively narrow, and individual characteristics such as education and family background are not observed. The main data source is the INPS 01M form, which employers have to compile in order to pay social security contributions for employees. Moreover, information derived from the DM10 form, which refers to employers' characteristics, has also been obtained and merged onto individual level records.

Data refers to employees from the private non-agricultural sector of the economy; the sample originally available is a 1% random drawing representative of all full-time workers from these sectors registered in the INPS archive during the period examined. Information about workers consists, in each year, of the gross annual wage (inclusive of any over-time and extraordinary compensation), year of birth, gender, occupation and number of weeks worked. Information on the firm refers to its size and industry measured at the five digit level.

For the purposes of this study, male workers born between 1936 and 1959 have been selected. The first selection criterion mitigates issues of endogenous female labor market participation, which may well be exacerbated when analysing earnings dynamics. The second criterion has the aim of selecting out those birth cohorts who are at the extremes of the life-cycle of earnings and thus can be characterised by more turbulence in earnings profiles. The birth cohort selection criterion implies that I analyse earnings over practically the whole working career (individuals born in 1959 are 20 in 1979, while those born in 1936 are 59 in 1995), but not at its ends, where earnings volatility arising just after labor market entry or before retirement can be confounded with volatility due to structural labor market changes.[7]

After applying the selection criteria outlined above, I end up with a panel covering 50,761 earnings histories, with a total of 791,374 person-year observations, whose structure is described in Table 1. As can be seen from the bottom line of the Table, the number of observations changes from one wave to the next, as a result of movements into and out from the sample. These movements can be due to unemployment spells, early retirement and mobility to or from the public, agricultural or self-employed sectors of the economy. This is a potential source of bias as long as individuals abandoning or entering the sample are characterised by intrinsically lower or higher earnings volatility with respect to those observed in each wave. The limited amount of information available in INPS data, however, makes it difficult to model panel attrition by applying some sort of correction technique, due to the lack of instruments. Thence, to mitigate sample selection here I follow the approaches of Moffitt and Gottschalk (1995) and Dickens (2000) and utilise the whole unbalanced panel, i.e. I use observations with positive earnings in any wave to estimate the autocovariance function. While not formally controlling for attrition, this unbalanced panel design maximises sample size while avoiding the likely overestimation of permanent earnings that would arise from balanced samples in which only continuous earnings profiles (i.e. individuals with positive earnings in each wave) are used in estimation.

The first set of characteristics considered in Table 1 refers to the age structure of the INPS panel. The birth cohort structure of the data reflects the entry of younger cohorts into the labor market, which attenuates the progressive ageing of the sample with

[7] The age range is 20-59 in Moffitt and Gottschalk (1995), 24-59 in Baker and Solon (1998) and 22-59 in Dickens (2000). Besides the two selection criteria mentioned in the text, top and bottom 5 observations have also been excluded from each tail of the cross-sectional distribution in order to improve the convergence properties of the GMM estimator. Such a “trimming” of observations is common practice in the literature, see Abowd and Card (1989) and Dickens (2000) among others.

calendar time. 8 3-year birth cohorts have been formed, which will provide the base for the analysis of earnings dynamics. Each birth cohort is imputed its central age in each year: for example the birth cohort 1936-38 will be imputed ages 42 (in 1979) through 58 (in 1995), while birth cohort 1957-59 will be imputed ages 21 (in 1979) through 37 (in 1995). This will enable us to study the evolution of the covariance structure of earnings with age while preserving cell size.

The next part of the Table presents the sample structure with respect to some workers' characteristics. The occupational classification available in the INPS sample allows us to distinguish between blue collar workers, white collar workers and managers, thus providing some indication of workers' skills. The proportion of manual workers tended to decrease over time, while the relative weight of non-manuals (both white collars and managers) rose during the period, a fact which can both reflect occupational mobility of older cohorts and a higher propensity of younger cohorts to be employed in non-manual jobs. A slight shift away from larger firms can be also observed, while the industrial structure tended to stay constant over time.

The bottom panel of Table 1 presents some descriptive statistics of the cross-sectional distribution of log weekly real earnings, which I will focus on in the empirical analysis.[8] Evidence for the mean indicates that after a phase of stability during the early 1980s, the earnings distribution have shifted upwards over the decade - especially in its second half - while similar trends are less evident during the first half of the 1990s. It is interesting to parallel these dynamics with the evolution of bargaining practices. In particular, the pronounced earnings growth of the second half of the 1980s occurred in the period when wage drift became a widespread instrument to counteract wage compression induced by centralised bargaining. The slow down in the early 1990s, on the other hand, is contemporaneous with the implementation of income policies aimed at controlling inflation via wage moderation. Overall, mean log weekly earnings grew by 5.7% from 1979 to 1995, to which corresponds a 52% growth of mean earnings levels (not shown in the Table).

I next turn to some measure of earnings dispersion. The pattern of change over time of the standard deviation of log weekly earnings resembles, to some extent, the trends of Italian earnings inequality singled out in previous research on Italy (see Section 1). Wage differentials dropped over the early 1980s, while, after 1982 a tendency towards a reopening of the distribution can be observed, which continues until the end of the observed period. Again a parallel with the evolution of wage bargaining can be drawn. Falling differentials characterise the phase of fully egalitarian wage indexation, while, on

[8] Nominal figures are deflated with the CPI (1995=100).

the other hand, their reopening in the second 1980s occurs when both wage indexation was partially reformed towards proportionality and individual wage premia were used at the firm level to neutralise compressionary effects induced at the central level. Finally, the early 1990s, during which wage indexation was abolished, witness a further growth of earnings dispersion.

I conclude my inspection of changes in earnings dispersion by looking at the log of some percentile ratios which, compared to the standard deviation, are robust to the presence of outliers and approximate the percentage difference between the upper and lower percentiles considered. The path over time of the p90/p10 ratio resembles the patterns for the standard deviation of log earnings. A phase of narrowing differentials stopped in 1982 and was followed by growing dispersion. Estimates imply that the approximate percentage differentials between the upper and lower tenth of the distribution grew from 72% to 107% between 1982 and 1995. Evidence from the p95/p5 ratio depicts a similar pattern, while some difference can be observed between dynamics at the bottom and top halves of the distribution, described by the p90/p50 and p50/p10 ratios, respectively. In particular, while dispersion grew within both halves of the distribution after 1982, growing differentials were evident mainly at the top of the distribution over the second part of the 1980s and the early 1990s. On the other hand inequality grew at both ends of the distribution after the income policies round of 1992.

3 The statics and dynamics of earnings differentials

In this Section I provide some descriptive evidence on the features of the cross-sectional and longitudinal distribution of earnings. Such a descriptive exercise will offer a first glance at the patterns of earnings dispersion and covariance and will be useful to guide the specification of formal models of the earnings covariance structure in Section 4.

The previous Section has shown that earnings differentials grew over the most of the period considered. Such evidence, however, being based on raw figures, may reflect changes in mean earnings through time in turns induced by changes in the age or birth cohorts composition of the sample. As long as the various age groups or birth cohorts are characterised by systematically different earnings levels, changes in the sample structure according to these characteristics may determine spurious changes in the earnings covariance structure. In order to abstract from these compositional effects, I first adjust raw earnings for age, calendar time and birth cohorts effects, which should capture the effect of the life cycle, business cycle and of secular productivity trends – respectively - on the evolution of earnings levels. This is achieved by pooling the data from all the panel waves and regressing log-earnings on a set of year dummies and a quadratic in age separately for each birth cohort. Residuals from these adjusting regressions - let us call them adjusted earnings - will be the object of analysis.

I start by providing some evidence on the evolution of earnings dispersion in Figure 1. The panel in the top left corner jointly considers all birth cohorts; it shows that trends of inequality for adjusted earnings tend to reproduce those of unadjusted figures reported in Table 1, with an initial phase of earnings compression followed by a steady increase in inequality through the end of the sample period. The remaining panels in the graph plot the standard deviation of adjusted earnings for each cohort separately. The evidence points towards a substantial heterogeneity in earnings differentials across cohorts. Men from older cohorts, observed at late stages of their working lives, are characterised by larger values of the dispersion measure and present increasing trends both during the 1980s and - especially - the first half of the 1990s. For intermediate cohorts, the level of earnings dispersion at any point in time is lower compared to that of the oldest cohort, and standard deviation plots shift downwards as younger cohorts are taken into account. Moreover, while trends for intermediate cohorts are similar to those of older cohorts over the 1980s, changes during the early 1990s were less pronounced. For example, the 1989-95 increase in the standard deviation of adjusted log earnings for the 1948-50 birth cohort is less than half that of the 1936-38 group (11% compared to 25%). The panels in the bottom row of Figure 1 refer to younger cohorts. Earnings dispersion throughout the period is even lower. The widening of earnings differentials over the 1980s appears to be less evident, especially for the two younger cohorts. On the other hand, trends in the 1990s were comparable to those of older cohorts; for example, the measure of dispersion grew by 20% between 1989 and 1995 for the youngest cohort, compared to 25% for the oldest group.

On the whole, evidence from Figure 1 suggests that while seniority is associated with the level of earnings dispersion, trends in inequality were relatively more homogeneous across birth cohorts. Also, the timing in the evolution of earnings differentials for all cohorts is consistent with that of wage setting reforms.

The evidence above refers to the cross-sectional earnings distribution and does not exploit the longitudinal dimension of INPS data. As such, it is informative about earnings differences at a point in time (and their evolution over the sample period) but does not offer any insight into the extent by which individual earnings dynamics determine movements through the earnings distribution over time, i.e. on earnings persistence. To this end, an assessment of the joint earnings distribution over different points in time is required.

To achieve this, I estimate, separately for each birth cohort, the covariance of adjusted log-earnings between each pair of years available in the INPS sample, say *t* and

t-k, with t=1979,…,1995; k=0,...,16 and $k \leq t$-1979.[9] Second moments are estimated as sample averages of individual cross-products earnings. To assess their statistical significance, I also estimate fourth moments of earnings using deviations of individual cross-products from their sample average, and find that all variances and covariances are significantly different from zero at conventional confidence levels.[10]

In order to provide a compact description of estimated earnings autocovariances, I next regress them on a set of dummy variables for lag length (i.e. k), calendar time[11] and birth cohort using OLS.[12] The first set of dummies is intended to capture the expected decline in earnings correlation as we consider years further apart, the second is aimed at identifying secular trends, while the third looks at the presence of cohort specific components.

Results from this exercise are reported in Table 2. Estimated coefficients on lag dummies are all negative, indicating that earnings persistence declines when years further apart are considered, meaning that the chance of movements within the earnings hierarchy increases as the interval of observation widens. Also, the decrease is more pronounced for the first couple of lags, while, afterwards, a tendency to approach a long term level is apparent. Such a pattern could be consistent with an underlying autoregressive process of earnings dynamics augmented by a long run component. Evidence on calendar time dummies resembles findings emerging from the inspection of Figure 1. Earnings variances and covariances fall during the early 1980s, while positive signs characterise estimated coefficients since 1983. In particular, the growth of earnings dispersion and persistence is concentrated in the second half of the 1980s and the first half of the 1990s, with a marked increase in the last couple of years observed, 1994 and 1995. Again, a parallel with the evolution of the wage setting framework can be drawn. Finally, evidence on birth cohort dummies shows that earnings autocovariances are lower for younger cohorts, mirroring the finding of lower standard deviations in Figure 1. Thence, INPS data indicate that earnings persistence significantly varies over the various stages of the working life and that earnings dynamics are characterised by larger rigidity at later stages of the working life.

I turn now to a formal analysis of these patterns of earnings autocovariance.

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[9] For a panel of length T there are $[T(T+1)/2]$ pair of years between which covariances can be estimated. In the INPS panel T=17, so that the covariance matrix of each cohort has 153 distinct elements, with a total of 1244 covariances which can be estimated.

[10] Seconds and fourth moments matrices are available on request.

[11] 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.

[12] 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, I adjust standard errors using the fourth moments matrix.

4 Theoretical models of the earnings covariance structure

The last Section has revealed some clear trends in the earnings distribution over the 1979-1995 period. The aim of the present Section is to outline an analytical framework with which these empirical patterns can be parsimoniously modelled.

I exploit the longitudinal dimension of the data to distinguish between permanent and transitory earnings components in order to assess whether trends in the earnings distribution arose from changes in the remuneration of stable individual attributes or if they were the result of variations in labor market volatility. I start by describing the canonical decomposition of earnings levels into permanent and transitory components and its implications in terms of the covariance structure of earnings. Although too simplified to describe the patterns emerged in Section 3, this canonical model is useful in providing an introduction to the more complex models used in this paper. I next expand the analytical framework and add several features to the model's structure in order to capture the patterns indicated by the findings of the previous Section.

4.1 Model specification

The simplest way to characterise the autocovariance function of earnings in terms of permanent and transitory components is to assume that individual 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, $i = 1,..., N, \quad t = 0,...,T-1, \quad a = 0,..., A$.[13] This simple model postulates that:

$$\begin{aligned} &w_{iat} = \mu_i + v_{it} \\ &\mu_i \sim (0, \sigma^2_\mu) \quad v_{it} \sim (0, \sigma^2_v) \quad E(\mu_i v_{it}) = 0. \end{aligned} \tag{1}$$

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. It follows from the assumptions about the second moments that:

[13] Age is measured in deviations from the minimum observed age in the sample, i.e. 21 years.

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

Thus, while the permanent earnings component contributes to both variances and covariances, transitory fluctuations only contribute to the variance of earnings. The larger transitory variation, the more earnings are re-shuffled from one year to the next so that differentials observed at a point in time are transient and vanish immediately.

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.[14] Several studies of the earnings covariance structure have therefore proposed a *random growth* model (RG, see Lillard and Willis, 1979, Hause, 1980, and, more recently, Baker, 1997, and Baker and Solon, 1998) in which individual specific components are characterised by an additional parameter measuring earnings growth with age or experience:[15]

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

where a P superscript denotes permanent earnings. 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 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 arising from models of 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

[14] 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.
[15] I use age since I do not observe age at labor market entry.

growth.[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 labor 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.a) is that the parameter is negative, supporting the OJT explanation of earnings dynamics.[17]

An alternative - more atheoretical - route to introduce dynamics into permanent earnings is by means of a *random walk* (RW) specification:[18]

$$\begin{aligned} & w_{iat}^{P} = w_{i(a-1)(t-1)}^{P} + \xi_{iat} \\ & w_{i00}^{P} \sim (0,\sigma_{\mu}^{2}), \quad \xi_{iat} \sim (0,\sigma_{\xi}^{2}), \quad E[w_{i(a-1)(t-1)}^{P}\xi_{iat}] = 0 \end{aligned} \tag{3.b}$$

This model uses a unit root hypothesis as a way to represent the features of slowly changing processes, as could result from slowly depreciating human capital investments or through the smoothing out of macroeconomic fluctuations via implicit contracts (Baker, 1997). In this context, the dispersion of individual growth rates over the life cycle is measured by the variance of innovations (σ_{ξ}^{2}).

The RG or RW specifications expand the canonical model by relaxing the assumption of constant permanent 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 a few lags. To accommodate these patterns, it is

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

[17] 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.

[18] Moffitt and Gottschalk (1995), Baker (1997) and Dickens (2000) estimate this type of permanent earnings model.

common to assume some low order ARMA process for transitory earnings.[19] In particular, here I will adopt an ARMA(1,1) process, i.e.:

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

in which the autoregressive parameter (ρ) captures the smooth decline of covariances over lag length, while the moving average component (θ) adjusts for short term deviations from it.[20]

Extension of the basic model of equation (1) presented up to this point do not account for aggregate changes in the covariance structure. Proposed specifications of permanent earnings in (3.a) or (3.b) allow for dynamics with respect to age, while the ARMA transitory component of equation (4) accommodates variation in autocovariances with lags. The model resulting from the combination of such extensions (either (3.a)+(4) or (3.b)+4) would still implicitly assume to observe earnings profiles in a "stationary" environment, where no perturbation occur to the earnings distribution. However, the preliminary inspection of the autocovariance function in Section 3 shows that there are well-determined calendar time patterns which, if not controlled for, might be picked up by RG, RW or ARMA parameters. To address this problem, I 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) thus 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. Apart from helping one isolating the dynamics of the two earnings components from structural changes in the economic environment, the two sets of shifters can offer some useful

[19] 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 I will still refer to transitory earnings, both for expositional compactness and for their more intuitive economic interpretation.

[20] I 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.

[21] Shifters for the first year (1979) are normalised to 1 for identification. This kind of specification is used by Baker and Solon (1998) and Dickens (2000), while Moffitt and Gottschalk (1995) adopt polynomials in calendar time.

insights into the forces driving such changes. Variations in π_t might reflect changes in the remuneration of stable individual characteristics, such as skills; conversely, variations in τ_t are more likely to arise from changes in aggregate labor market instability. 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 estimating separate covariance matrices for each birth 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 and RW parameters) but neither permanent nor transitory components parameter 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:

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

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 volatility characterising the different life cycle phases in which birth cohorts are observed.

To sum up, the model which I will estimate on INPS data in the next Section will be characterised by dynamic permanent earnings (either RG or RW), ARMA(1,1,) transitory earnings and calendar time and birth cohort shifters on both earnings components.

4.2 Estimation

Parameters of the model outlined above will be estimated by minimum distance (see Chamberlain, 1984, and Abowd and Card, 1989). This technique is an application of the GMM method and, as such, allows estimation of parameters of interest without imposing any distributional assumption on earnings levels.

[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. Given that I construct 3-year birth cohorts and impute them their central age, the *(a-t)* index takes on values {0,3,6,…,18,21} from the youngest (1957-59) to the

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:

$$\vartheta = \arg\min((m - f(\vartheta))' A(m - f(\vartheta)) \tag{7}$$

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.[23]

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.a), (4) and (6) (i.e. RG permanent component, ARMA(1,1) transitory one, calendar time and birth cohort shifters on both components), theoretical second moments are given by:

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oldest (1936-38) cohort. Again, identification requires normalisation of birth cohort shifters on each component, and I set those for the older cohort to 1.

[23] 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. I derive standard errors that are robust to these problems, i.e. adjusted using the empirical covariance matrix of m: $\widehat{\mathrm{var}}(\hat{\vartheta}) = (G'G)^{-1} G'VG(G'G)^{-1}$, where $G = \partial f(\vartheta)/\partial\vartheta|_{\vartheta*}$ is the gradient matrix evaluated at the solution of (7).

$$f(\vartheta) = \sum_{(a-t)=0}^{(A-T+1)} c_{(a-t)} \kappa_{(a-t)}^2 \left\{ \sum_{t=0}^{T-1} \sum_{k=t}^{T-1} p_t \pi_t p_{(t-k)} \pi_{(t-k)} E[w_{iat}^P w_{i(a-k)(t-k)}^P] \right\} + \tag{8}$$

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

where

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

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

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.

5 Results

This Section presents results obtained by applying the EWMD estimator to the INPS panel. The data consist of 17 annual waves and I distinguish 8 3-year birth cohorts, which yields a total of 1224 empirical moments. By stacking autocovariance vectors across cohorts it is possible to separately identify time and age effects. For the latter I impute to each cohort its central age in each period. Estimated permanent earnings specifications are the RG or RW ones (equations (3.a) or (3.b), respectively), while transitory earnings are specified as an ARMA(1,1) process (equation (4)). Moreover, calendar time and birth cohort specific shifters on both components will be allowed. The resulting general model can be obtained by substituting equations (3.a) (or (3.b)) and (4) into (6).

Before estimating the general model, Table 3 shows estimates from "stationary" models, i.e. models where there are no perturbations due to calendar time or birth cohort heterogeneity, but everything is as if we were observing the whole life cycle of earnings for a single cohort and there were no structural changes in the relative importance of the two earnings components. Thus, permanent autocovariances evolve with age according to either the RW or the RG specification and the decline in autocovariances with lags is captured by the ARMA parameters of the transitory component. The RG model implies that permanent covariances have a quadratic relationship with age (see (8) above), whereas for the RW model the implied trend is linear, with the slope given by the variance of innovations.[24] Estimates of the RW model in column 1 imply that permanent earnings inequality in the 37[th] year of a working life is about ten times the dispersion in the first year. The RG model estimates, on the other hand, imply that permanent earnings dispersion after 37 years would be 8 times larger than the initial level. RG estimates also imply that permanent earnings grow at 1% per year for individuals with a growth parameter one standard deviation above the mean in the distribution of γ_i. Moreover, the estimated covariance between intercepts and slopes of individual earnings profiles ($\sigma_{\mu\gamma}$) is positive. This means that individuals who have an advantage in terms of initial permanent earnings also experience faster growth rates, and that, consequently, the permanent earnings distribution becomes increasingly unequal over the life-cycle. Estimates of the same parameter reported by Lillard and Weiss (1979), Hause (1980), Baker (1997) and Baker and Solon (1998) are, by contrast, negative, indicating a catching-up of permanent earnings over the life-cycle. Although some caution should be exerted when making cross-studies comparisons of results due to differences in the earnings variable and sample composition, this finding suggests that life-cycle earnings dynamics in Italy are different from those of the Countries considered in the studies above and, in particular, earnings inequality in Italy rises over the life-cycle.

ARMA parameters are precisely estimated. The autoregressive coefficient ρ is larger when permanent earnings are specified as RG compared to the RW specification; in the RG case, reported estimates imply that 20% of a shock is still present in transitory earnings after 5 years, while the corresponding figure is 15% when permanent earnings are specified as RW. Also, the moving average parameter θ is larger when permanent earnings are RW than when the RG specification is adopted, implying that shocks drop more markedly after 1 year. On the whole, it appears that when permanent earnings have a unit root, the degree of serial correlation of transitory shocks is lower compared to the RG specification.

The bottom line of Table 3 reports some goodness of fit measures, namely the sum of squared residuals, both unweighted and weighted by the inverse of an estimate of the variance of residuals.[25] Under the null of correct model specification, this latter measure is distributed as a χ^2 with *CT(T+1)/2-P* degrees of freedom, *P* being the number of

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[24] In this case: $E[w_{iat}^P w_{i(a-k)(t-k)}^P] = \sigma_\mu^2 + \min\{\bar{a}_t, \bar{a}_{(t-k)}\}\sigma_\xi^2$

[25] The weighting matrix is given by $(WVW')^{-1}$, where W is the projection matrix of the minimisation problem.

restrictions (i.e. parameters to estimate) imposed on the empirical covariance structure. However, a typical result in the literature is that the null is always rejected at conventional confidence levels and the statistic is used as measure of fit. As can be observed, when moving from the RW to the RG specification, both measure point towards a substantial improvement in the model's ability to fit the data, suggesting that the RG specification provides a better description of life-cycle earnings dynamics.

5.1 Birth cohort and calendar time heterogeneity

The next step in the investigation is to relax the "stationarity" hypothesis and introduce birth cohort and calendar time heterogeneity. Following indications emerging from the previous analysis regarding the fitting performance of alternative permanent earnings specifications, I utilise a RG model of permanent earnings. On the other hand, I restrict transitory earnings to be AR(1). When the full model in (8) was specified, convergence failed to be achieved, indicating that such model imposes an over-parametrisation on the data. These problems suggest that the parameter space should be reduced, and I did this by excluding the moving average component.[26]

Results from this model are reported in Table 4. The RG growth parameters now refer to the oldest cohort (i.e. the one used to normalise birth cohort shifters) and are purged from the effect of structural changes over the sample period. The dispersion of individual intercepts (σ^2_μ) is now roughly 10% its counterpart of Table 3, which reflects the fact that the parameter is not picking up heterogeneity between cohorts in the level of earnings at the beginning of the life cycle. On the other hand, the dispersion of individual growth rates (σ^2_γ) is notably larger compared to the previous estimate, indicating that growth rates are more dispersed within the oldest cohort than between cohorts. Finally, the covariance between individual intercepts and slopes remains stable, still indicating a tendency for permanent earnings to diverge with age, and it can now be observed how the result cannot be ascribed to differences between cohorts.

Estimated birth cohort-specific parameters are – typically - larger than one both for the permanent and the transitory earnings component, indicating that RG and AR(1) parameters are larger in size for younger cohorts compared to the oldest one. Moreover, the rise of birth cohort shifters over time is much more pronounced for the transitory component. Table 4 also reports the ratio between permanent and transitory birth cohort shifters ($\kappa_{(a-t)}/\lambda_{(a-t)}$) which gives indications about the extent of changes in

[26] Baker and Solon (1998) report similar problems and propose this kind of solution. The theoretical covariance structure used in estimation is the one in (8) with θ =0.

persistence over birth cohorts. Values of this ratio are all smaller than one, indicating that for each cohort the relative importance of the permanent component is lower compared to that of the reference cohort. It can also be observed that the ratio rises for the three younger cohorts, possibly counteracting low values of the age variable for these groups. On the whole, estimated birth cohort parameters indicate that earnings are more volatile for younger cohorts.

The last set of estimates reported in Table 4 refers to calendar time shifters. Weights on the permanent component follow a u-shaped profile, decreasing over the mid-1980s and then rising again, especially over the last couple of years. On the other hand, transitory earnings weights monotonically decrease over the sample period, with a marked drop over the last couple of years. Again, insights on changes in the relative importance of the two earnings components - this time over the sample period – are offered by the loadings ratio in each year (π_t / τ_t). The estimates suggest that permanent earnings have been increasing in importance over time. This result indicates that increases in the relative demand for permanent skills occurred all over the period investigated. Such a finding could be consistent, for example, with a story of skilled biased technical change as an explanation of inequality dynamics. However, institutional changes in the Italian labor market – in particular earnings bargaining practices – could also play a role in explaining these trends. In particular, as firm level bargaining and individual specific wage premia gained predominance over centralised bargaining, a widening in the distribution of individual ability remuneration can be expected. This latter view seems to be supported by the marked rise in permanent loadings during 1994 and 1995, i.e. after the completion of the income policies round of the early 1990s, with which automatic wage dynamics imparted at the central level by the wage indexation mechanism were eliminated.

In order to gain a more complete picture of results obtained from the model in Table 4, Figure 2 plots, for each birth cohort, the predicted decomposition of earnings variance for each sample year into permanent and transitory components. Predictions are obtained using equation (8), with the moving average parameter set to 0, and are plotted assuming *k=0*, i.e. variances are considered. Trends in predicted total variance resemble quite closely the patterns of the standard deviation of logs in Figure 1. While older groups experienced a marked growth of earnings inequality after 1982, increases become less pronounced as we move towards younger cohorts. Also a marked heterogeneity in the levels of permanent and transitory dispersion can be observed across cohorts. For older cohorts, permanent dispersion accounts for almost all of earnings differentials, and its profile is similar to the one for total variance, especially in the last years of the sample period. The permanent variance series is lower for intermediate and especially young cohorts compared to the oldest cohort. A reverse pattern can be observed for transitory components of earnings inequality. These are very low for old cohorts, whereas they become increasingly important when youngest groups are considered, where they dominate permanent variance, at least for a considerable part of the period investigated. However, a common pattern underlying cohort-specific inequality dynamics can be singled out, namely the dispersion of permanent earnings trends upward for each cohort, indicating that between 1979 and 1995 earnings differentials have become not only wider, but also more persistent. This finding also suggests that changes in Italian earnings differentials have different features compared to those observed in Canada, the UK and the US, where studies reviewed in Section 1 find an equal contribution of the two earnings components to rising aggregate inequality.

5.2 The covariates of permanent and transitory inequality

With the exception of workers' year of birth, I have made no use of the set of individual characteristics available in the INPS so far.[27] On the other hand, the vast literature on earnings inequality suggests that, for example, measures of workers skills different than experience (proxied here by age) can also be important in understanding trends depicted in Figure 2. Also, institutional developments in the Italian wage setting framework point towards the relevance of occupational earnings differentials, as individual wage premia were used at the firm level to counteract the compressionary effects of the indexation system and to re-establish differentials in favour of non-manual workers (Dell'Aringa and Lucifora, 1994). Thence, in the remainder of this Section I will assess the impact of observable characteristics on estimated variance components models. In particular, I will focus on workers occupation, the firm size and the sectoral affiliation.

As a first strategy, I use a modified definition of "adjusted earnings" and run first stage regressions including each of the three additional effects in turn, using empirical covariances obtained from residuals of these regressions to re-estimate the model of Table 4. Any change in estimated parameters has then to be ascribed to earnings differentials between the groups identifiable according to each of the characteristics considered.[28] Results from this exercise are reported in Table 5 and Figure 3, which plots the variance decompositions predicted in the three cases and provides a quick glance on the evidence emerging after removing between-groups effects. Estimates obtained after

[27] In a sense, this is approach is typical of the literature on the earnings covariance structure, where the focus is placed on the characterisation of earnings second moments through the specification of dynamic earnings processes, without controlling for the impact of personal characteristics on second moments.

[28] In particular, occupational and sectoral effects are specified through dummy variables defined according to the splits reported in Table 1, while to control for firm size I use the log of the number of employees.

removing the effects of firm size or sectors from log-earnings (panel (a) and (b)) do not alter conclusions reached in Section 5.1. Clearly, the effect of including additional variables in the first stage regression is to lower the levels of predicted variances, but the changes of variance components quite closely resemble those emerged from Figure 2.

On the other hand, the inclusion of occupational dummies in the first stage regression produces a remarkable alteration in variance decomposition series, both in their level and - especially – evolution (panel (c)). First of all, there is no longer clear evidence of overall earnings differentials growing over the period. The predicted total variance follows a rather flat profile, with some growth concentrated at the end of the sample period. Secondly, the behaviour of overall differentials does not appear to be heterogeneous across cohorts as it was in Figures 1 and 2. Finally, the growth of permanent inequality over the 1980s and the early 1990s is not continuous, but appears to be concentrated over the first half of the 1980s and the mid-1990s. Some parallels with the between-occupations analysis remain, however, namely the fact that transitory inequality is higher for younger cohorts. On the whole, evidence in panel (c) suggests that the growth of overall differentials, their heterogeneity across cohorts and the growth of permanent differentials in the second half of the 1980s were a result of between-occupations differences in earnings dynamics.

The evidence emerged after removing workers' occupation from log-earnings indicates that occupational differentials are a key factor behind the observed changes in the autocovariance structure. Such evidence may either be consistent with skill biased technical change explanations of inequality and/or institutional developments in the pay setting framework. It is difficult to distinguish between the two explanations, given the limited amount of information available in the INPS data. However, it seems worth to develop the analysis further by looking at the covariance structure of earnings within each occupational group. To do this, I first identify the occupational group in which individuals spent the largest share (in terms of weeks worked) of the observed working career. I use these time-invariant groups to assign individual earnings profile to an occupational category.[29] The number of individuals selected in each group is 33,617 for blue collar and 16,275 for white collar workers.[30]

Covariance structure vectors obtained for blue and white collar workers are then simultaneously analysed. In particular, I estimated the same model as above (i.e. RG

[29] An alternative strategy is used in Dickens (2000), where occupational groups are defined according to initial occupations. Occupational covariance structures are used in that paper to estimate separate models by occupation, rather than to estimate a joint model with parameters shifted according to occupations as in the present analysis.

[30] I do not consider managers because cell size is extremely reduced in this case, especially for younger cohorts. As will be evident soon, the blue/white collar workers split seems to capture all the relevant features in the data.

permanent earnings, AR(1) transitory ones plus time and cohort specific loading factors on each component) and allow each parameter to be constituted by a base blue collar component and a shift in correspondence of white collar covariances, so that the theoretical covariance structure becomes:

$$f(\tilde{\vartheta}) = f(\vartheta + w\vartheta_w) \tag{8'}$$

where *w* is a dummy for second moments estimated from white collar data and ϑ_w is a vector of shifters.[31] In this way it is possible to test the significance of differences in parameters between the two groups, (i.e. the significance of the elements of ϑ_w), and to use estimated parameters to predict within-occupations decomposition of the covariance structure using $f(\hat{\vartheta})$ for blue collar workers and $f(\hat{\vartheta} + \hat{\vartheta}_w)$ for white collar workers.[32]

Results from the model with occupation-specific coefficients are reported in Table 6. The RG model estimates indicate that, compared to blue collar workers, individual specific earnings profiles are characterised by less dispersed intercepts and more dispersed slopes for white collars, for which, thence, time varying components of ability seem to play a predominant role. On the other hand, the covariance between the two components of individual profiles is positive for blue collar workers, while the white collar shifter is equal in size but opposite in sign compared to the base component, suggesting that for this group there is no clear association between fixed and time varying components of heterogeneity. Occupational differences may also be detected for AR(1) parameters; in particular, shock persistence appears to be much higher for the white collar sub-sample. Taking birth cohort shifters into account, no significant difference can be observed for permanent earnings, the more precisely estimated shifter being that for the youngest cohort (t-statistic = 1.62). By contrast. clear differences may be detected for cohort shifters on transitory earnings: white collar differentials are positive and precisely estimated for all cohorts. Evidence from calendar time shifters, finally, indicates positive and significant differentials for white collar worker's permanent earnings from 1992 onwards, while, in parallel, shifters on the transitory earnings are significantly lower for this group over the last couple of years. This suggests that the overall earnings distribution for white collar workers has been characterised by increasing persistence during the first half of the 1990s.

[31] Remember that ϑ differs from the one in (8) in that the moving average parameter is restricted to be 0.

[32] The fourth moment matrix of the problem is block diagonal, with blocks given by the fourth moments matrices of blue and white collar workers.

Predicted variance decompositions by birth cohort and occupations, which help in assessing the implications of occupational differentials on earnings dynamics within each occupation, are reported in Figure 4. The trend in within-occupation autocovariance components differs markedly when moving from blue to white collar workers. The first group presents a flat profile for all three variance components, which resembles the ones in Figure 3 – panel (c), estimates for white collar workers reproduce what emerged in Figure 2 when analysing the whole sample. Figure 4 thence suggests that overall earnings differentials, and in particular those between occupations, appear to be driven by dynamics within the earnings distribution for white collar workers. By matching this evidence with parameter estimates, it can also be said that the reopening of differentials within white collar workers and between occupations worked through two distinct phases. During the 1980s - especially the second half – it occurred through individual earnings growth rates, a likely result of firm level wage policies and individual wage premia. Over the 1990s, on the other hand, differentials also showed up in calendar time shifters, as could result from aggregate structural changes in the labor market, like the ones introduced with the income policy round of that period. On the whole, these results indicate that permanent earnings differentials in favour of non-manual workers at the top of the earnings distribution increased throughout the period.

6 Concluding remarks

In this paper I have used individual panel data to analyse earnings dynamics and inequality among Italian men between 1979 and 1995. Previous research on Italy has shown that earnings inequality grew in recent years and stressed that increasing flexibility and decentralisation in pay setting played a role in explaining these trends. The data utilised in this paper indicate that earnings differentials grew for most of the 1980s and the first half of 1990s. This rise has been accompanied by growing persistence, suggesting that the earnings distribution has become increasingly segmented. Relevant birth cohort effects also seem to be apparent both in the static and dynamic measures of earnings differentials, younger birth-cohorts being characterised by less dispersion and rigidity than older groups.

The econometric analysis has been based on GMM estimates of dynamic earnings processes using earnings second moments, applying the minimum distance method of Chamberlain (1984), and replicating several features of recent studies for Canada, the UK and the US. I find that fixed and time varying components of individual heterogeneity are positively correlated, implying a divergence of earnings profiles, and more persistence, over the working career. Moreover, when allowing for secular trends in the earnings covariance structure, changes in the variance of permanent earnings are found to entirely account for the widening of aggregate differentials. This last result is opposite to what has been found for other Countries, where both earnings components have a role in explaining aggregate trends, and suggests that earnings differentials have become increasingly persistent in recent years.

Additional insights on earnings dynamics and inequality have been provided by allowing for occupational differentials in models of the autocovariance structure. Results show that the growth of persistent differentials arose within the earnings distribution for white collar workers. In particular, two distinct factors are evident behind this pattern for white collar workers, namely more dispersed individual earnings growth rates and a tendency for overall persistence to increase during the 1990s. On the other hand, no clear evidence of growing permanent differentials can be detected for manual workers.

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Table 1: Sample descriptive statistics

	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995
age	32.14	32.91	33.81	34.73	35.69	36.63	37.63	38.63	39.64	40.63	41.58	42.52	43.43	44.27	44.97	45.69	46.16
birth cohort 1936-38	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.11	0.11	0.10	0.10	0.08	0.07	0.06
birth cohort 1939-41	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.12	0.11	0.10	0.09
birth cohort 1942-44	0.13	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.13	0.12	0.12	0.11
birth cohort 1945-47	0.15	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.15	0.15	0.15	0.16
birth cohort 1948-50	0.14	0.14	0.14	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	0.17
birth cohort 1951-53	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.14	0.14	0.15
birth cohort 1954-56	0.11	0.11	0.11	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.13	0.13	0.14
birth cohort 1957-59	0.08	0.10	0.10	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.12	0.12	0.13
blue collar	0.70	0.69	0.68	0.68	0.67	0.67	0.67	0.67	0.66	0.66	0.65	0.64	0.63	0.63	0.62	0.62	0.61
white collar	0.29	0.30	0.31	0.31	0.31	0.31	0.31	0.32	0.32	0.32	0.33	0.33	0.34	0.34	0.35	0.35	0.36
manager	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.03
size<15	0.18	0.17	0.17	0.18	0.18	0.19	0.18	0.18	0.18	0.17	0.17	0.17	0.16	0.16	0.17	0.17	0.17
15<=size<100	0.24	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26
100<=size<500	0.20	0.20	0.20	0.20	0.19	0.19	0.20	0.20	0.20	0.20	0.21	0.21	0.21	0.21	0.21	0.21	0.21
500<=size	0.38	0.39	0.38	0.38	0.38	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.36	0.36	0.36
stone, clay, glass, basic metal	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.08	0.08	0.08	0.08	0.08	0.08	0.07
food, wood and paper	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
textiles	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
fabricated metal oducts and	0.29	0.29	0.28	0.28	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.26	0.26
energy and chemicals	0.09	0.09	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
constructions	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.09
transports and communications	0.07	0.07	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.09	0.09	0.09
insurance, banking and	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.08	0.07	0.08	0.09
retail trade and other services	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
others	0.05	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
mean log earnings [(a)]	6.32	6.36	6.40	6.40	6.41	6.43	6.46	6.48	6.53	6.56	6.60	6.63	6.68	6.69	6.68	6.73	6.69
standard deviation log earnings	0.42	0.38	0.37	0.36	0.38	0.38	0.40	0.40	0.41	0.42	0.41	0.43	0.43	0.44	0.45	0.48	0.48
log(p90/p10)	0.80	0.80	0.75	0.72	0.76	0.77	0.79	0.81	0.86	0.89	0.90	0.93	0.95	0.98	0.98	1.03	1.07
log(p95/p5)	1.16	1.14	1.07	1.04	1.09	1.11	1.14	1.15	1.22	1.24	1.25	1.29	1.33	1.38	1.39	1.47	1.48
log(p50/p10)	0.35	0.34	0.33	0.32	0.33	0.34	0.34	0.34	0.36	0.37	0.37	0.37	0.38	0.38	0.38	0.41	0.43
log(p90/p50)	0.45	0.47	0.43	0.40	0.44	0.43	0.46	0.47	0.51	0.52	0.52	0.56	0.57	0.60	0.59	0.62	0.64
observations	45699	47268	48211	48815	49336	50257	50225	50158	50100	50052	48623	47414	45931	44000	40299	39253	35733

Notes:
(a) all earnings statistics refer to real weekly earnings (1995=100)

Table 2: Descriptive regressions of the earnings autocovariance matrix (t-ratios[a] in parentheses)

Lag structure			Calendar time effects			Birth cohorts effects		
lag1	-0.022	(81.20)	1980	-0.008	(6.29)	1939-41	-0.010	(1.18)
lag2	-0.009	(59.97)	1981	-0.004	(4.96)	1942-44	-0.035	(4.57)
lag3	-0.007	(48.01)	1982	-0.003	(3.75)	1945-47	-0.071	(10.30)
lag4	-0.007	(54.17)	1983	0.009	(17.22)	1948-50	-0.088	(13.04)
lag5	-0.006	(47.96)	1984	0.004	(7.64)	1951-53	-0.102	(15.24)
lag6	-0.006	(48.12)	1985	0.008	(13.68)	1954-56	-0.116	(17.70)
lag7	-0.006	(40.22)	1986	0.005	(8.51)	1957-59	-0.136	(21.02)
lag8	-0.006	(43.04)	1987	0.009	(18.98)			
lag9	-0.006	(42.61)	1988	0.007	(13.56)			
lag10	-0.006	(35.68)	1989	0.001	(2.45)			
lag11	-0.006	(35.89)	1990	0.009	(18.22)			
lag12	-0.005	(27.01)	1991	0.007	(12.53)			
lag13	-0.006	(26.36)	1992	0.009	(14.36)			
lag14	-0.003	(11.92)	1993	0.006	(7.69)			
lag15	-0.005	(11.40)	1994	0.014	(14.30)			
lag16	-0.008	(12.15)	1995	0.015	(12.99)			
constant				0.214			(35.05)	
R-squared				0.99				
N [(b)]				50761				

Notes:

(a) T-ratios adjusted using earnings fourth moments

(b) Number of individuals in the panel. The number of covariances used as dependent variable in regression is 1224.

Table 3: Models for the covariance structure of earnings (asymptotically robust standard errors in parenthes)

	(1) Random Walk + ARMA(1,1)		(2) Random Growth + ARMA(1,1)	
Permanent component				
$\sigma^2\mu$	0.0265	(0.0020)	0.0309	(0.0049)
$\sigma^2\gamma$			0.0001	(0.00002)
$\sigma^2\xi$; $\sigma\mu\gamma$[(a)]	0.0069	(0.0002)	0.0012	(0.0003)
Transitory component				
$\sigma^2\varepsilon$	0.0363	(0.0021)	0.0320	(0.0010)
$\sigma^2 0$	0.0407	(0.0016)	0.0603	(0.0027)
ρ	0.6856	(0.0505)	0.7219	(0.0187)
θ	-0.4532	(0.0072)	-0.2364	(0.0180)
SSR[(b)]	0.2549	18670.03	0.1617	7841.26
N[(c)]	50761		50761	

Notes:

(a) $\sigma\xi$ refers to the RW specification and $\sigma\mu\gamma$ to the RG one.

(b) The statistic is unweigheted (left) and weighted with the inverse of estimated variance of residuals (right).

(c) Number of individuals in the panel. 1224 empirical moments used in non linear least squares estimation

Table 4: Model with RG permanent component, AR(1) transitory components, birth cohort and time shifters on both components (asymptotically robust standard errors in parentheses).

	Permanent component			Transitory component		Ratio[a]
$\sigma^2\mu$	0.0036	(0.0050)	$\sigma^2\varepsilon$	0.0247	(0.0044)	
$\sigma^2\gamma$	0.0002	(0.00003)	$\sigma^2 0$	0.0427	(0.0059)	
$\sigma\mu\gamma$	0.0015	(0.0004)	ρ	0.8917	(0.0077)	
Birth cohort						
1939-41	1.0453	(0.0278)		1.1537	(0.1130)	0.91
1942-44	1.0217	(0.0290)		1.4282	(0.1131)	0.72
1945-47	0.9802	(0.0297)		1.4111	(0.1055)	0.69
1948-50	0.9974	(0.0341)		1.4662	(0.1070)	0.68
1951-53	1.0730	(0.0406)		1.3735	(0.1025)	0.78
1954-56	1.1077	(0.0479)		1.4294	(0.1059)	0.77
1957-59	1.1233	(0.0549)		1.3873	(0.1060)	0.81
Year						
1980	0.9800	(0.0075)		0.7888	(0.0234)	1.35
1981	0.9207	(0.0096)		0.6647	(0.0271)	1.54
1982	0.8674	(0.0110)		0.6004	(0.0276)	1.62
1983	0.8914	(0.0131)		0.5877	(0.0289)	1.72
1984	0.8795	(0.0147)		0.5540	(0.0279)	1.79
1985	0.8806	(0.0161)		0.5631	(0.0289)	1.78
1986	0.8793	(0.0175)		0.5259	(0.0272)	1.96
1987	0.8959	(0.0190)		0.5226	(0.0268)	2.02
1988	0.8774	(0.0199)		0.5410	(0.0273)	1.87
1989	0.8586	(0.0211)		0.4963	(0.0243)	2.04
1990	0.8634	(0.0225)		0.5123	(0.0249)	1.98
1991	0.8624	(0.0235)		0.4959	(0.0239)	2.01
1992	0.8829	(0.0253)		0.4733	(0.0234)	2.14
1993	0.8906	(0.0272)		0.4283	(0.0259)	2.27
1994	0.9721	(0.0311)		0.3066	(0.0307)	3.37
1995	1.0393	(0.0375)		0.1642	(0.0363)	5.51
SSR[b]	0.0406			7351.53		
N[c]			50761			

Notes:
(a) ratio between permanent and transitory components shifters
(b) The statistic is unweigheted (left) and weighted with the inverse of estimated variance of residuals (right).
(c) Number of individuals in the panel. 1224 empirical moments used in non linear least squares estimation

Table 5: Model with RG permanent component, AR(1) transitory components, birth cohort and time shifters on both components, firm size (1), sector (2) and workers occupation (3) removed in first stage regression (asymptotically robust standard errors in parentheses).

	(1)						(2)						(3)				
	Permanent component			Transitory component			Permanent component			Transitory component			Permanent component			Transitory component	
$\sigma^2\mu$	0.0084	(0.0037)	$\sigma^2\varepsilon$	0.0350	(0.0056)	$\sigma^2\mu$	0.0070	(0.0033)	$\sigma^2\varepsilon$	0.0375	(0.0059)	$\sigma^2\mu$	0.0145	(0.0021)	$\sigma^2\varepsilon$	0.0552	(0.0050)
$\sigma^2\gamma$	0.0002	(0.00002)	$\sigma^2 0$	0.0504	(0.0050)	$\sigma^2\gamma$	0.0002	(0.00002)	$\sigma^2 0$	0.0526	(0.0048)	$\sigma^2\gamma$	0.0001	(0.00002)	$\sigma^2 0$	0.0669	(0.0030)
$\sigma\mu\gamma$	0.0006	(0.0003)	ρ	0.8439	(0.0074)	$\sigma\mu\gamma$	0.0004	(0.0002)	ρ	0.8694	(0.0068)	$\sigma\mu\gamma$	0.0005	(0.0002)	ρ	0.7537	(0.0089)
Birth cohort																	
1939-41	1.0766	(0.0317)		1.0141	(0.0785)		1.0395	(0.0324)		1.0982	(0.0748)		1.0349	(0.0315)		1.0368	(0.0293)
1942-44	1.0653	(0.0320)		1.2177	(0.0737)		1.0732	(0.0329)		1.2329	(0.0703)		1.0611	(0.0398)		1.0959	(0.0293)
1945-47	1.0390	(0.0313)		1.1923	(0.0671)		1.0343	(0.0313)		1.2063	(0.0624)		1.0785	(0.0490)		1.0155	(0.0266)
1948-50	1.0571	(0.0345)		1.2309	(0.0667)		1.0697	(0.0334)		1.2554	(0.0617)		1.1202	(0.0642)		1.0343	(0.0277)
1951-53	1.1240	(0.0409)		1.1344	(0.0640)		1.1598	(0.0392)		1.1634	(0.0600)		1.1984	(0.0842)		1.0173	(0.0277)
1954-56	1.1478	(0.0470)		1.1740	(0.0651)		1.2150	(0.0461)		1.2026	(0.0603)		1.2352	(0.1055)		1.0700	(0.0297)
1957-59	1.1582	(0.0536)		1.1282	(0.0648)		1.2594	(0.0522)		1.1589	(0.0594)		1.2323	(0.1238)		1.0752	(0.0309)
Year																	
1980	0.9807	(0.0082)		0.7717	(0.0285)		0.9504	(0.0092)		0.7359	(0.0265)		1.0089	(0.0117)		0.7551	(0.0222)
1981	0.9245	(0.0099)		0.6733	(0.0331)		0.9037	(0.0114)		0.6428	(0.0306)		0.9474	(0.0165)		0.6785	(0.0251)
1982	0.8738	(0.0114)		0.6326	(0.0346)		0.8525	(0.0127)		0.5984	(0.0316)		0.8778	(0.0196)		0.6546	(0.0258)
1983	0.8899	(0.0133)		0.6201	(0.0359)		0.8532	(0.0144)		0.5696	(0.0323)		0.9271	(0.0253)		0.6303	(0.0260)
1984	0.8743	(0.0148)		0.5884	(0.0347)		0.8436	(0.0160)		0.5484	(0.0316)		0.9092	(0.0295)		0.6143	(0.0251)
1985	0.8778	(0.0163)		0.6126	(0.0363)		0.8477	(0.0174)		0.5562	(0.0325)		0.9114	(0.0335)		0.6209	(0.0260)
1986	0.8706	(0.0175)		0.5624	(0.0333)		0.8486	(0.0185)		0.5286	(0.0309)		0.9255	(0.0383)		0.5564	(0.0218)
1987	0.8798	(0.0189)		0.5557	(0.0323)		0.8468	(0.0196)		0.5145	(0.0295)		0.9474	(0.0434)		0.5299	(0.0205)
1988	0.8553	(0.0197)		0.5935	(0.0333)		0.8366	(0.0209)		0.5465	(0.0305)		0.9020	(0.0440)		0.5880	(0.0232)
1989	0.8324	(0.0208)		0.5414	(0.0292)		0.8189	(0.0222)		0.5093	(0.0272)		0.8777	(0.0471)		0.5214	(0.0198)
1990	0.8407	(0.0220)		0.5649	(0.0299)		0.8261	(0.0237)		0.5152	(0.0268)		0.8542	(0.0484)		0.5543	(0.0222)
1991	0.8372	(0.0229)		0.5515	(0.0289)		0.8189	(0.0246)		0.5101	(0.0258)		0.8450	(0.0504)		0.5527	(0.0226)
1992	0.8567	(0.0246)		0.5318	(0.0283)		0.8318	(0.0264)		0.4871	(0.0246)		0.8321	(0.0522)		0.5590	(0.0239)
1993	0.8717	(0.0266)		0.4832	(0.0295)		0.8411	(0.0282)		0.4563	(0.0261)		0.7971	(0.0518)		0.5696	(0.0263)
1994	0.9101	(0.0289)		0.4647	(0.0336)		0.9081	(0.0313)		0.3793	(0.0298)		0.8313	(0.0574)		0.6354	(0.0301)
1995	0.9741	(0.0342)		0.2478	(0.0535)		0.9556	(0.0366)		0.2356	(0.0493)		0.8896	(0.0668)		0.5603	(0.0297)
SSR[(a)]	0.0313			6792.49			0.0311			6884.30			0.0228			6548.83	
N[(b)]			50761						50761						50761		

Notes:
(a) The statistic is unweigheted (left) and weighted with the inverse of estimated variance of residuals (right).
(b) Number of individuals in the panel. 1224 empirical moments used in non linear least squares estimation

Table 6: Model with RG permanent component, AR(1) transitory components, birth cohort and time shifters on both components. Each parameter allows a shifter for White collar autocovariances (asymptotically robust standard errors in parentheses).

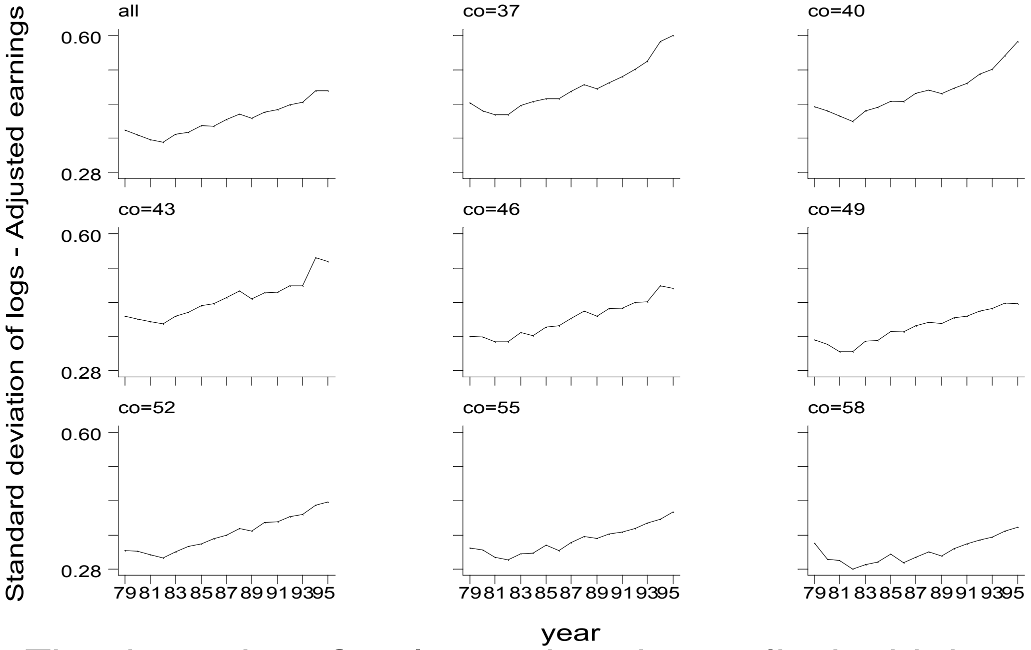
	Base parameter (Blue collar workers)						Shifter (White collar workers)				
$\sigma^2\mu$	0.0198	(0.0035)	$\sigma^2\varepsilon$	0.0539	(0.0060)	$\sigma^2\mu$	-0.0160	(0.0045)	$\sigma^2\varepsilon$	-0.0393	(0.0069)
$\sigma^2\gamma$	0.00005	(0.0000)	$\sigma^2 0$	0.0632	(0.0034)	$\sigma^2\gamma$	0.0001	(0.00003)	$\sigma^2 0$	-0.0222	(0.0069)
$\sigma\mu\gamma$	0.0005	(0.0002)	ρ	0.6168	(0.0099)	$\sigma\mu\gamma$	-0.0005	(0.0002)	ρ	0.2689	(0.0157)
Birth cohort											
1939-41	1.0397	(0.0372)		0.9767	(0.0323)		-0.0516	(0.0575)		0.4076	(0.1267)
1942-44	1.1163	(0.0484)		1.0706	(0.0358)		-0.0895	(0.0662)		0.2308	(0.1159)
1945-47	1.1137	(0.0590)		0.9756	(0.0317)		-0.0464	(0.0731)		0.3294	(0.1095)
1948-50	1.1963	(0.0782)		0.9702	(0.0316)		-0.0674	(0.0919)		0.3491	(0.1069)
1951-53	1.2517	(0.1002)		0.9681	(0.0317)		0.0835	(0.1161)		0.2880	(0.1057)
1954-56	1.3185	(0.1278)		1.0234	(0.0338)		0.1910	(0.1467)		0.2398	(0.1059)
1957-59	1.3200	(0.1499)		1.0521	(0.0347)		0.2760	(0.1695)		0.1562	(0.1063)
Year											
1980	0.9870	(0.0121)		0.7798	(0.0313)		0.0284	(0.0217)		0.1335	(0.0497)
1981	0.9328	(0.0175)		0.7306	(0.0357)		0.0483	(0.0273)		0.0628	(0.0617)
1982	0.8996	(0.0221)		0.7180	(0.0356)		-0.0008	(0.0310)		-0.0144	(0.0649)
1983	0.9139	(0.0276)		0.7295	(0.0359)		0.0371	(0.0366)		-0.0405	(0.0698)
1984	0.9110	(0.0330)		0.6804	(0.0336)		-0.0269	(0.0419)		0.0482	(0.0735)
1985	0.8977	(0.0365)		0.7308	(0.0376)		-0.0181	(0.0470)		-0.0173	(0.0761)
1986	0.9076	(0.0416)		0.6316	(0.0303)		-0.0294	(0.0507)		0.0457	(0.0716)
1987	0.8959	(0.0453)		0.6058	(0.0296)		-0.0121	(0.0551)		0.0975	(0.0741)
1988	0.8752	(0.0474)		0.6673	(0.0338)		-0.0228	(0.0581)		0.0500	(0.0773)
1989	0.8332	(0.0494)		0.5457	(0.0268)		0.0203	(0.0631)		0.1268	(0.0661)
1990	0.8025	(0.0506)		0.5968	(0.0311)		0.0402	(0.0655)		0.1162	(0.0715)
1991	0.7853	(0.0522)		0.6035	(0.0307)		0.0715	(0.0678)		0.0821	(0.0677)
1992	0.7528	(0.0527)		0.6102	(0.0315)		0.1396	(0.0680)		0.0269	(0.0663)
1993	0.7200	(0.0522)		0.6345	(0.0344)		0.1388	(0.0700)		0.0156	(0.0746)
1994	0.7312	(0.0569)		0.7890	(0.0433)		0.2076	(0.0791)		-0.3193	(0.0883)
1995	0.7534	(0.0636)		0.6769	(0.0380)		0.2502	(0.0837)		-0.3973	(0.1043)
SSR[(a)]			0.05776						8636.02		
N[(b)]			33617						16275		

Notes:

(a) The statistic is unweigheted (left) and weighted with the inverse of estimated variance of residuals (right).

(b) Number of individuals in the panel for each occupational group. 2448 empirical moments simultaneously used in non linear least squares estimation.

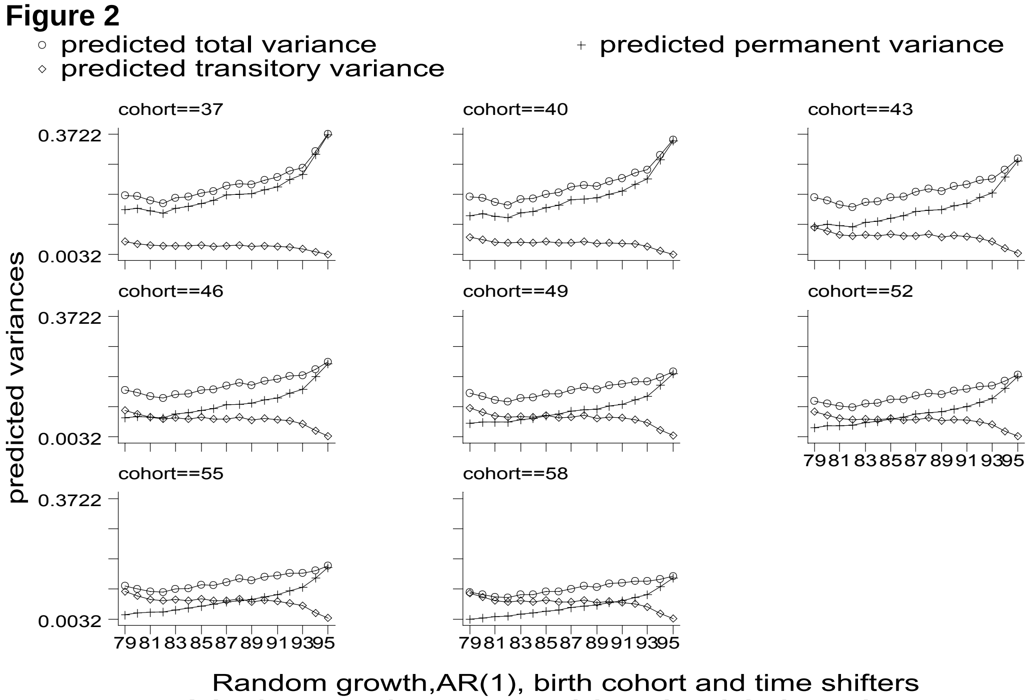
Figure 1



The dynamics of male earnings inequality by birth cohort

Note: 3-year birth-cohorts, the central year of birth is indicated.

Figure 2



Variance decomposition by birth cohort

Note: 3-year birth-cohorts, the central year of birth is indicated.

Figure 3 (a)

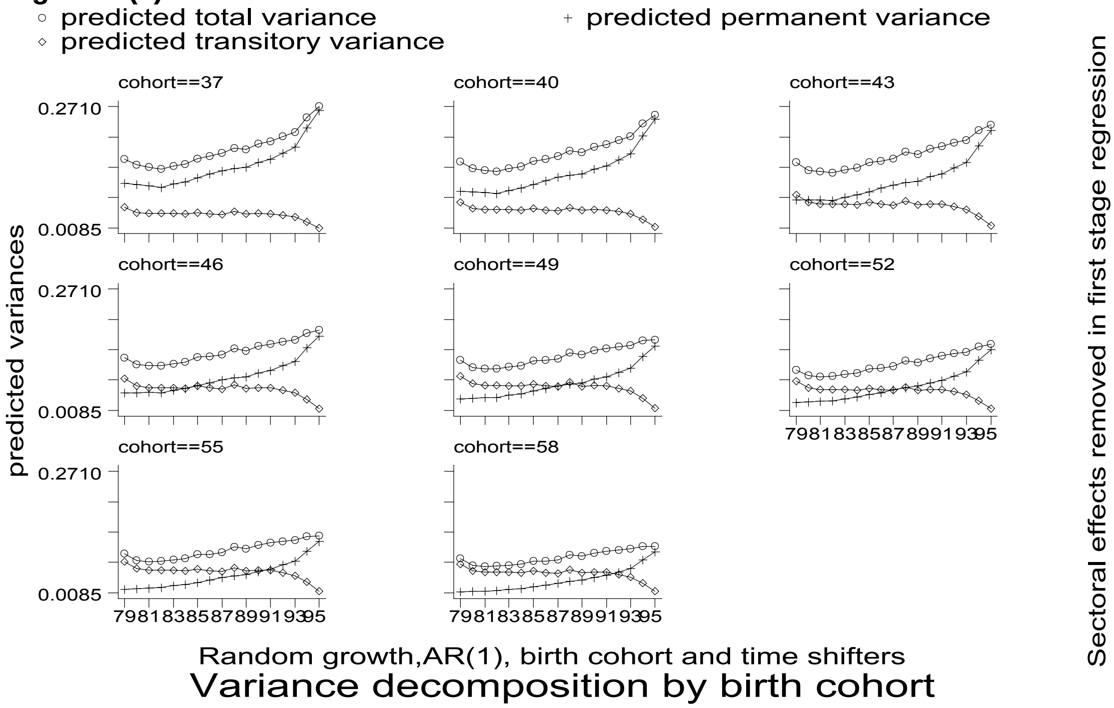


Figure 3 (b)

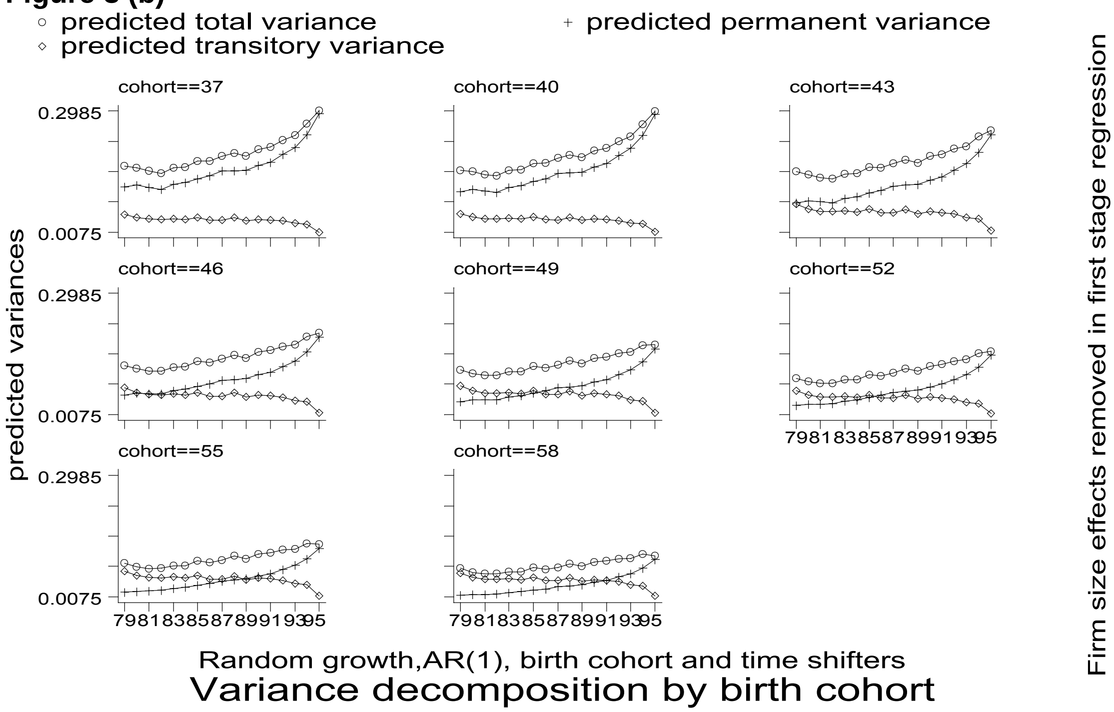
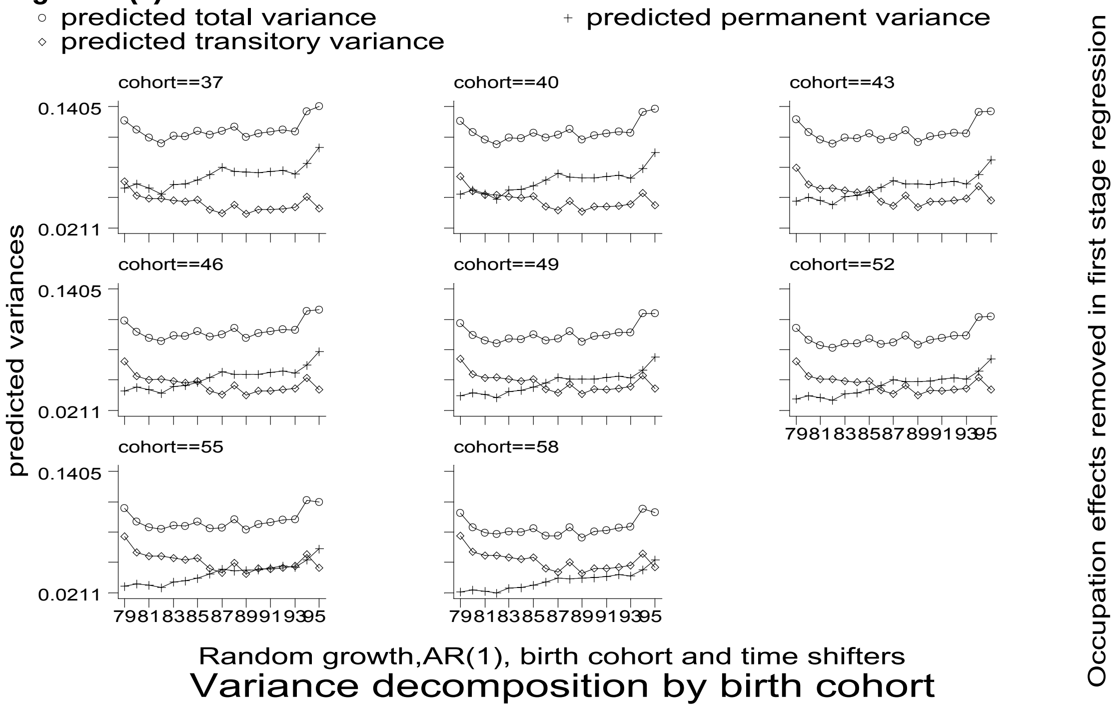
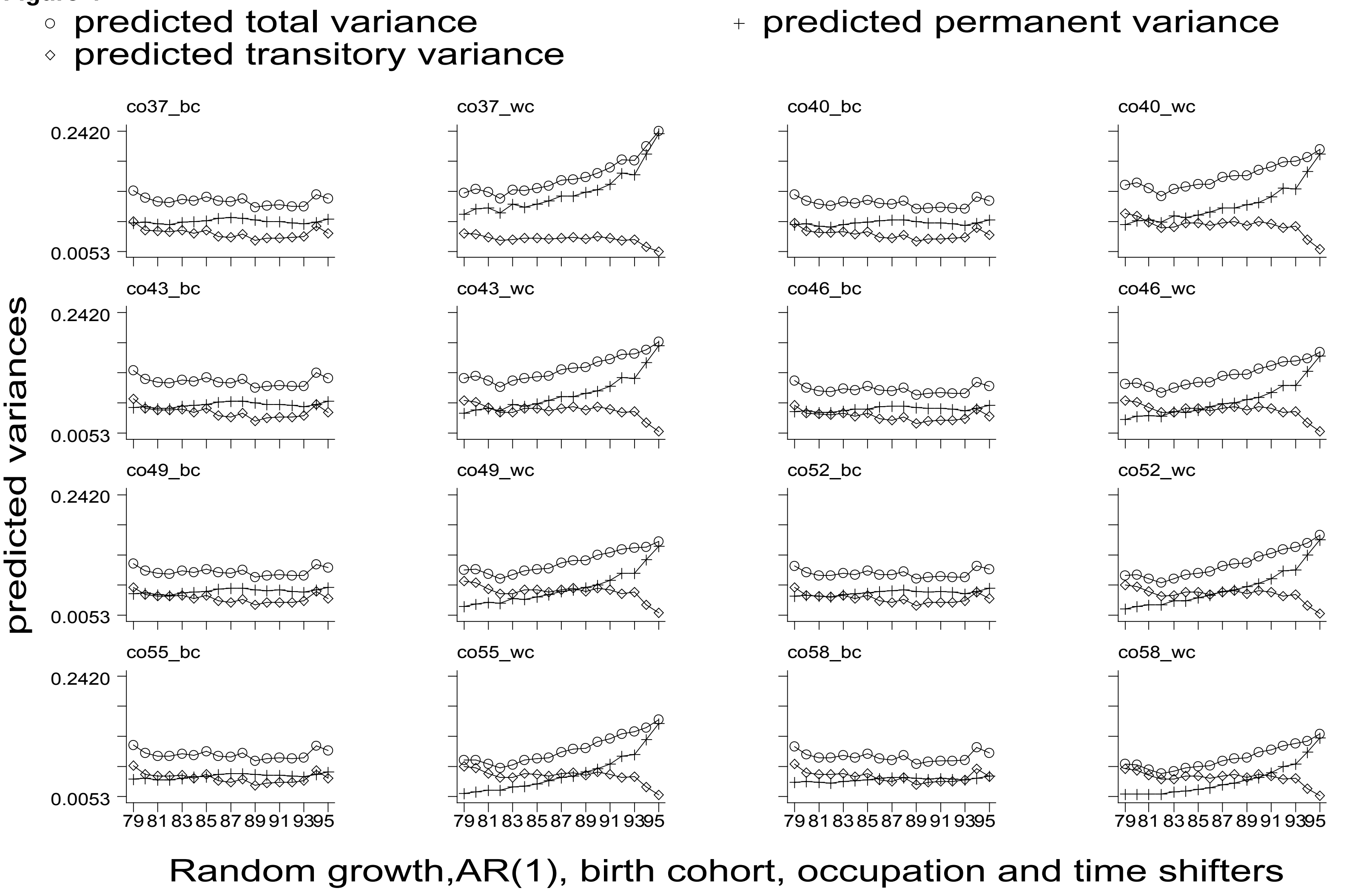


Figure 3 (c)



Note: 3-year birth-cohorts, the central year of birth is indicated.

Figure 4



Variance decomposition by birth cohort and occupation

Note: 3-year birth-cohorts, the central year of birth is indicated; occupations are blue collar (bc) and white collar (wc) workers.