The dynamics and inequality of Italian male earnings: permanent changes or transitory fluctuations?☼

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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. Using these estimates to analyse low pay probabilities shows that it became more persistent for all birth cohorts; consequently, the probability of repeated low pay episodes also increased during the sample period. When allowing for occupation-specific components in the parameters of interest, life time earnings divergence is found to characterise the non-manual earnings distribution.

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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 e.g. Gottschalk and Smeeding, 1997).

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 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. 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 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).

[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.

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.[2]

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).[3] 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.[4] 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 earnings dispersion from the mid-1970s to the mid-1980s. His findings suggest that the rise of earnings inequality was mainly driven by

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[2] 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.

[3] 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.

[4] 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.

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. Similar models have also been estimated by Haider (2001) using a different PSID sample compared to Baker (1997) and showing that both life-time inequality and transitory variability contributed to aggregate US trends.

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.[5] 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

[5] 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.

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 earnings profiles, similarly previous studies of individual earnings dynamics (see Lillard and Weiss, 1979, Hause, 1980, Baker, 1997, Baker and Solon, 1998 and Haider, 2001). 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. Parameter estimates are next used to derive implications for low pay, showing that the rise of long term inequality translated into increasing persistence at the bottom end of the earnings distribution and into a growth in the probability of repeated low pay events. Finally, I explicitly allow for occupational effects within long term earnings profiles, finding that part of overall trends arise within the earnings distribution of non-manual workers.

2 Data description and patterns of the earnings autocovariance structure

This study uses longitudinal data on individual earnings made available by the Italian National Social Security Institute (*Istituto Nazionale di Previdenza Sociale*, INPS) for the 1979-95 period. The INPS archive collects information from social security records. The administrative nature of the archive implies a good reliability of the earnings data but, on the other hand, the available information is rather limited and individual characteristics such as education and family background are not observed. Data refers to employees from the private non-agricultural sector of the economy; the sample originally available is a 1% random draw representative of full-time workers registered in the INPS archive. Besides the individual social security number that allows reconstruction of the panel, 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 is also available and refers to its size, industry measured at the 3-digits level and the INPS code.

For the purposes of this study, male workers aged between 25 and 58 (with the age variable defined as explained below) and born between 1930 and 1965 have been selected. The selection of men’s data is aimed at mitigating issues of endogenous female labor market participation, which may well be exacerbated when analysing earnings dynamics. The choice of the age range has the objective of selecting out the extremes of the life-cycle of earnings, where volatility arising just after labor market entry or before retirement can be confounded with volatility due to structural labor market changes. Finally, workers born before 1930 and after 1965 where excluded from the analysis due to small sample size. [6]

After applying the selection criteria outlined above, I end up with a panel covering 67,768 individuals, with a total of 935,333 person-year observations, whose structure is described in Appendix Table A1. I analyse the fully unbalanced panel, i.e. use all observations with positive earnings and allow individuals to enter and exit the sample over time.[7] Movements into and out from the sample can be due to unemployment spells, early retirement and mobility to or from the public, agricultural or self-employed sectors of the economy. While not formally controlling for attrition due to lack of instruments, the use of the unbalanced panel helps in mitigating the likely overestimation of earnings persistence that would arise from balanced samples in which only individuals with positive earnings in each wave contribute to estimation.

In order to separately identify age and time effects it is necessary to observe earnings autocovariances at different phases of the life cycle in each year, which is achieved by estimating the covariance structure separately by birth cohorts. In order to preserve cell size within cohorts, observations have been grouped into 12 3-year birth cohorts. 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 1951-53 will be imputed ages 27 (in 1979) through 43 (in 1995). The two oldest cohorts leave the sample altogether when they reach age 59 (in 1990 and 1993) while the four youngest cohorts join the sample at the age of 25 (in 1980, 1983, 1986 and 1989). Such an unbalanced design by cohorts allows multiple observations on the life cycle extremes. Table A1 shows how 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 calendar time.

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 a distinction between blue collar workers, white collars and managers. 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-

[6] Besides the 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.

[7] I also experimented using the revolving balanced design suggested by Haider (2001), i.e. exclude individuals with discontinuous earnings profiles, and found no relevant differences in results.

manual jobs.[8] A slight shift away from larger firms can be also observed, while the industrial structure tended to stay constant over time.[9]

The table presents the evolution of the standard deviation of log weekly earnings which 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. A parallel with the evolution of the wage bargaining framework can be drawn. Falling differentials characterise the phase of fully egalitarian wage indexation, while, on 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 by wage indexation. Finally, the early 1990s, during which wage indexation was abolished, witness a further growth of earnings dispersion.

The remainder of this section provides a preliminary exploration of the earnings autocovariance structure. While complementing the cross-sectional description of earnings differentials in Table A1 by looking at earnings persistence, such a descriptive analysis will provide insights on the features of earnings second moments that will prove useful when specifying more formal models in the next section.

For each birth cohort I estimated the empirical covariance structure and pooled estimated second moments across birth cohorts. I next regressed the covariance structure on a set of dummy variables defined according to birth cohorts, time periods and the width of the interval for which covariances are estimated. While the first set of regressors is meant to capture variations of earnings persistence across groups that enter the sample at different stages of the life-cycle, time dummies allow for changes in the earnings distribution over the sample period and interval-width dummies control for the likely drop of earnings persistence which should be observed as pairs of years further apart are taken into account.

Results from this exercise are reported in Table 1. Estimated coefficients on interval width are all negative and decline over lags, indicating that earnings persistence diminishes when years further apart are considered, meaning that the chance of movements within the

[8] Tabulations from raw data show that the latter might be the relevant explanation: changes of occupation from manual to non-manual are rare in the INPS panel and around 1% of the sample changes status in each year.

[9] The rather high share of workers in the manufacturing sector (between 55% and 60%) reflects the sample selection criteria, in particular the restriction to full-time males, and is consistent with evidence from other micro-data set on the Italian labor market. Slightly lower figures (around 53%) can be computed from the Survey on Households Income and Wealth of the Bank of Italy when the sample is restricted using the criteria of this paper (full-time male employees from the private sector in the indicated age and birth cohort ranges).

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 Table A1. 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. 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. This fact is consistent with two not mutually exclusive explanations. First, if life-cycle earnings growth is heterogeneous across individuals, then we should expect the size of earnings differentials to increase as we consider birth cohorts at later stages of the career. Second, job search models predict that recent labor market entrants are more likely to change job compared to their older counterparts, so that the observed lower persistence could result from earnings instability attached to job changes.

3 Earnings dynamics, long term inequality and transitory fluctuations

In this section I fit an earnings components model to the empirical covariance structure and use parameter estimates to decompose overall earnings inequality into a long term and a volatile component. In order to separate life cycle earnings dynamics from secular changes in inequality, I analyse earnings differentials within the 3 year birth cohorts defined in Section 2. With this aim, let us write the log of real earnings for the i-th member of birth cohort c in year t, y_{ict}, as the sum of a year-cohort specific mean and the individual specific deviation from it:

$$y_{ict} = \bar{y}_{ct} + \omega_{ict}, \quad i = 1,...,N_c, \quad t = t_{0c},...,T_c, \quad c = 1,...,C \tag{1}$$

where $\bar{y}_{ct}$ is the mean log earnings for cohort c in period t and ω_{ict} is the deviation from the mean.[10] Earnings differentials within each birth cohort can be characterised by modelling mean-adjusted earnings ω_{ict} and their covariance structure $E(\omega_{ict}\,\omega_{ic(t-k)})$.

3.1 Specification and estimation

I model the dynamics of mean-adjusted earnings according to the following process:

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[10] The panel length T_c and the initial year t_{0c} are cohort specific due to the cohort-wise unbalanced panel design, see Section 2.

$$\omega_{ict} = \pi_t(\mu_i + \gamma_i a_{it}) + \lambda_c \tau_t v_{it}, \qquad (2)$$

where a_{it} is the age variable defined in Section 2 and $E(\mu_i v_{it})=E(\gamma_i v_{it})=0$. The term in parentheses on the right hand side of (2) is formed by individual-specific time invariant coefficients that index the long term (or permanent) earnings component. The term v_{it}, on the other hand, is individual-specific but varies in each period and represents the volatile or transitory earnings component. The orthogonality assumption allow separate identification of the two earnings component. As noted in Section 2, one reason for the lower degree of autocorrelation characterising younger cohorts compared to their older counterparts could reside in the presence of heterogeneous life-cycle earnings growth. To accommodate this possibility, long-term earnings deviations from the cohort mean are assumed to evolve over the life cycle following an individual specific linear trend.[11] The individual specific intercept μ_i represents earnings capacity at the beginning of the working life, determined by schooling or other time invariant ability shifters. The growth parameter, γ_i, captures age related earnings capacity, resulting, for example, from the ability to acquire skills on the job.[12] First and second order moments of individual specific coefficients are given by:

$$(\mu_i, \gamma_i) \sim [(0,0); (\sigma_\mu^2, \sigma_\gamma^2, \sigma_{\mu\gamma})] \qquad (3)$$

The two variances represent heterogeneity in time invariant and age related aspects of ability. A key role for assessing the development of earnings differentials over the working life is played by the covariance between individual specific coefficients, $\sigma_{\mu\gamma}$. A negative value of this coefficient implies that the two sources of heterogeneity offset each other. Within groups with homogeneous educational attainment (and assuming the absence of other shifters of initial earnings) such an outcome can be interpreted as the effect of generic on-the-job training, which lowers initial earnings for investors and raises their earnings growth rates (see Hause, 1980). Positive values of the coefficient, on the other hand, might arise when individuals with large initial ability (or schooling) have also a high propensity to learn skills on the job. While in the first case we should expect long term differentials to drop over the working life, the opposite is true in the second case. Estimates of this coefficient thence provide indications on the extent of mobility within the distribution of long-term earnings.

[11] This type of model is usually refereed to as a *profile heterogeneity* or *random growth* model. As an alternative, individual specific earnings dynamics earnings could follow a *random walk* process, which also predicts earnings differentials to increase over the life-cycle (see Moffitt and Gottschalk, 1995). Baker (1997) finds evidence supporting the random growth against the random walk on a sample of PSID male heads of households. Baker and Solon (1998) model long term earnings using a mixture of the two processes. Cappellari (2000) provides evidence from INPS data that favours the random growth.

[12] I use age since labour market experience, actual or potential, is not observed in the INPS data.

In order to isolate life-cycle earnings dynamics from the secular changes in the earnings distribution singled out in Section 2, I allow the individual trend to be shifted by year-specific coefficients, π_t. For example, growing earnings inequality driven by changes in the demand for skills will result in a rise in the πs over time. Variations in the πs affect the size of long term earnings differentials, but leave their hierarchy unaltered.

The second term on the right hand side of (2) captures deviations from long-run components due to earnings shocks, the transitory or volatile earnings component. To allow for the possibility of serially correlated shocks suggested by the decline of covariance with lags width observed in Section 2, v_{it} can be specified according to some low order ARMA process; in particular, here I adopt an AR(1) process:[13]

$$v_{it} = \rho v_{it-1} + \varepsilon_{it}, \quad \varepsilon_{it} \sim (0, \sigma_\varepsilon^2), \quad v_{i0c} \sim (0, \sigma_0^2)\,. \tag{4}$$

The two variances σ^2_0 and σ^2_ε measure shocks volatility at the start of the sample period and in subsequent years, respectively, while the autoregressive coefficient measures shocks persistence.[14] As I did for the long run component, I allow shocks to impact on earnings through a set of time specific shifters τ_t, which can capture the effect of changes in labor market competition and instability. Moreover, cohort specific shifters λ_c are also included to allow for the possibility that persistence differs across birth cohorts, as emerged from the preliminary exploration of the covariance structure in Section 2.

Parameters of the model outlined above will be estimated by minimum distance (see Chamberlain, 1984, and Abowd and Card, 1989) by fitting the empirical covariance structure of earnings to its theoretical counterpart implied by the model. The theoretical covariance structure can be derived by working out second moments from the specified model of earnings levels. For the long term component – $\omega^P_{ict}=\pi_t(\mu_i+\gamma_i a_{it})$ – it is given by:

$$E(\omega^P_{ict}\omega^P_{ic(t-k)}) = \pi_t \pi_{(t-k)}\{\sigma_\mu^2 + [E(a_{it}) + E(a_{i(t-k)})]\sigma_{\mu\gamma} + E(a_{it}a_{i(t-k)})\sigma_\gamma^2\} \tag{5}$$

For the transitory component – $\omega^T_{ict}=\lambda_c\tau_t(\rho v_{it-1}+\varepsilon_{it})$ – the theoretical covariance structure is:

[13] Experiments with ARMA(1,1) specifications failed to converge suggesting lack of identification. Baker and Solon (1998) report similar problems, which they solve by setting the MA coefficient to 0. As Moffitt and Gottschalk (1995) note, autoregressive processes are not transitory, 'mean reverting' being a more accurate label. For compactness I will still refer to transitory earnings in the remainder of the paper.

[14] The variance initial conditions of the AR(1) process is treated 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.

$$E(\omega_{ict}^{T}\omega_{ic(t-k)}^{T}) = \lambda_c^2 \tau_t \tau_{(t-k)} \{d_0\sigma_0^2 + \tilde{d}[\sigma_\varepsilon^2 + E(v_{i(t-1)}v_{i(t-1)})\rho^2] + (1-d_0-\tilde{d})E(v_{i(t-1)}v_{i(t-k)})\rho\} \quad (6)$$

where d_0 is a dummy variable for variances in the first year of the panel (d_0=1 if k=0 and $t=t_{0c}$; d_0=0 otherwise) and $\tilde{d}$ is a dummy variable for variances in subsequent years ($\tilde{d}$=1 if k=0 and $t> t_{0c}$; $\tilde{d}$=0 otherwise). The overall theoretical covariance structure to be fitted to empirical second moments is the sum of (5) and (6).

Let $f(\vartheta) = [E(\omega_{i1t}\omega_{i1(t-k)}),...,E(\omega_{iCt}\omega_{iC(t-k)})]$ – say a column vector – be the theoretical covariance structure of all cohorts – a non-linear function of the parameter 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:

$$\vartheta = \arg\min[m - f(\vartheta)]'[m - f(\vartheta)] \quad (7)$$

where m is the vector of dimension $\left(\sum_c T_c(T_c+1)/2\right)\times 1$ obtained by stacking m_c over cohorts, m_c=vech(M_c) and M_c is the empirical covariance matrix for birth cohort c.[15]

3.2 Results

Minimum distance estimates of the model resulting from (2), (3) and (4) are reported in Table 2. Individual earnings deviations from the cohort mean of each year have been obtained as residuals from pooled OLS regressions of log real weekly earnings on year dummies, run separately by cohort. The age variable used for the estimation of second moments of individual earnings profiles has been constructed as described in Section 2.

Estimated coefficients for the long run earnings component indicate that both time invariant and age related heterogeneity matter in the formation of long term earnings differentials. The advantage in terms of initial earnings levels for an individual one standard deviation above the mean in the distribution of μ is approximately 16%.[16] On the other hand, an individual located one standard deviation above the mean in the distribution of γ see his earnings growing 1.4% faster than the cohort mean.[17] Moreover, the positive estimate of the

[15] This is the so-called equally weighted minimum distance estimator (EWMD), equivalent to non-linear least squares. Chamberlain (1984) shows that using the inverse earnings fourth moments matrix to weight the minimisation problem yields asymptotic efficiency. 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, and suggest to use the EWMD. 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 fourth moments matrix V: $\text{var}(\hat{\vartheta}) = (G'G)^{-1}G'VG(G'G)^{-1}$, where $G = \partial f(\vartheta)/\partial\vartheta|_{\vartheta*}$ is the gradient matrix evaluated at the solution of (7).

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

[17] This is given by $\sigma\gamma$, the standard deviation of individual growth rates.

covariance between intercepts and slopes implies that initial and life-cycle heterogeneity are positively associated, consistently with a framework in which more educated workers have also a high propensity to acquire skills on the job, with a resulting divergence of earnings profiles over the life cycle. The association between intercepts and slopes is rather strong: estimated coefficients imply that an individual one standard deviation above the mean in the distribution of μ will have a growth coefficient 87% standard deviation of γ.[18] Overall, estimated second moments of the coefficients of individual specific trends indicate that long term inequality grows over the life cycle: after 20 years of career the share of long term variance explained by initial heterogeneity is roughly 12%, while the rest builds up during the career as a result of both growth rate heterogeneity and the positive association between intercepts and slopes.

Coefficients for the AR(1) model are precisely estimated and indicate that the variance of initial conditions, which represents the accumulation of shocks up to the starting year of the panel, is larger compared to that of subsequent innovations. Also, the autoregressive coefficient is rather large, signalling that shocks are highly persistent: the estimates indicate that 53% of a shock to the transitory component is still present after ten years.

Calendar time loading factors for the transitory component are declining over the entire sample period.[19] On the other hand, time shifters on the long term component present a declining trend only over the first part of the sample period, when aggregate earnings differentials are dropping (see Table 2). After a phase of relative stability in the mid-1980s, long-term loading factors begin to rise and follow an upward trend up until the end of the period. In particular, an acceleration of such trend is evident from the last couple of panel waves, i.e. when automatic wage indexation was completely effective. Thence, the estimated loading factors suggest that the growth of aggregate earnings differentials is entirely driven by the long term component. Going back to the implications of variance components in explaining changing inequality, this result is consistent with a scenario of structural labor market changes in favour of skilled workers, as might result from bargaining decentralisation and reforms to wage indexation.

Estimated cohort specific shifters in Table 2 indicate that earnings volatility tends to be larger for younger cohorts, thus confirming a pattern already emerged from the descriptive regression of Section 2, where autocovariances were found to be lower for younger cohorts.[20] Differently from the descriptive regression, however, the model of this section controls for

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[18] This is obtained as $\sigma\mu\gamma/\sigma\mu\sigma\gamma$, the linear correlation coefficient between intercepts and slopes.
[19] Loading factors on both earnings components are normalised to 1 in 1979 for identification.
[20] The shifter on birth cohort 1930-32 is normalised to 1 for identification.

heterogeneous life cycle earnings growth, so that the behavior of estimated coefficients can be imputed to differences in volatility across cohorts that could stem from differences in job change propensities.[21]

In order to gain an overview of the implications of these estimates for cross-sectional and long term earnings inequality, Figure 1 plots the predicted overall and long term variance by birth cohort. For all birth cohorts, earnings differentials display increasing trends since the early 1980s, confirming the descriptive evidence presented in Section 2 and the findings from previous literature on Italy. Long term inequality appears to be at higher levels the older the cohort considered, consistently with the evidence of life-cycle earnings divergence provided by the estimates of long term earnings. In addition, the incidence of long term variance on overall inequality tends to be larger the older the cohort considered, reflecting lower volatility. Finally, long term dispersion approaches overall inequality during the last years of the panel for all cohorts, signalling a generalised diffusion of earnings persistence.

4 Implications for low pay persistence

Estimation in the previous section was based on assumptions on the second moments of the earnings distribution that enabled decomposing the covariance structure into long term and volatile components. As Lillard and Willis (1978) showed, by making additional functional form assumptions on the log-earnings distribution, estimated covariance components can be used to investigate low pay probabilities. In particular, the probability that long term earnings (as opposed to total earnings) fall below some pre-determined low pay threshold can be computed. In addition, estimates of the intertemporal covariance structure can be used to retrieve the probability of repeated low pay events over sequences of time periods. Such exercises provide insights into the welfare implications of the estimated earnings process by showing to what extent the evolution of earnings differentials translates into persistent low pay, a symptom of labour market segmentation.

With this aim, let us rewrite equation (1) distinguishing between permanent and transitory unobserved earnings components:

$$y_{ict} = \bar{y}_{ct} + \omega_{ict}^{P} + \omega_{ict}^{T} \qquad (1.b)$$

Let us define y^*_t as the log of the low pay threshold of year t, common to all birth cohorts. The probability of low pay in year t for individuals from cohort c is then :

[21] Tabulations from raw data confirm that younger cohorts change firm more frequently compared to older groups.

$$P_{ict} = \Pr(y_{ict} < y_t^*) = \Pr(\omega_{ict} = \omega_{ict}^P + \omega_{ict}^T < y_t^* - \bar{y}_{ct}) . \tag{8}$$

By assuming bivariate normality of μ_i and γ_i and normality of ε_{it} and v_{i0c}, it follows that ω_{ict} is normally distributed with variance $\sigma_{\omega ct}^2 = E(\omega_{ict}^{P\,2}) + E(\omega_{ict}^{T\,2})$, the variances of earnings components being given in (5) and (6). The probability of low pay in year t for cohort c is then:

$$P_{ict} = \Phi[(y_t^* - \bar{y}_{ct}) / \sigma_{\omega ct}] \tag{9}$$

where Φ is the cumulative density function (c.d.f.) of the normal distribution. P_{ict} can be estimated for each cohort from pooled cross-sections by regressing a low pay dummy on a set of time dummies by probit. Note that predictions from such regressions will be constant within year-cohorts cells.

The expression in (9) refers to what Lillard and Willis (1978) define the *aggregate* low pay (poverty in their phrasing) probability, i.e. the probability that observed and both unobserved earnings components fall below the threshold. Hence, this probability also refers low pay episodes due to fluctuations of the transitory component. From the point of view of labor market segmentation and social welfare, it is relevant to neat low pay probabilities from the effect of such transitory fluctuations, providing a measure of long run low pay. This probability is given by:

$$P'_{ict} = \Pr(\bar{y}_{ct} + \omega_{ict}^P < y_t^*) = \Phi[(y_t^* - \bar{y}_{ct}) / \sigma_{\omega ct}^P] , \tag{10}$$

where $\sigma_{\omega ct}^P$ is the standard deviation of long term earnings for cohort c in year t. P'_{ict} can be estimated by evaluating $\Phi[\ ]$ at the low pay probit estimates from (9) scaled by the factor $\sigma_{\omega ct} / \sigma_{\omega ct}^P$, which can be computed from estimated variance components models.

Low pay probabilities computed according to (9) and (10) are illustrated in Figure 2. Low pay is defined as two-thirds the median of the male earnings distribution and is computed from the INPS panel. In order to allow for variation over time in the low pay threshold besides changes in median earnings of the estimation sample, the sample used for estimating the threshold has been enlarged in two directions. First, employees born in 1928 and 1929 and from 1966 to 1970 have been included. Second, no age constraint has been applied for inclusion in the sample.

For older birth cohorts aggregate probabilities present increasing trends over the period, particularly during the last couple of years. Intermediate cohorts, on the other hand, present flat profiles: even if their within group earnings dispersion tended to increase (see Figure 1), these variations were not enough to increase the likelihood of low pay, since employees from this cohorts are located in high earnings quantiles. For younger cohorts, finally, the low pay probability rises again, showing that low pay is more likely at the start of the carrier compared to intermediate phases. Life cycle effects are evident from the estimated probability of long term low pay. In particular, for older cohorts aggregate and permanent low pay profiles practically coincide, a result which is consistent with the positive covariance between intercepts and slopes of individual earnings profiles found in the previous Section: Given that earnings profiles diverge over the life cycle, individuals in low pay in one year at later stages of their career are very likely to be experiencing a long term low pay event. For younger cohorts, on the other hand, these effects are counteracted by the larger earnings volatility, and virtually none of the aggregate low pay likelihood can be ascribed to the long run component. For all cohorts, however, we can note that the relevance of permanent low pay increases over time, consistently with the rising importance of the long term component singled out in the previous section, and the last couple of time periods mark a sharp increase in low pay persistence for all cohorts.

Minimum distance estimates can be utilised to compute the probability of repeated low pay over a sequence of years, providing an additional perspective on low pay persistence. In particular, one should expect the rise in low pay persistence singled in Figure 2 to result in an increase in the probability of being continuously low paid. The normality assumptions made above imply that $\omega_{ic} \sim N_{Tc}(\mathbf{0},\mathbf{\Sigma_c})$, where ω_{ic} is the – say – column vector of mean adjusted earnings for individual i in cohort c, $\mathbf{0}$ is a column vector of zeros, $\mathbf{\Sigma_c}$ is the earnings autocovariance matrix implied by the model for cohort c and N_{Tc} is the multivariate normal distribution of dimension Tc.[22] Thence, the joint probability of a sequence of low pay states, say between t-k and t, is given by:

$$P_{kct} = \Phi_{k+1}[\hat{\mathbf{b}}_{\mathbf{c(t-k)t}};\hat{\mathbf{\Omega}}_{\mathbf{ct}}] \tag{11}$$

where, $\hat{\mathbf{b}}_{\mathbf{c(t-k)t}}$ is the (k+1) vector containing estimated coefficient on year dummies from the pooled cross-sections low pay probit for birth cohort c between (t-k) and t, $\hat{\mathbf{\Omega}}_{\mathbf{ct}} = diag(\hat{\sigma}_{ct})^{-1}\hat{\mathbf{\Sigma}}_{\mathbf{ct}}diag(\hat{\sigma}_{\mathrm{ct}})^{-1}$ is the correlation matrix of log-earnings – $\hat{\mathbf{\Sigma}}_{\mathbf{ct}}$ is the sub-matrix of the estimated $\mathbf{\Sigma}_c$ referring to the [t-k, t] interval and $diag(\hat{\sigma}_{\mathrm{ct}})$ is the diagonal matrix

[22] I am assuming that the earnings panel is balanced within each cohort. For individuals with discontinuous earnings histories, the multivariate normal distribution will be of dimensions Tc-h, where h is the number of "holes". The relevant covariance matrix will be given by Σ_c deprived of rows and columns corresponding to such "holes".

of the square roots of the diagonal elements of $\hat{\mathbf{\Sigma}}_{\mathbf{ct}}$ – and Φ_{k+1} is the (k+1)-variate normal c.d.f..[23] It is worth nothing that the sample analogues of these probabilities can be computed only for individuals who are continuously observed over the k+1 years, while the arguments of the multivariate normal in (11) are estimated using the whole unbalanced panel: the only arguments of (11) that need individuals to have continuous earnings histories over the (k+1)-year window in order to be estimated are the correlation coefficients in the off-diagonal corners of $\hat{\mathbf{\Omega}}_{\mathbf{ct}}$.

Figure 3 provides the evolution over the sample period of the estimated probability of being continuously low paid for 3 and 5 years. Since the probability of being continuously low paid decreases with the length of the interval considered, the 5-year series lies below the 3-year one in each of the years considered. Both series present upward trends, indicating that repeated low pay events have become more frequent from the late 1970s to the mid-1990s. Moreover, the two series tend to evolve in parallel, consistently with the fact that widening differentials are driven by the long term component: had the transitory earnings component had a relevant role, we should have observed 3-year probability to rise more rapidly compared to the 5-year series. Finally, the life cycle patterns observed for cross-sectional 1-year low pay in Figure 2 are also present now, repeated low pay being more likely for cohorts at the extremes of the life cycle compared to intermediate groups.

5 The covariates of earnings components

With the exception of workers' year of birth, I have made no use of the set of individual characteristics available in the INPS data set so far. In a sense, this 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 earnings persistence.[24] 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 the previous sections.[25] Also, institutional developments in the Italian wage setting framework point towards the relevance of occupational earnings differentials, as

[23] Multivariate normal integrals are computed via simulation, in particular by applying the so-called GHK simulator.

[24] Typical of the literature is to consider the covariance structure of "adjusted earnings", i.e. residuals from first stage regressions that include some observable attributes. Alternatively, Dickens (2000) estimates earnings components models within groups defined according to occupational classifications.

[25] Flinn (2001) suggests that this case might be relevant also for Italy.

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).

A possible strategy to assess the relevance of observable attributes consists in removing their impact from raw earnings. Changes in parameter estimates with respect to the previous sections would then reflect the features of earnings differentials between the cells defined by the attributes removed from raw earnings. Given the available information, I focus on occupation, the firm size, sectoral affiliation and inter-firm mobility and estimate cohort-specific OLS log-earnings regressions including each of the four effects in turn, specified as dummies defined according to the splits reported in Table A1, fully interacted with year dummies. Residuals from these regressions measure deviations from the cohort-specific mean of a given group in each year. Estimating the covariance structure of earnings profile on these sets of "adjusted earnings", however, did not always produce statistically significant parameter estimates for the covariance structure of earnings profiles, as could result from the reduction of variation in empirical moments induced by the "adjustment".[26] I therefore proceeded by estimating an alternative earnings process that imposes fewer restrictions on the individual-specific part of long term earnings, namely one in which the long-term component is constant over the life cycle. In order to capture variation across cohorts, I also introduce a set of cohort-specific coefficients κs:

$$\omega_{ict} = \kappa_c \pi_t \mu_i + \lambda_c \tau_t v_{it} \tag{2.b}$$

Results from this experiment are reported in Appendix Table A2 which also includes as benchmark evidence from the estimation of model (2.b) on the empirical moments analysed in Section 2, i.e. without removing the effect of observable characteristics.[27] In this latter case, the growth of long term inequality is estimated to be 110% over the sample period (i.e. $\pi_{1995}{}^2$-1). When the effect of occupation is removed from raw earnings (column 2) the heterogeneity

[26] The variance of intercepts was estimated to be negative and with a t-ratio of 0.997 when firm size dummies where included in the first stage regression, while it was positive with a t-ratio of 0.234 when industry was taken into account.

[27] These latter results (Table A2, column 1) can also be compared with the ones from Table 2, providing insights on the implications of different modelling choices. There are three main differences between the two cases. First, the variance of individual specific intercepts is larger in Table A2, where it represents a combination of heterogeneity at the start and over the life cycle, rather than reflecting only initial heterogeneity as in Table 2. Second, estimates of calendar time shifters on the long term component are larger in Table A2, given that they also pick up growing dispersion over the life cycle within each cohort. Note, however, that time trends in these coefficients are similar in the two cases. Third, the variance of innovations is larger in Table A2. This result might arise from the fact that for the oldest cohort (i.e. the one used to normalise cohort specific shifters) earnings variation is predominantly captured by the age related component when the growth rate heterogeneity model is adopted, so that suppressing this source of heterogeneity inflates shocks volatility.

coefficient σ^2_μ drops by more than 50%, while the growth of long term inequality is reduced to 46%. Also, heterogeneity across cohorts in both earnings components is less pronounced after removing occupational differentials. Overall, these results suggest that occupation is a relevant element of long term differentials. As long as the long term component represents ability, these findings indicate that a relevant share of skill heterogeneity arises between occupational groups. Removing the effect of the other observable characteristics (columns 3, 4 and 5 of Table A2), also affects the size and growth of long term inequality (as should be expected), but the impact is not dramatic as the one of workers' occupation.

Another possibility for investigating the impact of observable characteristics is to directly specify them in the earnings model. Since Table A2 showed that occupation is the single most important factor in explaining long term inequality while less substantive changes in result occur for other observable characteristics, I will focus on modelling occupational differentials from now onwards. In particular, I allow long term earnings profiles to shift according to occupational status:

$$\omega_{ict} = \pi_t(\mu_i + \gamma_i a_{it} + \theta_i q_{it} + \varphi_i \tilde{a}_{it} q_{it}) + \lambda_c \tau_t v_{it} \tag{2.c}$$

where q_{it} is a dummy taking value 1 if the individual holds a non-manual occupation in year t and 0 otherwise, while $\tilde{a}_{it} = a_{it}$ if $a_{it} \geq 30$ and 0 otherwise.[28] The coefficients μ_i and γ_i now represent intercepts and slopes of individual-specific profiles that would apply if all individuals in the sample were manual workers. For non-manual workers, two additional individual-specific coefficients apply. θ_i represents the shift of the overall profile that occurs for a non-manual worker compared to the case in which he was a manual worker. For individuals starting their careers as non-manual workers, it represents idiosyncratic "initial" ability within the non-manual earnings distribution, while for those changing occupation from manual to non-manual during the sample period it picks up the "step" occurring in the earnings profile due to such change.[29] φ_i represents the differential in earnings growth characterising non-manual compared to manual workers; since differential growth between occupations might be difficult to identify at early stages of the career, I allow the shift φ_i to apply after age 30.[30]

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[28] White collars and managers are amalgamated within the group of non-manual workers. This choice is motivated by the tiny proportion of managers in the sample, which might complicate estimation of individual specific earnings profiles for this group. Cappellari (2000) restricts the attention to white collars and reaches conclusions similar to those presented in the paper.

[29] Recalling that changes of occupation are rather infrequent in the sample (see footnote 8), we can assume that in practice θi is a good proxy initial heterogeneity for non-manual long term earnings.

[30] Attempts at estimating the occupational differential since age 25 led to implausible results such as negative point estimates of $\sigma^2\mu$ and $\sigma^2\gamma$.

I assume that first and second order moments of individual specific coefficients are given by:

$$(\mu_i, \gamma_i, \theta_i, \varphi_i) \sim [(0,0,0,0); (\sigma^2_\mu, \sigma^2_\gamma, \sigma^2_\theta, \sigma^2_\varphi, \sigma_{\mu\gamma}, \sigma_{\varphi\gamma}, 0,0,0,0)]. \qquad (3.b)$$

The variances of intercepts and slopes measure initial and life-cycle earnings heterogeneity under the hypothesis that all individuals were employed in manual occupations during the sample period. On the other hand, the variances of individual-specific shifters, σ^2_θ and σ^2_φ, capture the contributions to long term heterogeneity that arise within the earnings distribution of non-manual workers. The covariance of intercepts and slopes measure the extent of earnings convergence over the life cycle for manual workers, whereas the covariance between shifters indicates if patterns of convergence are amplified within non-manual careers. The four potentially identifiable cross-occupational covariances have been set equal to zero since when they were included among moments restrictions the minimum distance estimator encountered convergence problems.[31]

Second moments of long term earnings are now given by:

$$\begin{aligned} E(\omega^P_{ict}\omega^P_{ic(t-k)}) = \pi_t \pi_{(t-k)} \{ & \sigma^2_\mu + [E(a_{it}) + E(a_{i(t-k)})]\sigma_{\mu\gamma} + E(a_{it}a_{i(t-k)})\sigma^2_\gamma + \\ & E(q_{it}q_{i(t-k)})\sigma^2_\theta + [E(\tilde{a}_{it}q_{it}) + E(\tilde{a}_{i(t-k)}q_{i(t-k)})]\sigma_{\theta\varphi} + E(\tilde{a}_{it}q_{it}\tilde{a}_{i(t-k)}q_{i(t-k)})\sigma^2_\varphi \} \end{aligned} \qquad (5.b)$$

which clarifies how additional coefficients are identified thanks to the proportion and the age of non-manual workers contributing to the computation of empirical earnings moments.

Table 3 presents results from the estimation of the model with occupation specific individual earnings profile. Allowing for occupational effects considerably reduces the variances of both intercepts and slopes compared to Table 2. The precision of the estimated σ^2_μ is also reduced. The variances of occupational shifters are both statistically significant at usual confidence levels. In order to assess the quantitative impact of these coefficients on earnings differentials, it has to be noted from equation (5.b) that their contribution to the estimated covariance structure is weighted by the proportions of non-manual workers in the sample. For example, the overall variance of individual specific coefficients not related to age is $\sigma^2_\mu + E(q_{it}q_{i(t-k)})\sigma^2_\theta$. Computed at the start of the career (when the average proportion of non-manual workers is 21%) this quantity amounts at 0.0104+0.21*0.1414=0.04, which is twice its analogous in Section 2. On the other hand, the implied variance of slopes is given by $\sigma^2_\gamma + E(q_{it}q_{i(t-k)})\sigma^2_\varphi$ and

[31] Cross-occupation covariances are identified by individuals moving from a manual to a non-manual occupation. As illustrated above, there are few changes of occupational status in the INPS sample. This suggests that the available information is not adequate for identifying these additional coefficients and might explain the difficulties encountered in estimation.

amounts at 0.0002: although the proportion of non-manuals varies across ages – it is 29% at 30, 36% at 40 and 29% at 58 – these variations are negligible in that at the fourth decimal digit slopes dispersion is constant across ages. Finally, the implied overall covariance between "intercepts" and slopes, computable as $\sigma_{\mu\gamma}+(E(q_{it})+E(q_{i(t-k)}))\sigma_{\theta\varphi}$, ranges from 0.0004 at age 30 to 0.0002 at age 40 and again 0.0004 at 58; these latter computations however, are based on a rather imprecisely estimated covariance between shifters of intercepts and slopes. These results indicate that within the distribution of manual workers earnings profiles are more homogeneous compared to non-manuals, both at the start of the career and during the life cycle. On the other hand, the association between initial and life-time heterogeneity is more pronounced compared to non-manuals, suggesting that initial positions in the earnings distributions are a better predictor of life-time earnings.

The introduction of occupation specific coefficients has an impact also on estimated coefficients in other parts of the model relative to Table 2. For example, the variance of initial conditions of the AR(1) is now smaller: since for birth cohorts that start the life cycle after 1979 this coefficient is identified using the same information that identifies time invariant heterogeneity, the observed drop is a consequence of the larger overall dispersion of intercepts that can be picked up thanks to occupational effects. Another difference can be observed for calendar time shifters on the long term component, that are now smaller compared to Table 2, though their evolution remains unchanged.

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 estimates of dynamic earnings processes and their implications for inequality. Results show that the driving force behind widening differentials is long term inequality, and that its effect works through two distinct channels.

First, initial earnings differentials are amplified over the life-cycle, as could be the case if those who have more schooling – and thus larger starting earnings– are also faster in learning skills on-the-job, thus experiencing quicker growth. Second, the overall distribution of permanent earnings widens since the second half of the 1980s, as could results from a shift of labor demand against the unskilled. Such an outcome is also in line with the type of wage policies implemented during the decade, which were aimed at re-establishing differentials in favour of skilled non-manual after the era of wage egalitarianism.

Parameter estimates have next been used to assess the consequences of inequality for labor market segmentation by analysing low pay probabilities. I find that for individuals at the end of the earnings career low pay probabilities are almost entirely due to the long term earnings component, consistently with the life-time divergence of long-term earnings singled out by the minimum distance analysis. On the other hand, young cohorts witness a remarkable rise in the share of low pay probability that can be ascribed to the long run component between mid-1980s and mid-1990s, possibly as a result of the structural labor market changes discussed above. I also analysed the probability of sequencies of low pay events, showing that the remarks above also apply to the probability of repeated low pay events.

Finally, I exploited the availability of workers occupation to condition the long term earnings component upon occupational status and found that life-time divergence is a feature on non-manual earnings career, while blue collar workers tend to evolve along homogeneous earnings profiles.

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Table 1: Descriptive regression of the earnings autocovariance matrix (t-ratios[(a)])

Lag structure			Calendar time effects			Birth cohort effects		
Lag			Year			Cohort		
1	-0.022	(84.62)	*1980*	-0.004	(3.10)	*1933-35*	-0.028	(2.60)
2	-0.031	(91.73)	*1981*	-0.009	(6.10)	*1936-38*	-0.034	(3.32)
3	-0.038	(95.13)	*1982*	-0.012	(7.39)	*1939-41*	-0.045	(4.56)
4	-0.044	(94.96)	*1983*	-0.002	(0.86)	*1942-44*	-0.071	(7.42)
5	-0.051	(95.52)	*1984*	0.002	(1.09)	*1945-47*	-0.107	(11.95)
6	-0.057	(94.23)	*1985*	0.010	(5.33)	*1948-50*	-0.123	(14.05)
7	-0.062	(91.95)	*1986*	0.015	(7.52)	*1951-53*	-0.137	(15.66)
8	-0.068	(90.78)	*1987*	0.025	(12.38)	*1954-56*	-0.152	(17.47)
9	-0.074	(88.33)	*1988*	0.032	(15.40)	*1957-59*	-0.175	(20.01)
10	-0.079	(86.14)	*1989*	0.036	(16.42)	*1960-62*	-0.198	(22.63)
11	-0.085	(84.39)	*1990*	0.045	(19.94)	*1963-65*	-0.229	(26.13)
12	-0.090	(80.99)	*1991*	0.052	(22.15)			
13	-0.095	(78.15)	*1992*	0.061	(24.63)			
14	-0.098	(73.50)	*1993*	0.066	(25.46)			
15	-0.100	(66.14)	*1994*	0.078	(28.70)			
16	-0.105	(56.73)	*1995*	0.093	(30.73)			
Constant				0.244 (28.73)				
R2				0.99				
N. obs[(b)]				N=67768; T×N=935333				

Notes:

a) Asymptotically robust t-ratios computed using earnings fourth moments

b) Observations used for estimating earnings moments, regression uses 1399 earnings variance and covariances

Table 2: Minimum distance estimates (asymptotic robust standard errors in parentheses)

Long term component			Transitory component		
$\sigma^2\mu$	0.0212	(0.0073)	$\sigma^2\varepsilon$	0.0148	(0.0033)
$\sigma^2\gamma$	0.0002	(0.00003)	$\sigma^2 0$	0.0452	(0.0115)
$\sigma\mu\gamma$	0.0018	(0.0003)	ρ	0.9414	(0.0093)
Year			Year		
1980	0.9725	(0.0075)	*1980*	0.8768	(0.0228)
1981	0.9101	(0.0095)	*1981*	0.7650	(0.0296)
1982	0.8591	(0.0108)	*1982*	0.7047	(0.0320)
1983	0.8723	(0.0129)	*1983*	0.7164	(0.0351)
1984	0.8477	(0.0142)	*1984*	0.6893	(0.0369)
1985	0.8408	(0.0155)	*1985*	0.7039	(0.0395)
1986	0.8353	(0.0165)	*1986*	0.6725	(0.0393)
1987	0.8543	(0.0182)	*1987*	0.6700	(0.0412)
1988	0.8455	(0.0193)	*1988*	0.6702	(0.0423)
1989	0.8489	(0.0204)	*1989*	0.6037	(0.0405)
1990	0.8560	(0.0215)	*1990*	0.6088	(0.0438)
1991	0.8581	(0.0232)	*1991*	0.5936	(0.0449)
1992	0.8918	(0.0251)	*1992*	0.5567	(0.0462)
1993	0.8935	(0.0250)	*1993*	0.5368	(0.0500)
1994	0.9745	(0.0265)	*1994*	0.4603	(0.0533)
1995	1.0494	(0.0302)	*1995*	0.4077	(0.0634)
			Cohort		
			1933-35	0.9402	(0.1608)
			1936-38	1.1325	(0.1700)
			1939-41	1.3716	(0.1762)
			1942-44	1.3896	(0.1721)
			1945-47	1.2120	(0.1461)
			1948-50	1.2676	(0.1533)
			1951-53	1.3109	(0.1591)
			1954-56	1.3825	(0.1718)
			1957-59	1.4227	(0.1846)
			1960-62	1.4634	(0.1979)
			1963-65	1.3955	(0.1988)
SSR	0.0768				
χ^2(d.f.)	9284.0895 (1350)				
N. obs[(a)].	N=67768; T×N=935333				

Notes:

a) Observations used for estimating earnings moments, regression uses 1399 earnings variance and covariances

Table 3: Minimum distance estimates conditional on occupational status (asymptotic robust standard errors in parentheses).

Long term component			Transitory component		
$\sigma^2\mu$	0.0104	(0.0077)	$\sigma^2\varepsilon$	0.0142	(0.0041)
$\sigma^2\gamma$	0.00013	(0.00006)	$\sigma^2 0$	0.0309	(0.0101)
$\sigma\mu\gamma$	0.0014	(0.0008)	ρ	0.9311	(0.0108)
$\sigma^2\theta$	0.1414	(0.0411)			
$\sigma^2\varphi$	0.0004	(0.0002)			
$\sigma\theta\varphi$	-0.0016	(0.0014)			
Year			Year		
1980	0.9713	(0.0077)	*1980*	0.8220	(0.0347)
1981	0.9046	(0.0108)	*1981*	0.7097	(0.0399)
1982	0.8482	(0.0131)	*1982*	0.6634	(0.0391)
1983	0.8607	(0.0163)	*1983*	0.6801	(0.0416)
1984	0.8325	(0.0185)	*1984*	0.6707	(0.0436)
1985	0.8222	(0.0203)	*1985*	0.6995	(0.0467)
1986	0.8134	(0.0222)	*1986*	0.6639	(0.0456)
1987	0.8303	(0.0245)	*1987*	0.6569	(0.0479)
1988	0.8187	(0.0257)	*1988*	0.6634	(0.0495)
1989	0.8145	(0.0272)	*1989*	0.5841	(0.0454)
1990	0.8171	(0.0307)	*1990*	0.5897	(0.0499)
1991	0.8147	(0.0324)	*1991*	0.5719	(0.0505)
1992	0.8456	(0.0345)	*1992*	0.5157	(0.0507)
1993	0.8318	(0.0379)	*1993*	0.5193	(0.0571)
1994	0.8821	(0.0444)	*1994*	0.4548	(0.0594)
1995	0.9302	(0.0541)	*1995*	0.4105	(0.0710)
			Cohort		
			1933-35	0.9755	(0.2102)
			1936-38	1.1357	(0.2144)
			1939-41	1.3616	(0.2201)
			1942-44	1.3750	(0.2187)
			1945-47	1.1221	(0.1819)
			1948-50	1.2051	(0.1946)
			1951-53	1.2754	(0.2038)
			1954-56	1.3788	(0.2226)
			1957-59	1.4256	(0.2352)
			1960-62	1.5354	(0.2576)
			1963-65	1.6551	(0.2924)
SSR	0.0731				
χ^2(d.f.)	8951.0160 (1347)				
N. obs.	N=67815; T×N=992218				

Figure 1: Predicted variances by birth cohort

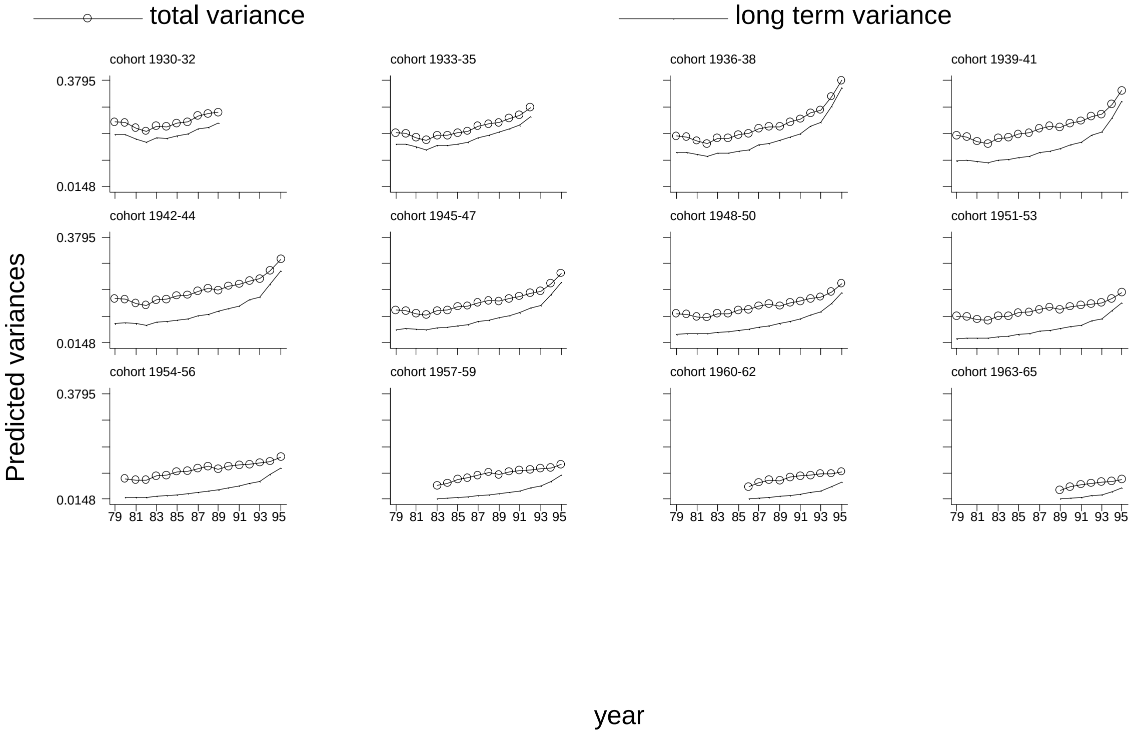


Figure 2: Predicted low pay probabilities by birth cohort

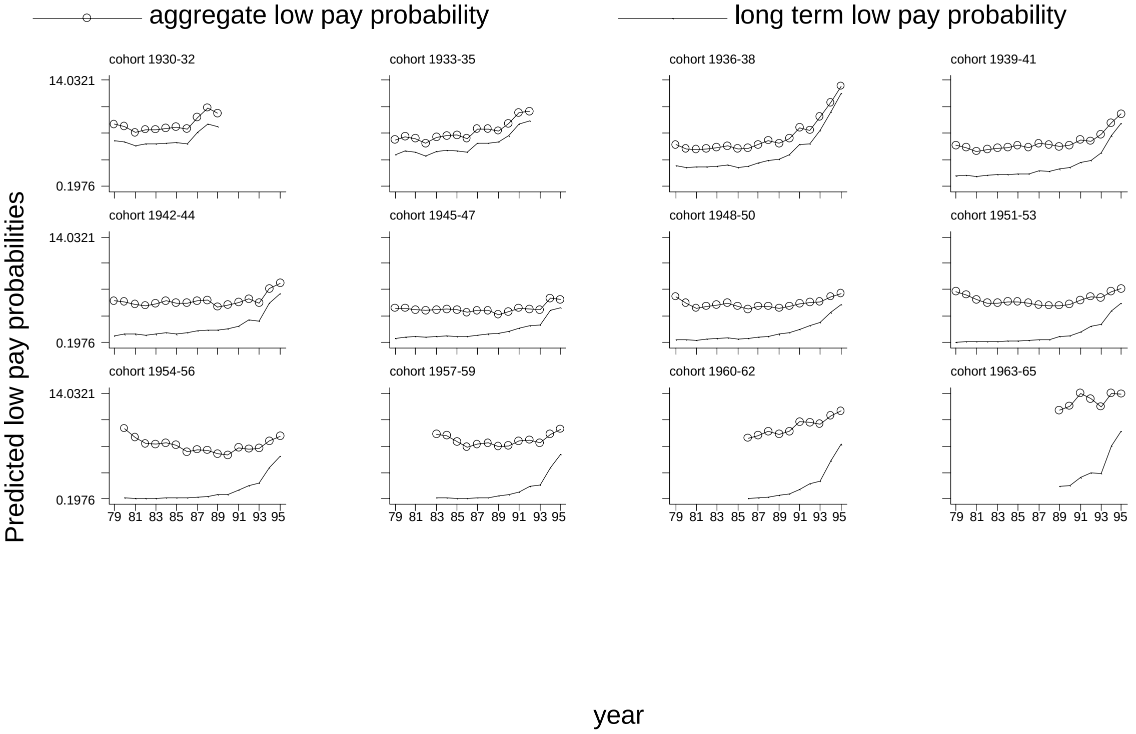
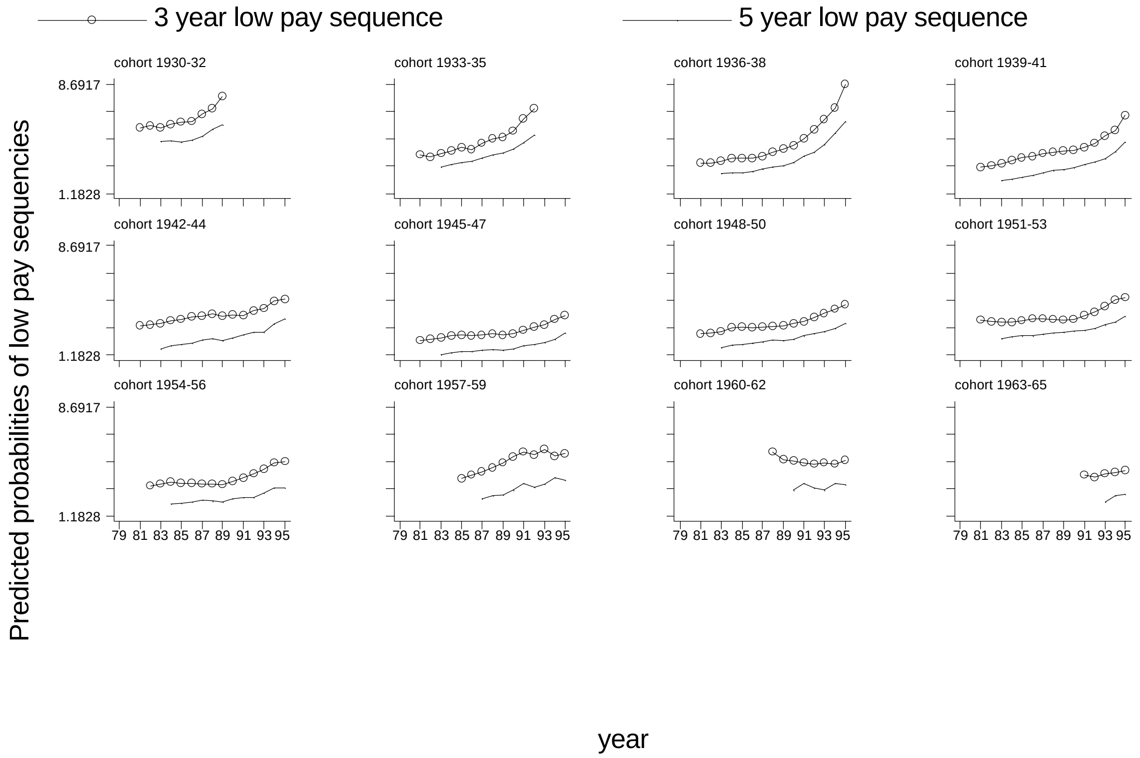


Figure 3: Predicted probabilities of low pay sequences by birth cohort



Appendix tables

Table A1: Sample description

	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995
Average age	36.48	36.12	37.08	38.04	37.73	38.65	39.65	39.40	40.40	41.37	41.16	41.28	42.13	42.91	42.74	43.48	43.92
Birth cohorts																	
1930-32	0.07	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.04	0.00	0.00	0.00	0.00	0.00	0.00
1933-35	0.11	0.09	0.09	0.09	0.08	0.08	0.08	0.08	0.08	0.08	0.07	0.06	0.06	0.05	0.00	0.00	0.00
1936-38	0.13	0.11	0.11	0.11	0.10	0.10	0.10	0.09	0.09	0.09	0.08	0.09	0.08	0.08	0.07	0.06	0.05
1939-41	0.14	0.13	0.13	0.12	0.11	0.11	0.11	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.09	0.09	0.07
1942-44	0.13	0.12	0.12	0.11	0.10	0.10	0.10	0.10	0.10	0.10	0.09	0.10	0.10	0.10	0.11	0.10	0.09
1945-47	0.15	0.13	0.13	0.13	0.12	0.12	0.12	0.11	0.11	0.11	0.11	0.11	0.11	0.12	0.13	0.13	0.14
1948-50	0.15	0.13	0.13	0.13	0.12	0.12	0.12	0.11	0.11	0.11	0.11	0.11	0.11	0.12	0.13	0.13	0.14
1951-53	0.13	0.12	0.12	0.12	0.11	0.11	0.11	0.10	0.10	0.10	0.10	0.10	0.10	0.11	0.11	0.12	0.13
1954-56	0.00	0.11	0.11	0.11	0.10	0.10	0.10	0.09	0.09	0.09	0.09	0.09	0.10	0.10	0.11	0.11	0.11
1957-59	0.00	0.00	0.00	0.00	0.09	0.10	0.09	0.09	0.09	0.09	0.08	0.09	0.09	0.09	0.10	0.10	0.11
1960-62	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.09	0.09	0.10
1963-65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.06	0.06	0.06	0.07	0.07	0.07
Occupation																	
Blue collar	0.69	0.69	0.69	0.68	0.68	0.68	0.68	0.69	0.68	0.68	0.68	0.67	0.66	0.66	0.65	0.64	0.64
White collar	0.30	0.30	0.30	0.31	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.31	0.32	0.32	0.33	0.33	0.34
Manager	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03
Firm size																	
up to 15	0.16	0.16	0.16	0.17	0.18	0.19	0.19	0.20	0.19	0.19	0.19	0.19	0.18	0.18	0.19	0.19	0.19
between 15 and 99	0.24	0.25	0.25	0.25	0.25	0.26	0.26	0.26	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
between 100 and 499	0.20	0.20	0.20	0.20	0.20	0.19	0.20	0.19	0.20	0.20	0.20	0.21	0.21	0.21	0.21	0.21	0.21
more than 500	0.41	0.40	0.39	0.39	0.37	0.36	0.36	0.34	0.34	0.34	0.33	0.33	0.34	0.34	0.33	0.33	0.34
Industry																	
stone, clay, glass, basic	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	0.08	0.08	0.07	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	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.04
fabricated metal products	0.26	0.27	0.27	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.27	0.27	0.27	0.27	0.27	0.27	0.27

energy and chemicals	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.09	0.10	0.09	0.09	0.09	0.10	0.10	0.10	0.10	0.10
constructions	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.10	0.10	0.09
transports and	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	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	0.06	0.07	0.07	0.07	0.07	0.07	0.08
retail trade and other	0.08	0.09	0.09	0.09	0.09	0.09	0.09	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
others	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	0.07	0.07	0.07
Changed firm		0.13	0.15	0.11	0.10	0.10	0.10	0.10	0.10	0.09	0.10	0.11	0.12	0.10	0.09	0.10	0.13
Standard deviation log-earnings	0.43	0.40	0.39	0.38	0.40	0.40	0.41	0.40	0.42	0.43	0.42	0.43	0.43	0.44	0.44	0.46	0.46
Number of observations	44652	50626	51267	51677	57397	58344	58299	63272	63214	63028	64248	59643	57459	54763	47792	46705	42947

Table A2: Minimum distance estimates removing the impact of observable attributes from raw earnings (asymptotic robust standard errors in parentheses)

	Without controls		Controls for occupation	
	Long term component	Transitory component	Long term component	Transitory component
$\sigma^2\mu;\sigma^2\varepsilon$	0.1878 (0.0090)	0.0249 (0.0033)	0.0798 (0.0043)	0.0419 (0.0031)
$\sigma^2 0$		0.0462 (0.0050)		0.0707 (0.0037)
ρ		0.9348 (0.0050)		0.7374 (0.0056)
Year				
1980	1.0014 (0.0071)	0.8162 (0.0202)	1.0205 (0.0080)	0.8465 (0.0161)
1981	0.9673 (0.0087)	0.6853 (0.0228)	0.9924 (0.0097)	0.7742 (0.0210)
1982	0.9355 (0.0097)	0.6376 (0.0239)	0.9530 (0.0105)	0.7696 (0.0237)
1983	0.9793 (0.0109)	0.6416 (0.0258)	1.0078 (0.0117)	0.7784 (0.0248)
1984	0.9779 (0.0118)	0.6180 (0.0263)	1.0109 (0.0126)	0.7538 (0.0257)
1985	0.9898 (0.0126)	0.6465 (0.0282)	1.0224 (0.0136)	0.7784 (0.0274)
1986	1.0058 (0.0132)	0.6240 (0.0278)	1.0634 (0.0144)	0.6908 (0.0231)
1987	1.0479 (0.0143)	0.6359 (0.0290)	1.1010 (0.0156)	0.6922 (0.0239)
1988	1.0549 (0.0151)	0.6525 (0.0301)	1.0853 (0.0163)	0.7597 (0.0264)
1989	1.0786 (0.0167)	0.6053 (0.0287)	1.0963 (0.0172)	0.6673 (0.0218)
1990	1.1051 (0.0178)	0.6276 (0.0304)	1.0877 (0.0183)	0.7179 (0.0252)
1991	1.1364 (0.0196)	0.6173 (0.0305)	1.1045 (0.0191)	0.7146 (0.0238)
1992	1.2055 (0.0218)	0.5988 (0.0308)	1.1202 (0.0200)	0.7162 (0.0243)
1993	1.2368 (0.0249)	0.5844 (0.0313)	1.0829 (0.0208)	0.7454 (0.0258)
1994	1.3681 (0.0270)	0.5496 (0.0310)	1.1435 (0.0218)	0.7903 (0.0282)
1995	1.5194 (0.0360)	0.5134 (0.0335)	1.2274 (0.0265)	0.7568 (0.0283)
Birth Cohort				
1933-35	0.9226 (0.0281)	0.9608 (0.0661)	0.9319 (0.0291)	0.9959 (0.0341)
1936-38	0.8875 (0.0261)	0.9287 (0.0668)	0.8863 (0.0272)	0.9459 (0.0306)
1939-41	0.8520 (0.0244)	0.9781 (0.0622)	0.8557 (0.0254)	0.9711 (0.0295)
1942-44	0.7385 (0.0218)	1.1739 (0.0672)	0.8162 (0.0242)	1.0147 (0.0306)
1945-47	0.6251 (0.0179)	1.1638 (0.0636)	0.7686 (0.0216)	0.9359 (0.0275)
1948-50	0.5500 (0.0163)	1.2056 (0.0651)	0.7338 (0.0208)	0.9481 (0.0280)
1951-53	0.5153 (0.0161)	1.1484 (0.0627)	0.7144 (0.0212)	0.9347 (0.0278)
1954-56	0.4680 (0.0151)	1.1553 (0.0634)	0.6782 (0.0205)	0.9810 (0.0291)
1957-59	0.4422 (0.0143)	1.0982 (0.0627)	0.6371 (0.0204)	0.9643 (0.0297)
1960-62	0.3973 (0.0144)	1.0943 (0.0641)	0.5844 (0.0203)	0.9199 (0.0299)
1963-65	0.3104 (0.0166)	1.1406 (0.0736)	0.5018 (0.0215)	0.8962 (0.0354)
SSR	0.0596		0.0266	
χ2 (d.f.)	9069.9512 (1352)		7413.1262 (1352)	
N. Obs	N=67768; T×N=935333		N=67768; T×N=935333	

Table A2 (continued)

	Controls for firm size		Controls for industry	
	Long term component	Transitory component	Long term component	Transitory component
$\sigma^2\mu;\sigma^2\varepsilon$	0.1332 (0.0075)	0.0331 (0.0041)	0.1339 (0.0078)	0.0241 (0.0030)
$\sigma^2 0$		0.0513 (0.0048)		0.0464 (0.0046)
ρ		0.9076 (0.0052)		0.9199 (0.0048)
Year				
1980	1.0127 (0.0080)	0.7806 (0.0210)	0.9865 (0.0091)	0.7920 (0.0195)
1981	0.9931 (0.0103)	0.6635 (0.0246)	0.9710 (0.0112)	0.7058 (0.0233)
1982	0.9733 (0.0115)	0.6245 (0.0262)	0.9412 (0.0128)	0.6841 (0.0255)
1983	1.0094 (0.0132)	0.6354 (0.0280)	0.9597 (0.0143)	0.6777 (0.0272)
1984	1.0095 (0.0142)	0.6064 (0.0281)	0.9547 (0.0157)	0.6709 (0.0283)
1985	1.0249 (0.0155)	0.6474 (0.0304)	0.9719 (0.0170)	0.6977 (0.0303)
1986	1.0368 (0.0162)	0.6180 (0.0292)	0.9862 (0.0178)	0.6868 (0.0302)
1987	1.0709 (0.0175)	0.6351 (0.0301)	1.0044 (0.0190)	0.6895 (0.0309)
1988	1.0632 (0.0187)	0.6736 (0.0316)	1.0255 (0.0204)	0.7207 (0.0325)
1989	1.0748 (0.0203)	0.6334 (0.0301)	1.0425 (0.0224)	0.6879 (0.0317)
1990	1.1070 (0.0218)	0.6616 (0.0317)	1.0835 (0.0241)	0.6988 (0.0328)
1991	1.1400 (0.0239)	0.6536 (0.0316)	1.1085 (0.0259)	0.6989 (0.0330)
1992	1.2077 (0.0265)	0.6433 (0.0318)	1.1635 (0.0289)	0.6829 (0.0334)
1993	1.2581 (0.0301)	0.6327 (0.0314)	1.2059 (0.0330)	0.6742 (0.0340)
1994	1.3413 (0.0329)	0.6378 (0.0321)	1.3150 (0.0363)	0.6579 (0.0344)
1995	1.4545 (0.0425)	0.6193 (0.0336)	1.4151 (0.0468)	0.6392 (0.0371)
Birth Cohort				
1933-35	0.9253 (0.0538)	0.9691 (0.0336)	0.9855 (0.0595)	0.9189 (0.0336)
1936-38	0.9497 (0.0533)	0.9216 (0.0316)	0.9738 (0.0575)	0.9029 (0.0322)
1939-41	0.9221 (0.0489)	0.9085 (0.0297)	0.9990 (0.0536)	0.8541 (0.0297)
1942-44	1.0533 (0.0525)	0.7984 (0.0267)	1.1204 (0.0579)	0.7725 (0.0273)
1945-47	1.0424 (0.0498)	0.6750 (0.0219)	1.0923 (0.0542)	0.6466 (0.0228)
1948-50	1.0709 (0.0508)	0.5846 (0.0195)	1.1376 (0.0559)	0.5621 (0.0205)
1951-53	1.0348 (0.0493)	0.5247 (0.0191)	1.1052 (0.0544)	0.5022 (0.0205)
1954-56	1.0233 (0.0497)	0.4604 (0.0178)	1.0996 (0.0550)	0.4557 (0.0192)
1957-59	0.9475 (0.0484)	0.4354 (0.0175)	1.0343 (0.0540)	0.4406 (0.0187)
1960-62	0.8991 (0.0469)	0.4066 (0.0182)	1.0079 (0.0537)	0.4077 (0.0196)
1963-65	0.8873 (0.0546)	0.3384 (0.0219)	1.0284 (0.0620)	0.3324 (0.0240)
SSR	0.0480		0.0454	
$\chi 2$ *(d.f.)*	8724.2180 (1352)		8425.3796 (1352)	
N. Obs	N=67768; T×N=935333		N=67768; T×N=935333	

Table A2 (continued)

	Controls for interfirm mobility	
	Long term component	Transitory component
$\sigma^2\mu;\sigma^2\varepsilon$	0.1882 (0.0091)	0.0255 (0.0033)
$\sigma^2 0$		0.0465 (0.0050)
ρ		0.9355 (0.0049)
Year		
1980	0.9877 (0.0072)	0.8021 (0.0202)
1981	0.9583 (0.0088)	0.6830 (0.0230)
1982	0.9220 (0.0097)	0.6349 (0.0242)
1983	0.9662 (0.0111)	0.6379 (0.0260)
1984	0.9623 (0.0119)	0.6118 (0.0265)
1985	0.9768 (0.0128)	0.6459 (0.0285)
1986	0.9946 (0.0134)	0.6198 (0.0280)
1987	1.0323 (0.0145)	0.6360 (0.0292)
1988	1.0404 (0.0154)	0.6521 (0.0303)
1989	1.0626 (0.0170)	0.6059 (0.0290)
1990	1.0946 (0.0181)	0.6251 (0.0305)
1991	1.1281 (0.0199)	0.6163 (0.0306)
1992	1.1902 (0.0222)	0.6000 (0.0311)
1993	1.2314 (0.0253)	0.5794 (0.0313)
1994	1.3599 (0.0275)	0.5449 (0.0310)
1995	1.5124 (0.0365)	0.5123 (0.0336)
Birth Cohort		
1933-35	0.9224 (0.0284)	0.9666 (0.0651)
1936-38	0.8873 (0.0264)	0.9318 (0.0654)
1939-41	0.8525 (0.0247)	0.9813 (0.0611)
1942-44	0.7390 (0.0221)	1.1676 (0.0660)
1945-47	0.6252 (0.0181)	1.1555 (0.0623)
1948-50	0.5490 (0.0164)	1.1980 (0.0639)
1951-53	0.5144 (0.0162)	1.1392 (0.0614)
1954-56	0.4684 (0.0153)	1.1422 (0.0620)
1957-59	0.4436 (0.0144)	1.0814 (0.0611)
1960-62	0.3991 (0.0145)	1.0795 (0.0626)
1963-65	0.3111 (0.0167)	1.1247 (0.0719)
SSR	0.0621	
χ2 (d.f.)	10058.8950	
N. Obs	N=67768; T×N=935333	