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Earnings Dynamics, Inequality and Firm Heterogeneity

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Abstract
Studies of individual earnings dynamics typically ignore firm heterogeneity, whereas worker and firm decompositions of earnings inequality abstract from the life-cycle. We study firm effects in individual earnings dynamics for the Italian private sector population, leveraging the covariance structure of co-workers earnings for identification. Our model allows for dynamics of both worker and firm effects, worker-firm sorting, worker segregation and correlation of firm effects among connected firms. While firms explain most of the earnings inequality when workers are young, workers explain most over the life cycle. Sorting of workers across firms is substantial, especially for younger workers. Standard earnings dynamics models overstate the relevance of individual heterogeneity.

JEL Codes: J24, J31
Keywords: Earnings inequality, Earnings dynamics, Co-workers' covariance

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1. Introduction

Understanding individual earnings dynamics is the subject of a large literature. Labor economists have studied the earnings process to distinguish the long-term determinants of wage inequality from wage instability, relating the former to heterogeneity in human capital investments and returns and the latter to labor deregulation (Baker and Solon, 2003; Moffitt and Gottschalk, 2012; Blundell, Graber and Mogstad, 2015; Magnac, Pistolesi and Roux, 2018; Hoffmann, 2019). Household economists and macroeconomists have characterised the statistical properties of labor incomes to understand patterns of consumption and the role of alternative policies for insuring income risk (Meghir and Pistaferri, 2004, 2011; Huggett, Ventura and Yaron, 2011; Blundell, 2014).

Studies of earnings dynamics often acknowledge the relevance of firm heterogeneity. There are several mechanisms through which the interaction between workers and firms may have an impact on life-cycle earnings. On-the-job, wages are affected by employer learning, informal insurance provision and firm-specific human capital accumulation. Worker mobility following employer and worker search for better matches is reflected in wage changes. While these theoretical mechanisms have found varying degrees of empirical support, a direct empirical assessment of the role played by firm heterogeneity in shaping earnings dynamics and inequality over the life cycle is still largely missing in the literature.[1]

To study the extent to which firms account for unequal earnings dynamics over working lives, in this paper we extend the standard earnings dynamics model to incorporate firm heterogeneity. Using data on the population of Italian private sector firms and workers, we estimate the stochastic earnings process resulting from individual- and firm-specific shocks over the life cycle, distinguishing between permanent and transitory shocks at both the worker and firm levels. We allow for the dynamics of firm effects, sorting of workers across firms, co-worker segregation – the tendency of similar individuals to work together— and for the correlation of firm-specific effects among firms

[1] Studies allowing for match-specific effects in wage dynamics, without accounting for firm-specific unobserved heterogeneity, include Low, Meghir and Pistaferri (2010) and Altonji, Smith and Vidangos (2013).

connected by worker mobility. We identify earnings variance components exploiting the empirical auto-covariance structure of earnings for both individuals and co-workers. While the covariance of individual earnings has been widely investigated (see among others Baker and Solon, 2003, Moffitt and Gottschalk, 2012, and Hoffmann, 2019) we are the first to study earnings dynamics leveraging the intertemporal covariance of co-worker wages.

The literature on firm effects in individual earnings dynamics is still scant and ours is among the few papers providing evidence about this interrelationship. Friedrich et al. (2019) use Swedish employer-employee wage and balance sheet data to estimate a structural model linking life-cycle wage shocks and firm productivity shocks, allowing for endogenous worker mobility between firms. We use only earnings data and do not model worker mobility, which allows us to make weaker assumptions – about second moments, rather than about the functional form of the shock distributions as would be required with more processes. Furthermore, we allow for non-idiosyncratic heterogeneity between workers and firms (sorting), among co-workers (segregation) and among connected firms, all features that are harder to incorporate in a structural framework.

Besides individual earnings dynamics, our paper is also closely related to the literature decomposing wage inequality into worker- and firm-specific effects abstracting from life-cycle considerations. In a perfectly competitive labor market, firm-specific wage premia would be wiped out and their existence is usually interpreted as violation of the 'law of one price' (Card et al., 2018). Abowd, Kramarz and Margolis (1999, AKM henceforth) were the first to successfully tackle the estimation challenges of modelling worker- and firm- specific effects, showing that their identification is feasible with two-way Fixed Effects (FE) models when data are available on the set of firms that are connected by chains of worker mobility. Their results for France show that worker heterogeneity is more important than firm heterogeneity in explaining wage inequality. Furthermore, they were able to estimate the degree of sorting – the extent to which high- (low-) wage workers work for high- (low-) wage firms – finding positive correlations, albeit of modest size.

Card, Heining and Kline (2013) spurred a resurgence of interest in questions of worker and firm effects, adapting the AKM framework to the analysis of changes in wage inequality. Estimating the AKM model on various sub-periods, they show that in Germany the increase in wage inequality 1985-2009 was driven by widening distributions of both worker- and firm-specific wage premia, and that sorting increased between periods. Card, Cardoso and Klein (2016) consider the implication of firm-specific wage premia and sorting for gender pay gaps in Portugal. They show that women tend to sort into lower paying firms compared with men, and that a combination of sorting and bargaining effects explains a fifth of the gender pay gap. Song et. al (2019) applied the AKM framework to population data for the US, considering five periods of seven years to find an increasing share of overall earnings inequality due to between-firm inequality. Decompositions show that this growth of firm-related inequality stems equally from worker sorting into firms and worker segregation.

Recent studies highlight that AKM-type estimators produce inconsistent decompositions of earnings dispersion due to limited mobility bias. Because firm effects are identified from worker mobility between firms, without sufficient mobility standard AKM models overestimate the share of earnings variance due to firms, and underestimate the sorting correlation between worker and firm effects, often finding a negative correlation. While awareness of these biases is not new, it is only recently that researchers have begun effectively making adjustments.[2] Kline, Saggio and Sølvsten (2020) introduce a bias-corrected estimator for the variance components showing that compared with the standard AKM-based decomposition, in the bias-corrected decomposition the weight of worker-firm sorting increases while the weight of the firm-specific component decreases. Using data for various countries, Bonhomme et al. (2022) apply this bias correction and a Correlated Random Effect (CRE) model, showing that both methods succeed in overcoming the limited mobility bias that plagues standard AKM-based variance decompositions.[3] Comparing FE with bias-robust estimates,

[2] The importance of handling limited mobility bias when deriving variance decompositions from two-way FE models was highlighted by Andrews et al. (2008), who proposed a bias correction derived under homoscedasticity assumptions.
[3] CRE models of variance components for worker and firm heterogeneity were introduced in Woodcock (2008).

they show that adjusting for bias causes the estimated share of wage variance accounted for by firm effects to decline from around 20 percent to 10 percent, and the share of wage variance due to sorting to increase from around 8 percent to 15 percent. Lachowska et al. (2022) apply the bias-corrected estimator to data from Washington State while allowing for time varying firm effects, showing that firm effects are highly persistent.[4]

We extend the standard earnings dynamics model, akin to those of Baker and Solon (2003), Moffitt and Gottschalk (2012) and Hoffmann (2019), to encompass firm heterogeneity. As with CRE, for identification our model relies on moment restrictions of co-worker covariances. In both approaches, the parameters to be estimated are the variance components themselves, rather than the fixed effects. Identifying moment restrictions irrespective of worker mobility, these models do not suffer from limited mobility bias. In contrast to the CRE model of Bonhomme et al. (2022), where individual effects are constant, we use co-worker covariances to supplement the moment restrictions on individual covariances that are typical of the standard earnings dynamics model.

We apply our model to wages from the Italian private sector 1985-2016. Italian wage setting features national contracts bargained at the industry level (with a coverage rate of about 80 percent) and complementary firm-level bargaining meant to adjust wages to local economic conditions. There is no legal minimum wage and wage floors are established in national contracts. Institutional changes over the last 20 years have been mostly aimed at increasing employment flexibility through the diffusion of temporary work contracts and, more recently, relaxing firing restrictions for permanent contracts. Previous reforms focussed on wage flexibility. During the 1970's an egalitarian system of wage indexation against inflation known as *Scala Mobile* (literally, escalator) caused a great compression of wage differentials between skill groups, a system that was reformed and eventually abolished in the 1980's (Erickson and Ichino, 1995; Manacorda, 2004). These changes formed the

[4] Lachowska et al. (2022), estimating a time-varying AKM model, allow firm effects to vary over calendar time while assuming worker effects to be fixed, as in the other studies of this literature. In another exercise, estimating separate bias corrected AKM models for different time periods, they find worker and firm effects to both be highly correlated between periods.

background for a re-opening of wage differentials throughout the 1990's and early 2000's (Hoffmann, Malacrino and Pistaferri, 2022).

We consider men aged 25 to 55 to limit issues of endogenous labour force participation, because a large proportion of women are outside the labor force with caring responsibilities, young individuals are making education and training decisions, and older individuals are often eligible for early pension benefits. Following the convention used in earnings dynamics studies, we estimate wage differentials by year of birth to separate life-cycle from calendar time variation. In our model, individual wages evolve over the life cycle through the arrival of shocks. Shocks can be long-lasting or transitory, and can be person- or firm-specific. Person-specific shocks accumulate during the life cycle as a consequence of, e.g., the accumulation of human capital, promotions, or worker mobility. Individual wages also evolve because of firm-specific shocks common to all co-workers. The model includes transitory earnings shocks both at the individual- and at the firm-specific levels. All types of shocks are allowed to impact the earnings process through period-specific loading factors that capture calendar time variation in the earnings distribution.

Traditionally, studies using the AKM approach keep firm effects constant and only recently researchers have allowed for changing firm effects, see Lachowska et al. (2022). We allow firm-specific effects to change with the age of the firm, because the firm's ability to impact wages may change as the firm ages. Furthermore, we allow for three different correlations. First, firm-specific effects may be correlated with individual-specific shocks, capturing the possibility of worker-firm sorting. Second, individual-specific effects may be correlated among co-workers, capturing the possibility of worker segregation, e.g., similar individuals working for the same firm. Third, firm effects may be correlated among firms connected by worker mobility, capturing the possibility that similar firms employ the same workers over time.

We find that, on average over the life cycle, person effects account for 60 percent of wage inequality, while firm effects and worker-firm sorting each account for about 15 percent, with the remainder due to transitory shocks. However, these averages mask tremendous variation over the working career. Among young workers, person-specific and firm-specific factors are equally important in accounting for earnings dispersion, each explaining about 30 percent of total inequality. Conversely, person effects account for 70 percent of earnings inequality for workers in their mid-50s, while firm effects only account for 8 percent.

The growing importance of worker heterogeneity over the life cycle suggests that both human capital accumulation and the search for better worker-firm matches require some time to impact wage inequality, and that firm differences are very relevant in the meantime. Over the life cycle, wage variance growth is non-linear, expanding faster for young than for middle-aged workers. This non-linearity is reflected in the sorting of workers across firms, which is strongest early in the career. While the worker-firm sorting correlation is 0.3 on average, it falls from 0.4 to 0.2 over the working life.

We find that more than half of earnings dispersion is explained by differences between firms, most of which is due to worker segregation. Measuring worker segregation as the correlation of person fixed effects for co-workers of the same age, we find a substantial correlation of 0.46. Similarly, we find a substantial 0.37 correlation of firm effects for firms connected by worker mobility.

Our model nests standard individual earnings dynamics models without firm effects and exploiting this property we show that the standard model overstates the importance of individual earnings dynamics in explaining life-cycle inequality, especially for young and prime age workers. Finally, considering regional variation, we find that firm effects and worker segregation contribute less to inequality in the North of Italy than in the South, a finding consistent with a better functioning labor market in the North.

The paper is organized as follows. The next section describes the population-based linked employer-employee data that we use. In Section 3 we set up the econometric model, while in Section 4 we present some descriptive statistics for the intertemporal covariance of individual and co-worker earnings. Section 5 discusses the baseline results, while Section 6 examines differences by geography. Section 7 concludes.

2. Data

We draw data from the archives of the Italian Social Security Institute (*Istituto Nazionale di Previdenza Sociale*, INPS) covering the population of firms and workers in the private non-agricultural sector of the Italian economy. The main source of information is the form that employers have to complete in order to pay state pension contributions for their employees, a form that is digitized from 1983. In this form employers report gross pay, covering all forms of monetary compensation and including employee pension contributions and labor income taxes. Besides the amount of gross pay, for each employment spell employers report total working days, start and end dates (start dates are censored at February 1974) and broad occupational categories (apprentices, blue collar, white collar or manager). These spell data are supplemented with firm-level information about location, date of establishment and date of closure. While spell data include workplace location, we maintain firms as the unit of analysis on the employer side.

Demographic information on workers includes gender and year of birth, but not education. Focusing on men to limit issues of endogenous labour force participation, for each man in each year we define the *prevalent employer* as the firm where he is employed for the most working weeks, excluding cases with prevalent employers of less than 8 full-time-equivalent weeks. We drop left-censored spells, i.e. where a prevalent employment that is ongoing in January 1983 started before February 1974. The resulting dataset matches all employers and male employees in Italy between 1983 and 2016, including 3,493,326 firms and 14,021,258 workers, totalling 192,112,742 person-year observations over the period.

We use data beginning in 1985 because digital records for 1983 and 1984 are incomplete. In keeping with much of the literature on individual wage dynamics we consider working careers between ages 25 and 55 to reduce selection out of the labor market. We exclude apprentices and managers, representing 0.5 and 1.5 percent of observations. We derive gross daily wages as the ratio between the gross annual pay with the prevalent employer and the corresponding number of full-time equivalent working days.

Because we are chiefly interested in life-cycle dynamics, we select individuals by year of birth, so that we can observe a certain portion of the life cycle for each cohort, and reconstruct the full life-cycle from age 25 to 55 by overlapping cohorts. To help identifying life-cycle profiles, we require that each cohort is observed for at least 10 years. Consequently, cohorts participating in the analysis range from those born in 1939 (aged 46 in 1985 and observed ten times until age 55 in 1994) to those born in 1982 (aged 25 in 2007 and observed ten times until aged 34 in 2016). The cohort structure of the data is represented in Figure 1.A. Two birth cohorts (1959 and 1960) are observed throughout the 25-55 age range, while the number of observations for other cohorts progressively decreases moving away from these two central cohorts. Each cohort born before 1954 or after 1979 accounts for between 1.5 and 2 percent of individuals in the sample, whereas each remaining cohort accounts for between 2 and 3 percent. We also require that individuals within cohorts are actually observed for at least five consecutive years.[5] We further winsorize the resulting wage distribution at the top and bottom 0.5 percent by year.

Applying the above selection rules gives an estimation sample of 12,216,798 men and 3,067,753 firms between 1985 and 2016, corresponding to 152,470,973 person-year earnings observations. Figure 1.B contrasts average age in the estimation sample with average age for the population of men aged 16-65. While there is some difference between the two, the former being slightly younger before the early 2000s and slightly older afterwards due to the revolving-by-cohort design of the data, especially after 2007, differences are not major. Next, we compare hourly wages for the estimation sample with the full population of men aged 16-65.[6] Figure 1.C shows no

[5] This selection rule is intermediate between that of Baker and Solon (2003) using continuous positive earnings sequences and Haider's (2001) approach, allowing individuals to move in and out of the sample, requiring only two positive, but not necessarily consecutive, earnings observations.
[6] We reflate nominal values to 2015 using the CPI.

substantial difference in average hourly wages between the two groups. Figure 1.D shows that similar trends between the estimation sample and the full population emerge also considering the standard deviation of logs, with the estimation sample consistently below the full population.

3. Econometric model

We allow earnings to evolve over the individual working life through the arrival of person-specific shocks, and firm-specific shocks common to all the workers employed by a given firm in the same year. Earnings shocks may be long-lasting or mean-reverting. Long-lasting shocks reflect persistent or slowly changing wage determinants. Mean-reverting shocks have transitory impacts reflecting economic volatility.

3.1 Model Specification

Let w_{ijt} denote the residualized log of daily earnings for worker i in year t and let $j = J(i,t)$ denote the firm in which i is employed in year t. We residualize raw log-earnings on a set of time dummies through cohort-specific regressions, such that residuals are centered on means by calendar year and birth cohort. This residualization is customary in the earnings dynamics literature and is also equivalent to the inclusion of age and calendar year controls in wage regressions within the AKM framework (see Baker and Solon, 2003; Bonhomme et al., 2022; Lachowska et al., 2022). Note that although wages are indexed by calendar year, the couple (i,t) unambiguously identifies the age of person i in year t, such that our notation effectively represents the individual life cycle.

We characterize residualized earnings through the following life-cycle model:

$$w_{ijt} = \alpha_t \lambda_{it} + \delta_t \phi_{jt} + \gamma_t \psi_{ijt} \tag{1}$$

where the components of earnings heterogeneity λ_{it} , ϕ_{jt}, and ψ_{ijt} are assumed to have an unconditional mean of zero, while the period loading factors α, δ and γ allow for aggregate changes in the wage distribution over calendar time. Following Hoffmann (2019), for identification we set the first two factor loadings – corresponding to 1985 and 1986—in each of the three groups equal to unity.

The first term on the right hand side of (1) represents the idiosyncratic persistent component resulting from life-cycle wage shocks that can stem from accumulation of, and returns to, human capital, or other sources of long-term wage changes, e.g., through job search and worker-firm matching. Life-cycle shocks permanently affect the age-wage profile irrespective of the firm at which person i is employed in a given year. Life cycle shocks are modelled as a unit root (Random Walk, RW) to allow for long-lasting effects of the shocks. Over the life cycle, the RW specification captures shock accumulation from age 25, which is the first age at which workers are observed in our sample design:

$$\lambda_{it} = \lambda_{i(t-1)} + u_{it} = \lambda_{i(c+25)} + \textstyle\sum_{k=c+26}^{t} u_{ik}; \quad (2)$$

$$var(\lambda_{i(c+25)}) = \sigma_{\lambda}^2;\ var(u_{it}) = \sigma_{u(t-c)}^2$$

where $c = c(i)$ is the year of birth of person i, such as $c + 25$ is the calendar year in which the earnings trajectory of person i conventionally starts, and $(t - c)$ is individual i's age in year t. The variance of the initial condition σ_{λ}^2 measures idiosyncratic wage dispersion at age 25, and the accumulation of shocks before age 25. Permanent shocks u_{it} are drawn from age-specific distributions with variance $\sigma_{u(t-c)}^2$ to allow their impact in shaping earnings inequality to change with age. For example, younger workers may have wages reflecting a greater variety of opportunities for learning on-the-job and for promotion compared to older workers. While studies of firm-based wage inequality typically assume that worker effects are constant, RW specifications for individual effects are standard in the life-cycle earnings literature (see e.g., Hoffmann, 2019).

The second term in Equation (1) represents firm effects, capturing firm-specific wage policies common to all co-workers. These effects determine the average position in the population earnings distribution for the employees of a given firm. Firm effects may originate from rent extraction, efficiency wages, or other frictions generating persistent wage heterogeneity among identical workers employed in different firms (Card et al., 2018). Monitoring technology or unions' ability to extract rents may vary over time. Lachowska et al. (2022) model time variation of firm effects by fully interacting them with calendar year dummies. We allow for time variation of firm effects in two ways. First, we account for calendar time variation of firm effects through the period shifters δ_t of Equation (1). Second, we allow for age-related variation by drawing firm-specific effects from a distribution that changes with the age of the firm, capturing the idea that firm heterogeneity may differ between younger and older firms. We model firm effects ϕ_{jt} as Random Effects (RE) with age-specific variances and unrestricted intertemporal covariances:

$$var(\phi_{jt}) = \sigma^2_{\phi(t-d)} \qquad\qquad cov(\phi_{jt}\phi_{jt'}) = \sigma_{\phi\phi(t-d)(t'-d)}$$

where $d = d(j)$ is the year in which the firm is established, such that $(t - d)$ represents the age of the firm in year *t*.

The third random component of Equation (1) ψ_{ijt} captures the impact of mean reverting shocks with short-lived effects on wages. We allow mean reverting shocks to depend on both individual-specific and firm-specific effects:

$$\psi_{ijt} = v_{it} + \xi_{jt}$$

It is customary in studies of individual earnings dynamics to include some form of autoregression in "transitory" wage shocks to accommodate gradual reversion to the mean (see e.g. Baker and Solon, 2003). Following this approach, we allow the individual-specific part of the shock to follow a non-stationary first-order autoregressive process (AR(1)), with cohort-specific initial conditions and innovations drawn from age-specific distributions:

$$v_{it} = \rho v_{i(t-1)} + \varepsilon_{it} \tag{3}$$

$$var(\varepsilon_{it}) = \sigma^2_{\varepsilon 26} g(t - c) \qquad\qquad var(v_{i(c+25)}) = \sigma^2_{vc}$$

where $v_{i(c+25)}$ is the initial condition of the process, $\sigma^2_{\varepsilon 26}$ is the variance of innovations at age 26, while the variance of subsequent innovations evolves with the exponential spline function $g(t-c)$.[7]

We specify firm-specific transitory shocks as a White Noise (WN) processes with innovations drawn from firm age-specific distributions:

$$var(\xi_{jt}) = \sigma^2_{\xi(t-d)}.$$

3.2 Moment restrictions and identification

Matching empirical second moments of the earnings distribution across cohorts and time periods to their counterparts implied by the model, the model is estimated by Minimum Distance (MD). To separate life-cycle wage variation from calendar time, we derive empirical moments by year of birth, and stack all cohort-specific moments into a single moment vector for estimation.

We assume that transitory shocks are uncorrelated among themselves and with everything else:

$$cov(\varepsilon_{it}, \xi_{jt'}) = cov(\varepsilon_{it}, \lambda_{it'}) = cov(\varepsilon_{it}, \phi_{jt'}) = cov(\xi_{jt}, \lambda_{it'}) = cov(\xi_{jt}, \phi_{jt'}) = 0, \forall t, t' \quad (4)$$

We model the sorting of workers into firms as the covariance between individual-specific and firm-specific effects. Because the individual-specific effects accumulate over the life cycle through the arrival of persistent shocks after age 25, we allow for a similar structure in the worker-firm sorting covariance:

$$cov(\phi_{jt}, \lambda_{it}) = \sigma_{\phi\lambda} + \sum_{k=26}^{(t-c)} \sigma_{\phi uk}. \quad (5)$$

While it is standard in the earnings dynamics literature to assume independence of individual-specific effects over individuals, studies of firm-based wage inequality highlight the relevance of worker *segregation*, the tendency of similar workers to be employed by the same firm (see Barth et

[7] The autocovariance function of the AR(1) process has a recursive structure (see Equation (8) later in the text) that depends on the initial condition. However, some cohorts are older than 25 when first observed, while the initial condition of the process is located at age 25. We handle this left censoring by modelling the variance of initial conditions for censored cohorts through cohort-specific parameters (see Baker and Solon, 2003). Because the autocovariance function of the RW process is closed form, RW initial conditions are not an issue.

al., 2016; Lopes de Melo, 2018; Song et al., 2019). One reason for segregation could be the sorting of workers into firms: if high-wage workers work in high-wage firms, then necessarily high-wage workers work together. However, even if worker- and firm-specific effects are uncorrelated, worker segregation may still emerge as consequence of informal labour market networks or residential segregation, because both factors imply that similar individuals work together.

Because we exploit co-worker wage covariances to derive moment restrictions, we need to characterize segregation. CRE models also need to deal with segregation. Bonhomme et al. (2022) wipe out individual *fixed* effects through first differencing before estimating co-worker covariances, thus eliminating segregation from the moment restrictions of the CRE. Such a strategy, however, would not be viable in our setting with life-cycle dynamics and calendar time effects, because differencing would not eliminate our time-varying individual-specific effects, and, consequently, would not eliminate segregation. We model segregation, rather than eliminating it, by allowing the individual-specific effects to be correlated among co-workers, where co-workers are defined as persons that have been observed working for the same firm, though not necessarily at the same time. Specifically, we allow segregation to be a fraction μ of the covariance of individual worker effects:

$$cov(\lambda_{it}, \lambda_{i't'}) = \mu cov(\lambda_{it}, \lambda_{it'}) \quad if\ J(i,t) = J(i',t') \tag{6}$$

Note that when $t = t'$ then $cov(\lambda_{it}, \lambda_{it'}) = var(\lambda_{it})$ and that for individuals i and i' of the same age $var(\lambda_{it}) = var(\lambda_{i't})$, then μ is the cross-sectional correlation coefficient of person-specific effects among co-workers of the same age.

One implication of the sorting of workers into firms is that, over time, an individual will tend to work in similar firms, such that firm-specific effects will be correlated for firms that are connected through worker mobility. Even in the absence of sorting of workers into firms, local firm agglomerations may contribute to such firm-firm correlations. We allow firm-specific effects to be correlated among firms connected by worker mobility. Bonhomme et al. (2022) assume zero correlation between groups of firms, and allow for within-group correlation. In our model, we relax the assumption that firm-specific effects are purely idiosyncratic and allow the cross-firm covariance among connected firms to be a fraction π of the covariance of firm-specific effects:

$$cov(\phi_{jt}, \phi_{j't'}) = \pi cov(\phi_{jt}, \phi_{jt'}) \text{ , } j = J(i,t),\ j' = J(i,t') \tag{7}$$

where π is the cross-sectional correlation of firm-specific effects for connected firms of the same age. Note that Equation (7) is the only equation of the model that requires mobility (i.e. firms j and j' are connected by worker i moving between them from t to t'), which implies that π is the only parameter in the model that needs the same individuals to be observed in different firms for identification, all remaining parameters being estimable even in the absence of mobility.

Given assumptions (4) – (7), the covariance of residualized individual log-wages between year t and $t' >= t$ is given by:

$$cov(w_{ijt}w_{ij't'}) = \underbrace{\alpha_t\alpha_{t'}\left(\sigma_\lambda^2 + \sum_{k=26}^{(t-c)}\sigma_{uk}^2\right)}_{worker\ permanent} + \tag{8}$$

$$\underbrace{\delta_t\delta_{t'}(\mathbb{I}[j=j'] + (1-\mathbb{I}[j=j'])\pi)\left(\sigma_{\phi(t-d)}^2\mathbb{I}[t=t'] + \sigma_{\phi\phi(t-d)(t'-d)}\mathbb{I}[t \neq t']\right)}_{firm\ permanent} +$$

$$\underbrace{(\alpha_t\delta_{t'} + \alpha_{t'}\delta_t)\left(\sigma_{\phi\lambda} + \sum_{k=26}^{(t-c)}\sigma_{\phi uk}\right)}_{worker-fir\quad sorting} + \underbrace{\gamma_t\gamma_{t'}\mathbb{I}[t=t']\sigma_{\xi(t-d)}^2}_{firm\ transitory} +$$

$$\underbrace{\gamma_t\gamma_{t'}\left(\mathbb{I}[t=t'=s]\sigma_{vc}^2 + \mathbb{I}[t=t'>s]\left(\sigma_{\varepsilon 26}^2 g(t-c) + var\left(v_{i(t-1)}\right)\rho^2\right) + \mathbb{I}[t \neq t']cov\left(v_{i(t-1)}v_{it'}\right)\rho\right)}_{worker\ transitory}$$

where $\mathbb{I}[\ ]$ is a binary indicator and $s = \max(1985, c + 25)$. Note that the correlation of firm effects across connected firms (π) only contributes to intertemporal wage persistence but not to cross-sectional wage dispersion (i.e. $\mathbb{I}[j = j'] = 1$ when $t = t'$ by construction). Also, because (8) is the covariance of *individual* wages, it does not depend on the segregation parameter μ, which only features in cross-worker moments. Thus, segregation does not affect overall wage inequality, but only the decomposition between/within firms (see also Song et al., 2019).

While permanent shocks contribute to the wage covariance function at all lags, transitory shocks either fade away rapidly with lags (individual-specific transitory shocks) or contribute exclusively to the wage variances at a single point in time (firm-specific transitory shocks). This contrast between shocks that persist with long lags versus shocks that fade away rapidly provides identification of permanent vs. transitory shocks.

In models of individual earnings dynamics without firm effects, permanent shocks over the life-cycle are identified by variation in the wage covariance function related to workers' age and their initial conditions are identified as the intercept of the age-related trends. We separate calendar time and age effects by computing the empirical covariance by birth cohort and by using all cohort-specific covariances simultaneously in estimation. Note, however, that in Equation (8) there are two broad sets of permanent earnings parameters related to worker age, a first set related to the life-cycle accumulation of RW shocks (σ_u^2) and a second set related to the life-cycle accumulation of the sorting covariance ($\sigma_{\phi u}$). Also, there are three (sets of) permanent earnings parameters that are constant with respect to worker age: the initial condition of the RW (σ_λ^2), the initial condition of the sorting covariance ($\sigma_{\phi\lambda}$) and the variances and intertemporal covariances of the firm effects (σ_ϕ^2 and $\sigma_{\phi\phi}$).[8] Intuitively, a single piece of information (the intertemporal covariance of individual wages in Equation (8)) can identify at most one set of age-related parameters and one set of parameters unrelated to age. Hence Equation (8) alone does not provide sufficient information for identifying all parameters of the permanent earnings component. To separate worker-specific effects from firm-related effects, additional information is needed.

The necessary information can be obtained by considering the *covariance of co-worker wages*, that is individuals i and i' working for the same firm at some point of their lives, i.e. $J(i,t) = J(i',t')$ for some t and t'. This covariance will reflect all the firm-related sources of wage variation

[8] The variance-covariance of firm effects varies with the age of the firm, and this dependence is identified by exploiting variation in average age of the firm across empirical earnings moments (both at the individual and co-worker level).

(permanent and transitory firm-specific effects, plus worker-firm sorting) and the fact that similar workers may work at the same firm independently of the characteristics of the firm, i.e., there may be worker segregation. The co-worker covariance is given by:

$$cov(w_{ijt}w_{i'jt'}) = \underbrace{\delta_t\delta_{t'}\left(\sigma^2_{\phi(t-d)}\mathbb{I}[t=t'] + \sigma_{\phi\phi(t-d)(t'-d)}\mathbb{I}[t\neq t']\right)}_{firm\,permanent} + \tag{9}$$

$$\underbrace{(\alpha_t\delta_{t'} + \alpha_{t'}\delta_t)\left(\sigma_{\phi\lambda} + \sum_{k=26}^{(t-c)}\sigma_{\phi uk}\right)}_{worker-fir\quad sorting} + \underbrace{\mu\alpha_t\alpha_{t'}\left(\sigma^2_\lambda + \sum_{k=26}^{(t-c)}\sigma^2_{uk}\right)}_{worker\,segregation} + \underbrace{1[t=t']\gamma_t^2\sigma^2_{\xi(t-d)}}_{firm\,transitory}$$

Equation (9) is the between-firm component of the wage covariance. Similar to Equation (8), separation of calendar time and age effects in Equation (9) is achieved by computing the empirical covariance by birth cohort and by using all cohort-specific covariances simultaneously in estimation. Combining Equations (8) and (9) gives two sets of age-dependent moment restrictions, identifying the two sets of age-related parameters (RW shocks and worker-firm sorting covariance). However, a similar identification argument does not apply for parameters that are not related to worker age, because in this case there are three (sets of) parameters (RW initial condition, sorting initial condition and the variance-covariance of firm-specific effects) and two sets of moment restrictions. We achieve identification constraining the initial condition of the sorting covariance by rescaling the RW initial condition using the ratio between life-cycle sorting covariances and RW life-cycle shocks to, i.e. we impose that:[9]

$$\sigma_{\phi\lambda} = \sigma^2_\lambda \sum_{k=26}^{(t-c)}\sigma_{\phi uk} \Big/ \sum_{k=26}^{(t-c)}\sigma^2_{uk}. \tag{10}$$

[9] Alternatively, we may simply fix this parameter to zero. This alternative strategy is akin to the one followed by Baker and Solon (2003) who, faced with the non-separability of initial conditions for a mixed RW-RG (Random Growth) process of life-cycle earnings, assumed that the initial condition of the RW was zero, such as the estimate of the initial condition of the RG would effectively be a convolution of the two parameters. In our case, assuming zero initial condition for worker-firm sorting covariance would inflate the estimated RW initial condition and the variances of the firm fixed effects. Importantly, due to the cumulative structure of sorting covariances, assuming away their initial condition would lead to underestimate sorting not only at age 25, but throughout the life-cycle. Empirically, using the constraint illustrated in the text or assuming a zero initial condition does not alter the estimates of remaining model parameters, or the ability of the model to predict empirical moments.

Equations (8), (9) and (10) plus the unit restrictions on the initial time loading factors provide the full set of restrictions on earnings second moments for workers and co-workers that are sufficient for identifying the model parameters. An important feature of these moment restrictions is that identification does not require workers to move between firms, and model parameters could be estimated even without mobility. The only parameter of the model requiring mobility for identification is the correlation of firm effects among firms connected through workers mobility (π), a parameter for which stayers, per se, are uninformative. In contrast to our model and the CRE approach, AKM-type two-way FE estimators require worker mobility for identification. To further illustrate that worker mobility is not needed for our model, in the Appendix (Table A2) we report estimates of the earnings dynamics model based only on stayers data.

3.3 Estimation

Let the earnings covariance defined by Equations (8), (9) and (10), be a non-linear function $f(\beta)$ of all model parameters collected in the vector β. The MD estimator minimises the quadratic distance between $f(\beta)$ and its empirical counterpart m, that is:

$$\beta = argmin[m - f(\beta)]'W[m - f(\beta)]$$

for some weighting matrix W. We follow most studies in the literature and set W equal to the identity matrix to avoid biases from sampling errors, resulting in the Equally Weighted Minimum Distance estimator (Altonji and Segal, 1996). We adopt a robust variance estimator:

$$Var(\beta) = (G'G)^{-1}G'VG(G'G)^{-1}$$

where V is the empirical fourth moments matrix and G is the gradient matrix evaluated at the solution of the minimisation problem (Haider, 2001).

4. Empirical covariance structures

We estimate cohort-specific wage covariances that we match to the set of moments discussed in the previous section to estimate the parameters of the model. There are two sets of moments of interest.

We estimate empirical moments of individual wages (denoted with I) by averaging the cross products of residualized log-wages across individuals:

$$m_{tt'}^{I} = \frac{\sum_i \omega_{ijt}\omega_{ij't'}}{\sum_i p_{ijt}p_{ij't'}} \tag{11}$$

where ω is the empirical counterpart of w in Equation (1), and p is an indicator for whether person i is observed in period t, thus allowing for an unbalanced panel.[10] Following other studies in the earnings dynamics literature, individuals entering or leaving the panel are assumed to be missing-at-random (see among others Haider, 2001; Baker and Solon, 2003; Blundell, Graber and Mogstad 2015; Hoffmann, 2019).

The co-worker covariance is estimated by adapting the weighting scheme of Page and Solon (2003) for the estimation of neighbourhood covariances in outcomes. First, the firm-specific covariance is estimated by averaging cross-products of log-wage residuals for all pairwise matches that can be formed across co-workers. Next, firm-specific covariances are averaged across firms using the square root of the number of pairwise matches as weights. The weighting procedure attributes more weight to larger firms and makes inference person-representative. For a given cohort, the co-worker covariance (denoted with C) is given by:

$$m_{tt'}^{C} = \sum_j \theta_j \frac{\sum_i \sum_{h>i} \omega_{ijt}\omega_{hjt'}}{\sum_i \sum_{h>i} p_{ijt}p_{hjt'}} \tag{12}$$

where $\theta_j = \sqrt{\sum_i \sum_{h>i} p_{ijt}p_{hjt'}} / \sum_j \sqrt{\sum_i \sum_{h>i} p_{ijt}p_{hjt'}}$ is the firm-specific weighting factor. For cohorts of up to 200 co-workers, we use all co-workers in the estimation of (12), while for larger cohorts, we use a random sample of 200 co-workers stratified by occupation.

There are 21,164 empirical moments in total, 10,582 each for individuals (estimated with Equation 11) and co-workers (estimated with Equation 12). We report estimated empirical moments over the life cycle in Figure 2. The line labelled "Total Variance" is the overall wage variance

[10] A discussion of MD estimation of earnings dynamics model with unbalanced panels is provided by Haider (2001).

estimated using deviations of individual wages from cohort means, averaging cohort variances across cohorts. Consistent with underlying heterogeneous wage dynamics across workers, the graph shows (left scale) a remarkable increase in overall wage inequality over the life cycle between ages 25 and 55. Consistent with the greater job mobility and training of younger workers, wage dispersion grows faster at the early stages of the career compared with mid-career. There is also an acceleration in the growth of dispersion after age 45, which could reflect greater labour market attachment at the tails of the wage distribution compared to the middle among older workers, because from the middle of the wage distribution (partial) early retirement is more common. Because our earnings dynamics model features age-specific variances of shocks, it can handle such changes in the nature of wage dispersion over the life cycle.

Figure 2 also reports a line labelled "Co-workers Variance", obtained using Equation (12) and providing a measure of how much co-workers *jointly* deviate from the overall cohort mean wage due to factors that are shared among co-workers. This line shows the evolution of wage dispersion between firms, due to either idiosyncratic firm effects or the similarities of wage-generating characteristics among co-workers, emerging from both the sorting of workers into firms and from worker segregation. The co-worker covariance does not reflect wage differentials due to purely idiosyncratic personal characteristics. Dispersion between clusters of co-workers follows an age profile that parallels that of overall dispersion, a similarity that is due to the heterogeneity of individual effects across workers, which contributes to between firm wage dispersion through segregation.

To rule out the possibility that the parallel evolution of total and co-worker variances is a statistical artefact related with ageing, Figure 2 also presents the life-cycle evolution of "Placebo Variance", which we obtain by using Equation (12) to match individuals to firms drawn at random from the economy. That there is only a negligible upward trend in dispersion among placebo co-workers, supports that the variance among true co-workers reflects a common firm effect, the sorting process underlying firm-worker matches, or worker segregation, and is not simply due to linking individuals born in the same year.

On the right scale of Figure 2, the share of variance between firms is derived as the ratio of co-worker variance to total variance, a share obtained in a fully non-parametric way, without estimating a model of worker or firm heterogeneity. There is a distinctive life-cycle decline in the relevance of between firm wage dispersion. At age 25, 70 percent of wage dispersion is due to between-firm heterogeneity. As workers age, the fraction of between-firm wage inequality declines, to 60 percent by age 55, which is consistent with the idea that individual-specific heterogeneity becomes increasingly important over working lives. On average over the life-cycle, 65 percent of wage dispersion is between firms. We disentangle individual-specific heterogeneity and the components of between-firm dispersion using the model estimates presented in the next section.

5. Baseline results

We begin the discussion of results by presenting model goodness-of-fit in Figure 3. Displaying the same sets of empirical moments of Figure 2 (without placebos), we overlay the corresponding moments predicted by the model, and perform the same exercise for the between-firm share of earnings inequality. Both for total and for co-worker variances, there is a close fit over the life cycle. The poorest fit appears to be for co-worker variance at age 25, with fitted variance marginally lower than the raw. However, fitted values rapidly catch up with raw variances, becoming indistinguishable from age 29. As a consequence, the same pattern emerges for the between-firm share of wage inequality (i.e., the ratio of co-worker variance to total variance), which is moderately under-estimated at age 25, with fitted and raw values converging by age 28. Recall from Section 3 that the parameter for the initial condition of the sorting process ($\sigma_{\phi\lambda}$) is not identified and we constrain it to equal the RW initial condition rescaled by the ratio of life-cycle sorting covariances to life-cycle RW shocks (see Equation 10). The evidence from Figure 3 suggests that, if anything, this parameter restriction has a mild predictive impact at age 25, quickly becoming irrelevant as life-cycle sorting covariances accumulate.

5.1 Permanent wages

We present estimates for the permanent component of the earnings dynamics model in Table 1. Panel A shows the estimated parameters for the variance of worker-specific effects derived from the RW process. The variance of the initial condition (σ_{λ}^2) captures not only the heterogeneity of individual-specific effects at age 25, but also the heterogeneity of individual wage histories up to that age. We account for life-cycle variation in the distribution of permanent shocks by allowing the variance of innovations to change at five-year intervals. Results suggest that the estimated life-cycle heterogeneity of earnings growth, as captured by the age-specific variances of innovations ($\sigma_{u(t-c)}^2$), evolves in two phases. First, wage dispersion grows substantially up to age 35, by about one quarter of the initial condition each year. Second, from the late 30's, the growth of earnings dispersion almost halves. This non-linearity is consistent with both a slow-down of human capital accumulation later in the career and with diminished job mobility for older workers. Overall, the life-cycle growth of person-specific wage dispersion is considerable: the variance of the RW is more than four times its initial level by age 40, and more than six times by age 55.

Panel B of Table 1 presents the estimates of the RE process for firm-specific effects. Variances of these effects are drawn from a distribution that changes with the age of the firm. While empirical moments vary by the age of individuals and not by the age of firms, for each moment we know the average age of the firms employing the workers. Computing the quartiles of these firm ages across all empirical moments, we allow the variance of firm effects to vary by firm age quartile ($\sigma_{\phi q}^2$). We model long-term persistence of firm-specific shocks through a set of cross-quartile covariances ($\sigma_{\phi qq}$). Estimated variances are sizeable and relatively stable over the firm age distribution. To put these variances in perspective, the average variance of the firm effect (0.0136) is approximately equal to the variance of the individual effects at the beginning of the careers, e.g., for a worker aged 28 ($\sigma_{\lambda}^2 + 3\sigma_{u26-30}^2 = 0.0134$). Also, the cross-period covariances of the firm-specific REs are sizeable, implying an average intertemporal correlation of 0.88.[11]

Panel C of Table 1 reports the parameters allowing for non-idiosyncratic heterogeneity, i.e., the sorting components between workers and firms (Panel C.1), worker segregation (Panel C.2) and firm connection (Panel C.3). The worker-firm sorting components of Panel C.1 ($\sigma_{\phi u(t-c)}$) are estimated as covariances between life-cycle shocks and the firm-specific effect. The life-cycle pattern of worker-firm sorting reflects individual life-cycle shocks in that it is larger for younger than for older workers. Indeed, the covariances between *innovations* of the individual-specific RW and the firm-specific RE become negative between ages 40 and 50. Negative covariances between innovations need not imply that sorting itself is negative, because at each age the sorting component of the wage covariance is given by the accumulation of all worker-firm sorting covariances up to that age due to the persistence of RW shocks. Our estimates imply that worker-firm sorting remains positive throughout the life-cycle, something we discuss in more detail later in the section. The negative covariance of innovations can be interpreted as a slowing down of the sorting process with age. For example, the probability that a high-wage worker leaving one high-wage firm can find a job in another high-wage firm may decline with age. The estimates imply that at age 40 the worker-firm sorting covariance is more than six times its initial level, but the covariance falls back to three times the initial level by age 50.

The instantaneous worker-firm sorting covariance becomes positive again for ages 51-55. As noted in the previous section, in that age range the growth of the empirical earnings variance accelerates and selective survival in the labour market due to, e.g., early retirement, could explain the pattern. This increase in worker-firm sorting above age 50 is consistent with early retirement due to workers that are negatively sorted into firms, for example high-wage workers (mis-)matched to low-wage firms.

[11] Lachowska et al (2022) report intertemporal correlations of firm-specific effects of similar size.

Panel C.2 reports the worker segregation parameter (μ), which is the loading factor of the covariance of individual effects into the co-worker covariance structure (Equation 9). This parameter measures the correlation of worker effects among co-workers of the same age. Worker segregation is sizeable, with a correlation coefficient of 0.46. Other studies measuring worker segregation using correlation coefficients report similar magnitudes. For example, Barth et al. (2016) estimate a segregation correlation on US data of around 0.35 based on observed workers' skills, which is consistent with our larger estimate based on all sources of workers heterogeneity – observed and unobserved. Lopes de Melo (2018) for Brazil reports a correlation of workers fixed effects of 0.52 after estimating an AKM model.

Panel C.3 reports the estimate of the correlation of firm-specific effects among connected firms. Firm connection correlation is smaller in magnitude than worker segregation, but is nevertheless still substantial at 0.36 and highly statistically significant. This estimate of firm connection indicates that part of the intertemporal persistence of wages stems from the fact that individuals tend to work for similar firms over time. We are not aware of any other estimates of this parameter.

5.2 Transitory wages

Table 2 reports estimates for the parameters of transitory wage components. In Panel A, worker-specific transitory parameters are given by an individual-specific non-stationary AR(1) with age-dependent innovations plus a firm-specific WN with age-dependent innovations. The spline coefficients for the age-dependency of the variance of AR(1) innovations indicate that these decline in the very first years of the observed working career, fluctuate at mid-career, before increasing at older ages. This broadly declining pattern of volatility is consistent with the evidence in the literature (see e.g., Baker and Solon, 2003). The degree of serial correlation in the AR(1) is moderate at 0.47, indicating that the impact of past shocks decays quickly, with, e.g., only about two percent of a shock surviving after five years. The serial correlation estimate is lower than those reported by Baker and Solon (2003; 0.7) or Hoffmann (2019; 0.8), neither of which considers firm-specific effects in the wage process. Indeed, as we show later in this section, ignoring firm effects increases the estimated AR(1) serial correlation. Finally, Panel A reports the estimated initial conditions, which are cohort-specific for left-censored cohorts (born 1939 through 1959), showing greater dispersion of initial conditions for uncensored cohorts, and a progressive reduction moving towards earlier cohorts.[12].

Panel B of Table 2 reports estimates of firm-specific transitory shocks, showing that their dispersion increases with the age of the firm, suggesting that workers in older firms may face more volatility of firm-specific wage effects compared to workers from younger firms. This pattern may reflect a greater propensity to access debt and equity markets –with consequent greater exposure to stock market volatility— as firms age.

5.3 Time effects

Figure 4 presents estimated factor loadings for the worker effects, firm effects, and transitory components.[13] Loadings on the individual components show a pronounced widening of permanent wage differentials between the mid-1980's and mid-1990's, with differentials remaining quite similar thereafter. The trend over the 1980's and 1990's resembles that of overall wage dispersion shown in Figure 1.D, suggesting that the growth of wage inequality in Italy has been driven by permanent wage differentials between workers over that period. The pattern is also in line with trends in labor productivity growth, which effectively stops around 2000 (see Figure 1 in Hoffmann, Malacrino and Pistaferri, 2022), consistent with the idea that aggregate shifts in the distribution of permanent earnings are driven by labor demand.

The period loading factors on the firm specific-components show greater fluctuations than loading factors for workers, and follow a pro-cyclical pattern. The correlation coefficient of the firm loadings with GDP growth is 0.55, while the correlation with the employment rate is 0.28. The pro-

[12] Baker and Solon (2003) report a similar pattern of initial conditions in Canadian social security records.
[13] Loading factors for 1985 and 1986 are set to unity for identification, see Hoffmann (2019).

cyclicality of firm wage heterogeneity is consistent with the pattern of firm entry and exit over the business cycle.

The last set of factor loadings in Figure 4 refers to the transitory wage component which declines over the 30 years spanned by our data. Most of this decline is due to the inclusion of firm effects in the model: estimating a standard earnings dynamics model without firm effects produces estimates of loading factors for the transitory components that do not decline over time, in contrast to those depicted in Figure 4.

5.4 Variance decompositions

In Figure 5 we report the variance decomposition implied by the model, corresponding to the variance components of Equation (8). At age 25, person-specific and firm-specific permanent shocks each account for about 30 percent of earnings dispersion, with a slightly smaller share (about 27 percent) due to person-specific transitory shocks. In contrast, at age 25 firm-specific transitory shocks explain less than 10 percent of the total variation, and even less (3 percent) is due to sorting. We argue at the beginning of this section that worker-firm sorting is underestimated at age 25, but underestimation quickly becomes irrelevant as sorting covariances accumulate over the life-cycle. For example, at age 30, the sorting component accounts for 20 percent of earnings dispersion, another 20 percent is explained by permanent firm heterogeneity, while transitory firm heterogeneity explains 5 percent of overall dispersion. In contrast, while individual-specific transitory shocks lose relevance as individuals age—their share of earnings inequality at age 30 is around 10 percent—individual-specific permanent inequality grows in importance, accounting for 45 percent of total earnings inequality at that age. The subsequent life-cycle development of earnings inequality shows that as workers age, the individual-specific component of permanent shocks becomes the predominant factor of earnings inequality, while all other factors (transitory shocks, firm effects and worker-firm sorting) lose relevance.

Overall, firm-related earnings factors (i.e., firm permanent and transitory effects and worker-firm sorting) are more relevant among younger than among older workers, with the firm-related share of total inequality being 45 percent at age 25 and 20 percent at age 55. On average over the life-cycle, the individual permanent component accounts for 59 percent of total dispersion, while the share of firm-specific permanent components is 14 percent; the individual-specific transitory shocks account for another 8 percent of overall inequality, while firm-specific transitory shocks account for 4 percent; finally, the remaining 15 percent is due to worker-firm sorting. Our estimates of the variance decomposition are in the range of those by Bonhomme et al. (2022) using bias corrected FE or CRE.

We already know from Figures 2 and 3 that about 60 percent of earnings inequality stems from between-firm heterogeneity and that this share declines somewhat over the life cycle.[14] The evidence from Figure 5 however shows that the relative importance of earnings components within the overall earnings distribution varies considerably over the life cycle, suggesting that this variation should also feature in the between-firm component of inequality. We provide a direct assessment of how the sources of between-firm earnings inequality change over the life cycle in Figure 6. Consistent with findings from the overall earnings distribution, Figure 6 shows that as workers age, segregation becomes the dominant component of between-firm dispersion, reflecting the growing relevance of worker heterogeneity, coupled with the fact that similar workers tend to work together. The life-cycle share of between-firm inequality due to worker segregation grows consistently from 25 percent at age 25 to 60 percent at age 55.

5.5 Sorting

Figure 7 illustrates the life-cycle evolution of the sorting covariances and correlations implied by the parameter estimates. All covariances and correlations are positive. The covariances (right scale) indicate that sorting initially grows at a relatively fast pace, reflecting both the underestimation of

[14] Barth et al. (2016) report that about 52% of earnings inequality is between establishment using US LEHD data. Using US social security records, Song et al. (2019) report that about one third of wage dispersion is between firms.

sorting at 25 and the fact that the covariances of RW innovations with firm effects between ages 26 and 30 are relatively large. The growth of sorting covariance levels-off and even becomes negative in mid- career, possibly reflecting that as workers age, it becomes less likely that high-wage workers leaving high-wage firms are re-hired at other high-wage firms. Figure 7 also shows the increase of sorting covariances over the final part of the life cycle, which as we have discussed, could reflect selective early retirement from the labour market.

To put our findings into perspective, Figure 7 also presents the evolution of sorting correlations, which are more informative than covariances about the strength of sorting, and also offer a metric for comparison with other studies. Sorting correlations follow a similar pattern to covariances in the initial years, after which correlations immediately start declining (in contrast to covariances that increase slowly before decreasing slowly), and both increase again from age 50. Correlations decline earlier than covariances because between ages 26 and 45 the growth of sorting covariances slows down, but the growth of individual-specific variances–belonging to the denominator of the correlation–does not slow (or slows to a lesser extent). This fact can be appreciated both from the variance decomposition of Figure 5, and from the parameter estimates of Table 1. On average throughout the life cycle the worker-firm sorting correlation is 0.28, a value that is in the range of estimates reported by Bonhomme et al. (2022) using either bias-corrected FE or CRE. Our average combines relatively large values around 0.4 at age 30 with relatively low values of less than 0.2 around age 50.

5.6 Comparison with a standard earnings dynamics model

Our model nests a standard individual earnings dynamics model with RW permanent shocks, AR transitory shocks and period-specific loading factors on each component. To the extent that worker and firm effects are correlated through sorting, by ignoring firm-specific heterogeneity, the standard model may exaggerate the importance of workers specific effects in explaining earnings inequality. To test this conjecture we estimate the standard earnings dynamics model using only the individual-level covariance structure. Estimates of the permanent wage component from the standard model in Panel A of Table 3 show that RW parameters are much larger than baseline estimates, for the initial part of the life-cycle, when firm heterogeneity matters most for explaining earnings dispersion. Also, the serial correlation of mean reverting shocks in the standard model is 0.65 (see Panel B of Table 3), in common with other individual earnings dynamics studies and larger than baseline 0.47.[15]

Figure 8 summarizes the findings from the standard model, showing the variance predictions over the life cycle. While the overall prediction is very close to that from the baseline model shown in Figure 3, the shares of earnings dispersion due to the individual permanent and transitory components are quite different. In the baseline, the share of permanent inequality went from 30 percent at the beginning of the life cycle to 75 percent at age 55, and the share due to individual transitory shocks went from 25 percent to less than 5 percent. In the standard specification underlying Figure 8, the model predicts that at age 25 about 60 (40) percent of inequality is due to individual-specific permanent (transitory) earnings, with the share becoming 80 (20) percent by age 55. These comparisons illustrate that the standard earnings dynamics specification without firm effects overestimates the relative importance of both the permanent and transitory individual components, especially while young, i.e., when firm effects and sorting matter the most.

6. Regional heterogeneity

Results from the previous Section highlight a prominent role of firm heterogeneity in accounting for earnings inequality in the early stages of the working life, before the influence of individual heterogeneity comes to dominate. Mechanisms behind this change in the relative importance of individual and firm heterogeneity are human capital accumulation and worker turnover, mechanisms that likely depend on how well the labor market and the economy as a whole function. In this respect, Italy offers the prospect of exploring how earnings dynamics differ between economic environments

[15] Estimates of period-specific loading factors for the standard earnings dynamics model without firm effects are reported in Appendix Table A3.

under a common institutional setting. One of the most salient features of the Italian economy is its regional divide. While regions in the north of the country feature large and innovative manufacturing firms, a well-developed financial sector and low unemployment rates, the South of the country is characterised by smaller firms concentrated on more traditional productions, and by relatively high unemployment especially among the youth. In terms of these contrasts, central regions fall somewhere in-between. These varying environments may well correspond to different patterns of earnings dynamics over the life cycle, especially in relation to firm heterogeneity, and in this Section we turn our attention to characterising these regional differences in earnings dynamics.

We split the estimation sample into three areas – North, Center, and South— based on the province of work.[16] The vast majority of person-year observations in the estimation sample has the province of work in the North (59 percent), followed by the Center (23 percent) and South (18 percent). Next, we assign individual earnings profiles to the area with most earnings observations; allocating 54 percent of individuals to the North, 24 percent to the Center and 22 percent to the South, with discrepancies between current and prevalent area being mostly due to temporary migrations to the North. The numbers of firms in the regional sub-samples are 1,685,499 (North), 952,386 (Center), 1,056,163 (South); a sum exceeding the firm count for the overall estimation sample due to multi-plant firms that may be located in several areas. Using the data partitioned by prevalent area, we re-estimate individual and co-worker moments and fit the earnings dynamics models separately by area.[17]

Table 4 presents estimates of the permanent earnings components by area; Table 5 presents estimates for the transitory components, and the period-specific loading factors are relegated to

[16] The North includes workers whose province of work is in the following regions: Valle d'Aosta, Liguria, Lombardia, Piemonte, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, Emilia-Romagna. The Center includes workers whose province of work is in the following regions: Toscana, Umbria, Marche, Lazio, Abruzzo. The South includes workers whose province of work is in the following regions: Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna.

[17] When estimating the earnings dynamics model on the sub-samples for the Center and South we adapted the age dependent specification for the variances of AR(1) innovations to overcome some convergence issues. Specifically, we reduced the number of spline knots beyond age 40 from three in the baseline model to two for the South and one for the Center. Also, the constrained estimation of the sorting initial condition described in Equation (10) resulted in convergence issues in the case of the Center, which we overcome by constraining the initial condition to zero.

Appendix Table A4. Comparing estimates of the individual-specific RW processes across areas, the South is very distinctive, especially at the beginning of the working career. In the South individual earnings dynamics among young workers are less important than in the rest of the country, with corresponding parameter estimates of between one half and a third of the size of those for the North or Center. This evidence for the South is consistent with difficulties in accumulating human capital on the job in the presence of high youth unemployment. Moreover, worker segregation and correlation of firm effects among connected firms are larger in the South than elsewhere. Another major difference by area is the level of firm heterogeneity, which is three times higher in the South than the North. Greater wage dispersion between firms may reflect a more rigid labour market and less worker reallocation/turnover, making firm-specific wage premia less likely to be competed away by worker mobility across firms.

We can see from Table 5 that transitory shocks are more persistent in the South, once again indicating greater labor market rigidity. Another contrast is the dispersion of firm-specific transitory shocks, which increases with firm age in the North and Center but not in the South. In Section 5 we have noted that the overall age pattern of firm-specific transitory shocks is consistent with greater exposure to stock market volatility among older firms, and evidence from Table 5 is consistent with more limited access to the stock market among southern firms than for firms in the rest of the country.

Figure 9 illustrates the implications of the estimates by area in terms of life-cycle variance profiles and between-firm variance shares, contrasting these with the corresponding empirical moments and between shares derived from the raw data. Both in the North and Center of Italy, overall earnings dispersion exhibits stronger growth before age 40 than after, replicating the pattern observed for the country as a whole, and consistent with greater worker turnover, more promotions, and faster human capital accumulation prior to age 40. The pattern from the South is in stark contrast, with little change in the growth of earnings dispersion over the life cycle, and the age gradient over the whole working life in the South resembling that for older workers in the North and Center. The other remarkable difference across areas is the share of variance between firms, ranging from 55 percent in the North to 70 percent in the Center and South.

There is much greater scope for individual heterogeneity to shape earnings trajectories in the North than elsewhere. This point is further illustrated in Figure 10, reporting variance decompositions over the life cycle. Compare the shares of variance due to the permanent individual component which is 45 percent at age 30 in the North, but only reaches 40 percent at age 40 in the South. Conversely, firm related wage components are more relevant throughout the working life in the Center and especially in the South than in the North. Figure 11 illustrates that worker-firm sorting is greater in the North than in the rest of the country.

7. Conclusion

By incorporating firm effects, we extend the standard empirical model of individual earnings dynamics based on permanent and transitory earnings shocks. Besides worker- and firm-specific heterogeneity, our model allows for worker-firm sorting, worker segregation and correlated heterogeneity among firms connected by worker mobility. While the standard model relies on restrictions on the empirical covariance structure of *individual earnings* for identification, to identify firm related earnings components we supplement these with restrictions on the covariance structure of *co-worker earnings*.

Besides the earnings dynamics literature, our paper is also related to the literature on firm-driven wage inequality. Our approach, based on the covariance structure of co-worker earnings, is akin to the Correlated Random Effect model of Bonhomme et al. (2022). For both approaches, identification does not require workers moving across firms, thereby avoiding the limited mobility bias that plagues two-way Fixed Effects specifications. Moreover, Bonhomme et al. (2022) highlight that absence of dynamics of both worker and firm effects could be a major source of miss-specification in two-way FE models. Lachowska et al. (2022) allow dynamics of firm effects while keeping worker effects constant. In our paper we allow for dynamics of both worker and firm effects.

Our results reveal a considerable degree of variation in the importance of workers and firms in shaping wage inequality over working lives. Firm-related heterogeneity is the dominant factor for explaining wage differences among young workers. As workers age, individual heterogeneity grows in importance, becoming the dominant factor for wage dispersion over the working life. The growth of worker heterogeneity is faster among young workers than for older workers, consistent with human capital investments and worker mobility that decline with age. The sorting of workers into firms is sizeable and characterised by life-cycle variation that reflects the evolution of individual heterogeneity, being strongest for young workers. We also find a good deal of worker segregation and firm-specific wage premia that are correlated among connected firms. Overall, about 60 percent of earnings inequality is due to wage differences between firms, the bulk of which stems from worker segregation.

We estimate our model using data on the population of private sector Italian employers and employees made available by the National Social Security Institute. Italy is an interesting context to study earnings dynamics because national wage floors co-exist with employer-set wage changes that are often worker-specific. Institutions, while important, are not the sole determinant of earnings dynamics, leaving scope for both worker and firm heterogeneity to play a role. In addition, Italy is characterized by a pronounced degree of regional variation in economic conditions, which we exploit to assess how earnings dynamics evolve in different economic contexts under a common institutional set-up.

For the South of Italy, we find firm-specific heterogeneity to be important throughout the working life, with worker-related heterogeneity growing more slowly over life-cycle than in the Center and North. Less individual heterogeneity is consistent with lower returns to human capital investments, returns that may suffer from career interruptions due to high youth unemployment. Greater firm heterogeneity is consistent with labour market frictions and less worker reallocation. Applying our model of individual earnings dynamics with firm effects to data from other countries would provide contrasting decompositions of inequality over the life cycle that could help improve our understanding of the functioning of labor markets more broadly.

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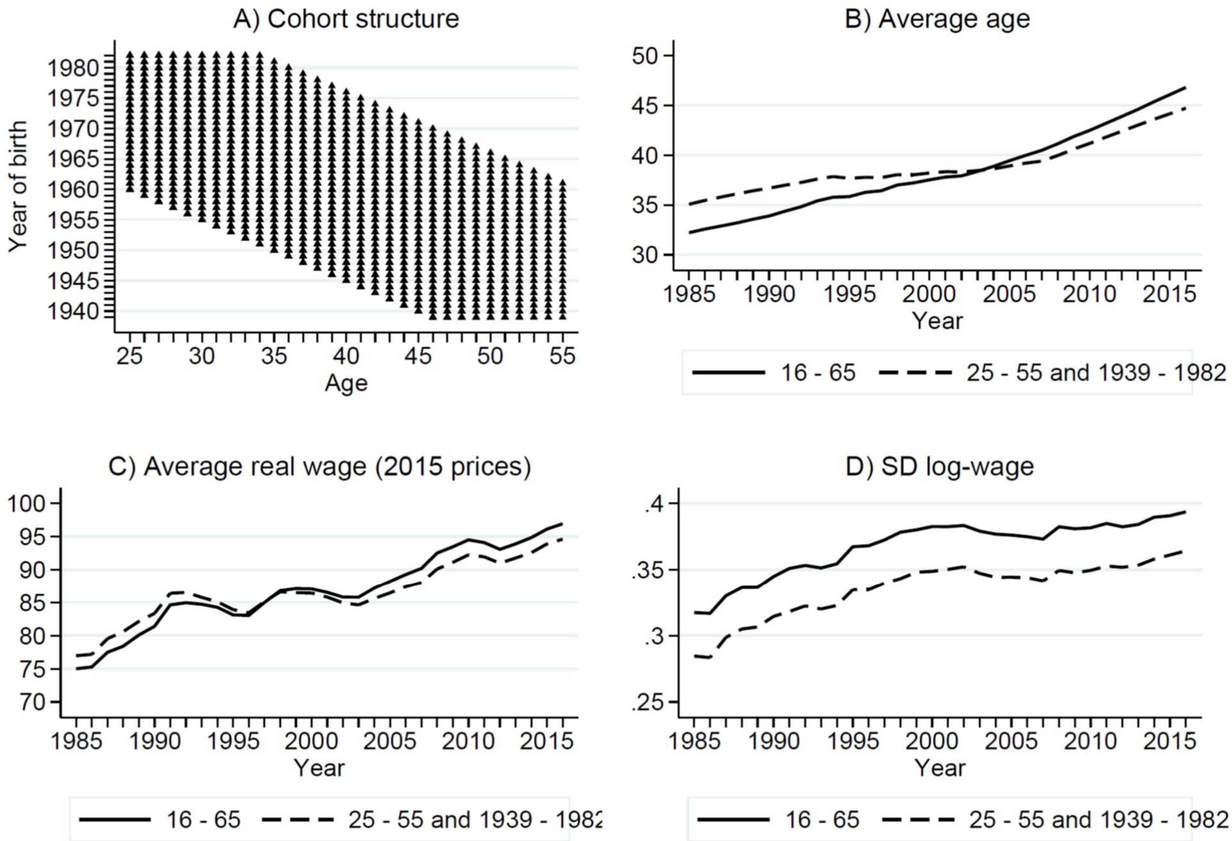
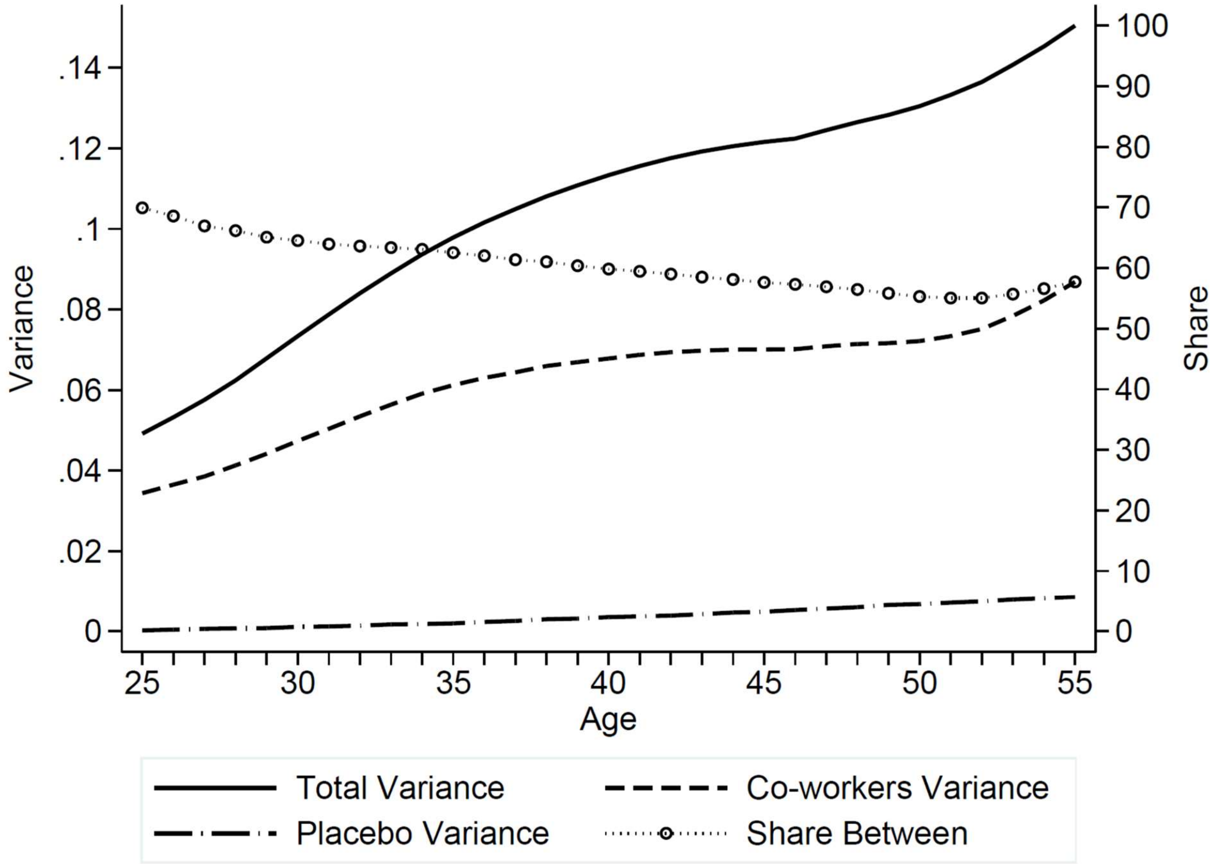
Figure 1 – Sample descriptives



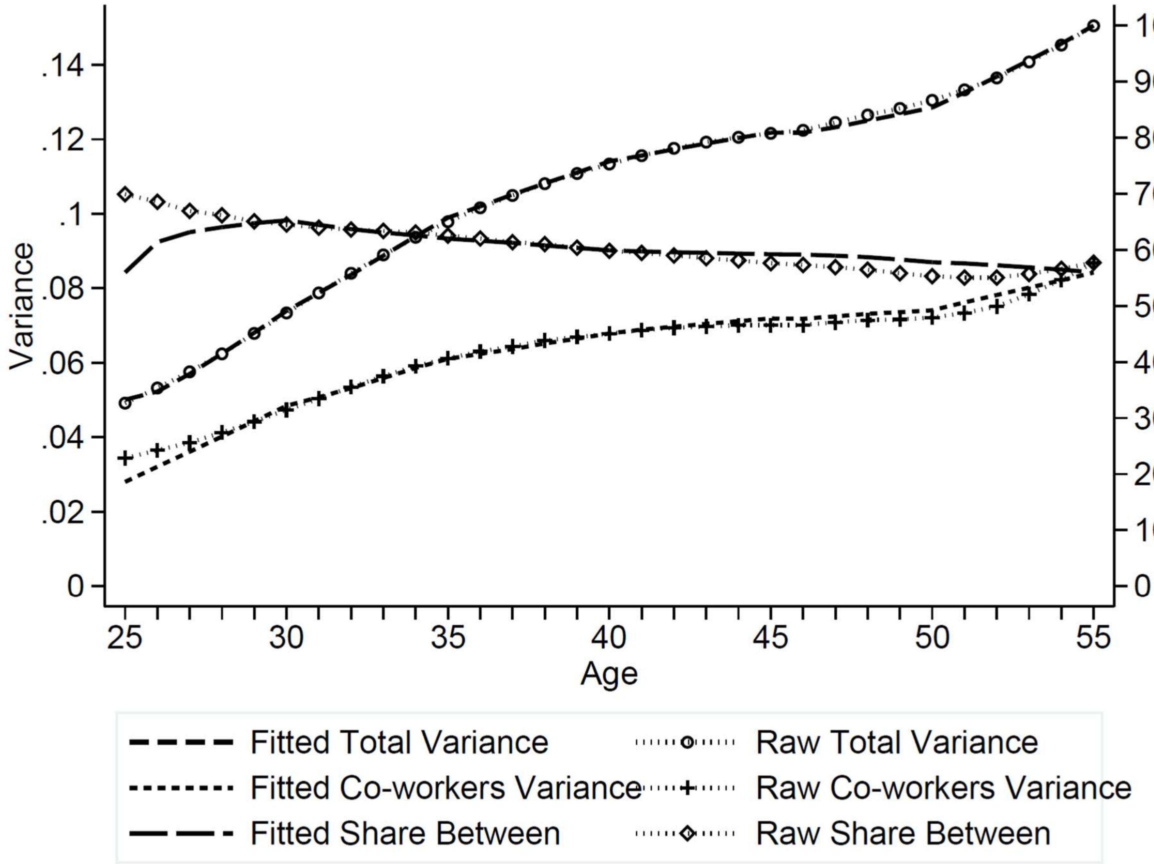
Notes: In panel A) each marker denotes a cohort-age combination that is present in the estimation sample. Panels B), C) and D) compare the time evolution of average age, average real daily wages and standard deviation of the logs of real daily wages (respectively) between the estimation sample and the population of working men aged 16-65. Real wages are in Euros at 2015 prices.

Figure 2 – Raw variances and between-firms variance share over the life cycle



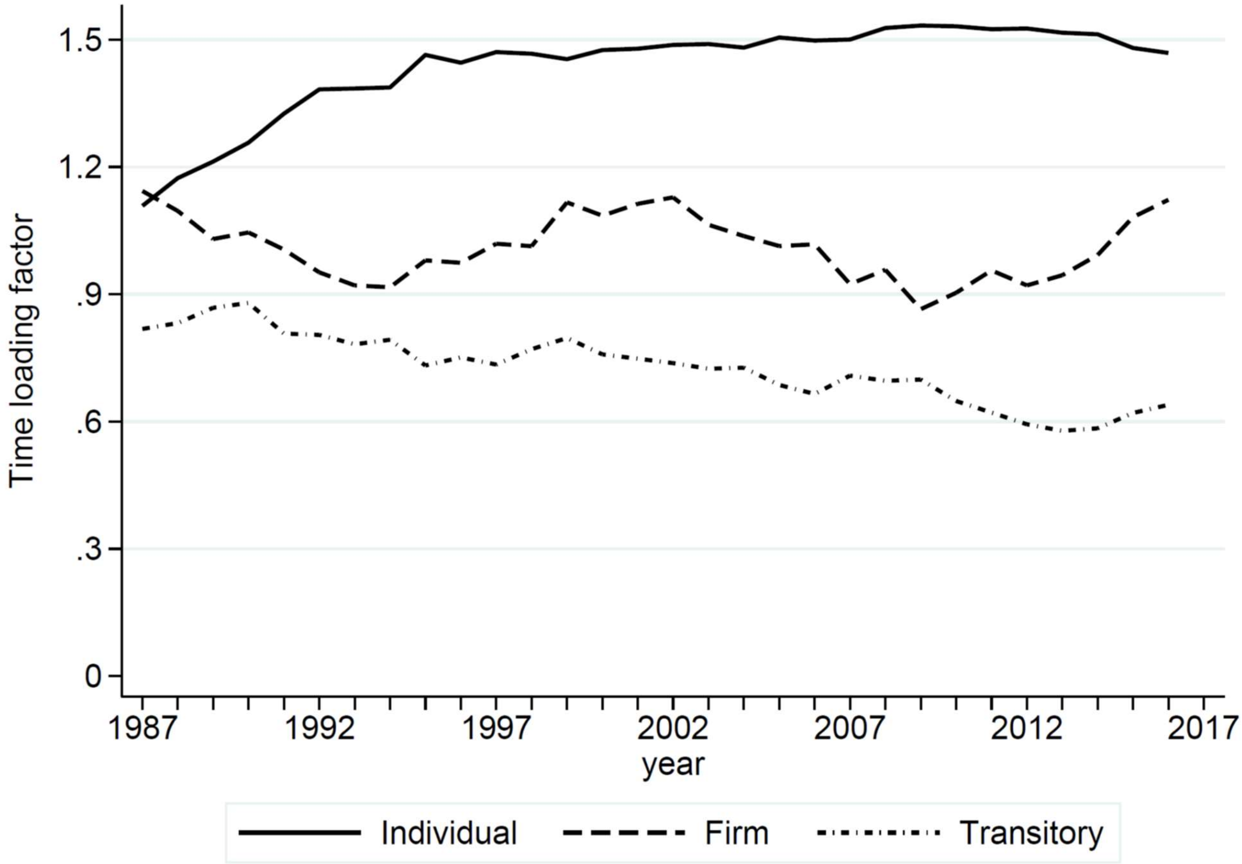
Notes: The figure reports the life-cycle evolution of the variance and of its between-firms component. Empirical moments are estimated by birth cohort and averaged across cohorts by age. Total Variance is the variance derived from the empirical second moments of individual wages. Co-workers Variance is the variance derived from the empirical second moments of co-workers wages. Placebo Variance is the variance derived from the empirical second moments obtained by linking the earnings of non co-workers matched at random from the economy. Share Between is the ratio of Co-workers Variance over Total Variance.

Figure 3 – Raw and predicted variances and between-firms variance share over the life cycle



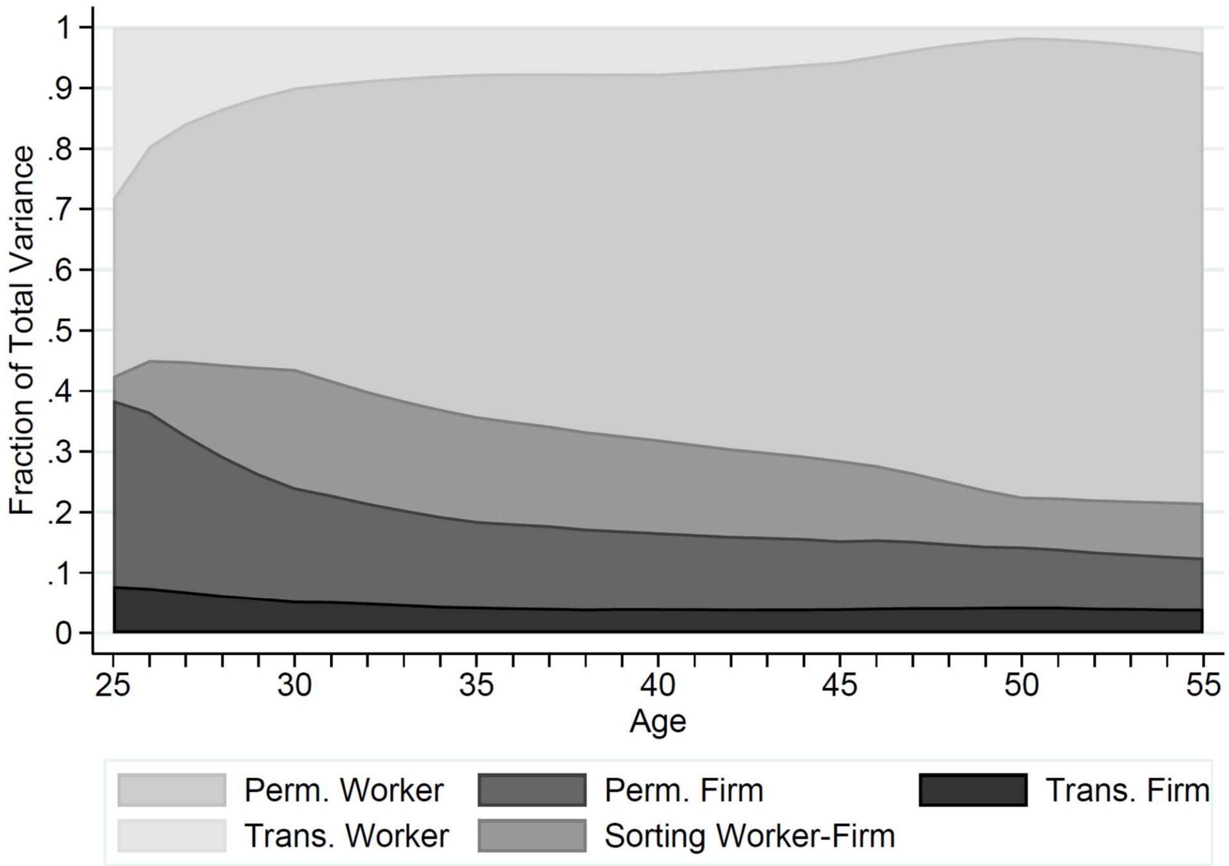
Notes: The figure reports raw empirical moments and their fitted counterparts derived from the econometric model. The raw figures are as in Figure 2. The fitted figures are predicted for each cohort-age combination that is present in the sample and then averaged across cohorts by age. Parameter estimates underlying the predictions are reported in Table 1, Table 2 and Appendix Table A1.

Figure 4 – Estimates of time loading factors



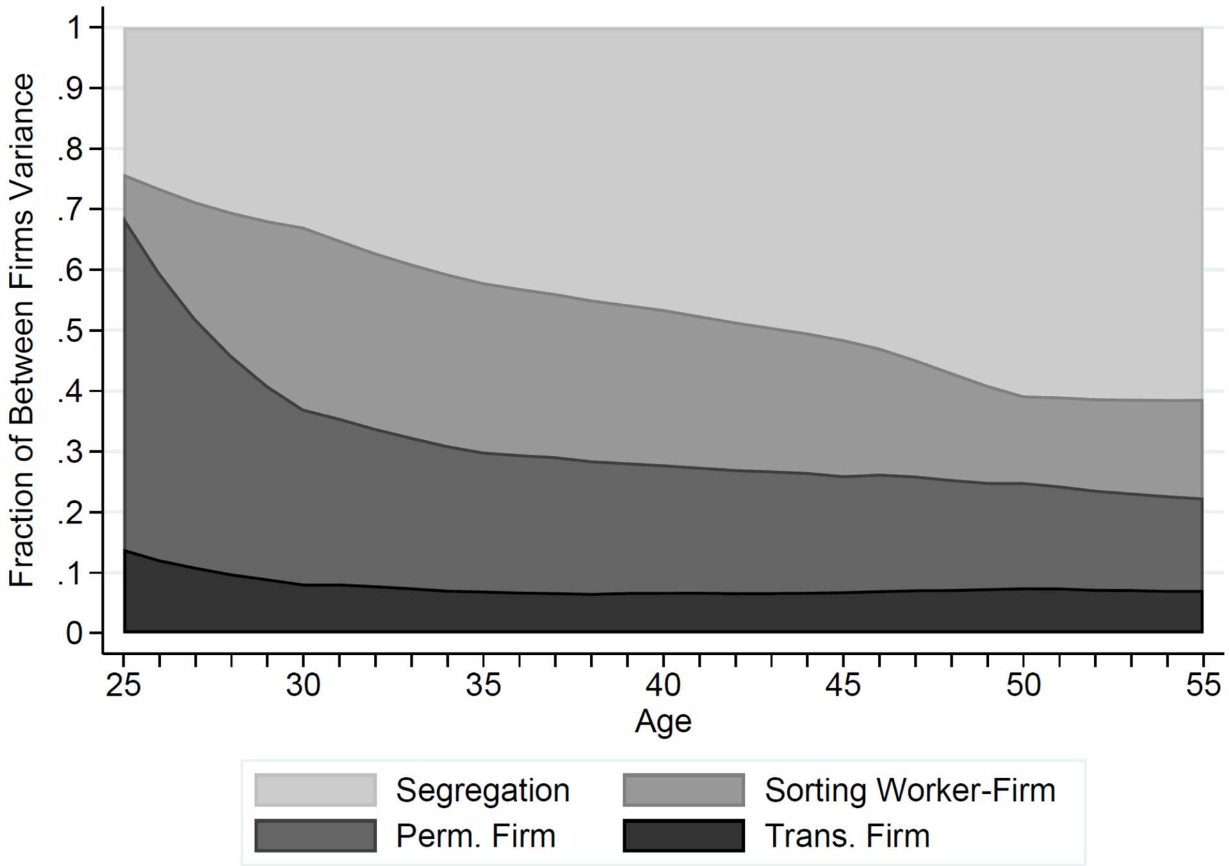
Notes: The figure reports the point estimates of the time loading factors for the individual permanent component, the firm permanent component and the transitory component, denoted α, δ and γ, respectively, in the earnings model of Equation (1). The loading factors are normalised to 1 in 1985 and 1986. All parameters are statistically significant at the 0.1% level of confidence; parameter estimates are reported in Appendix Table A1.

Figure 5 – Decomposition of total variance over the life cycle



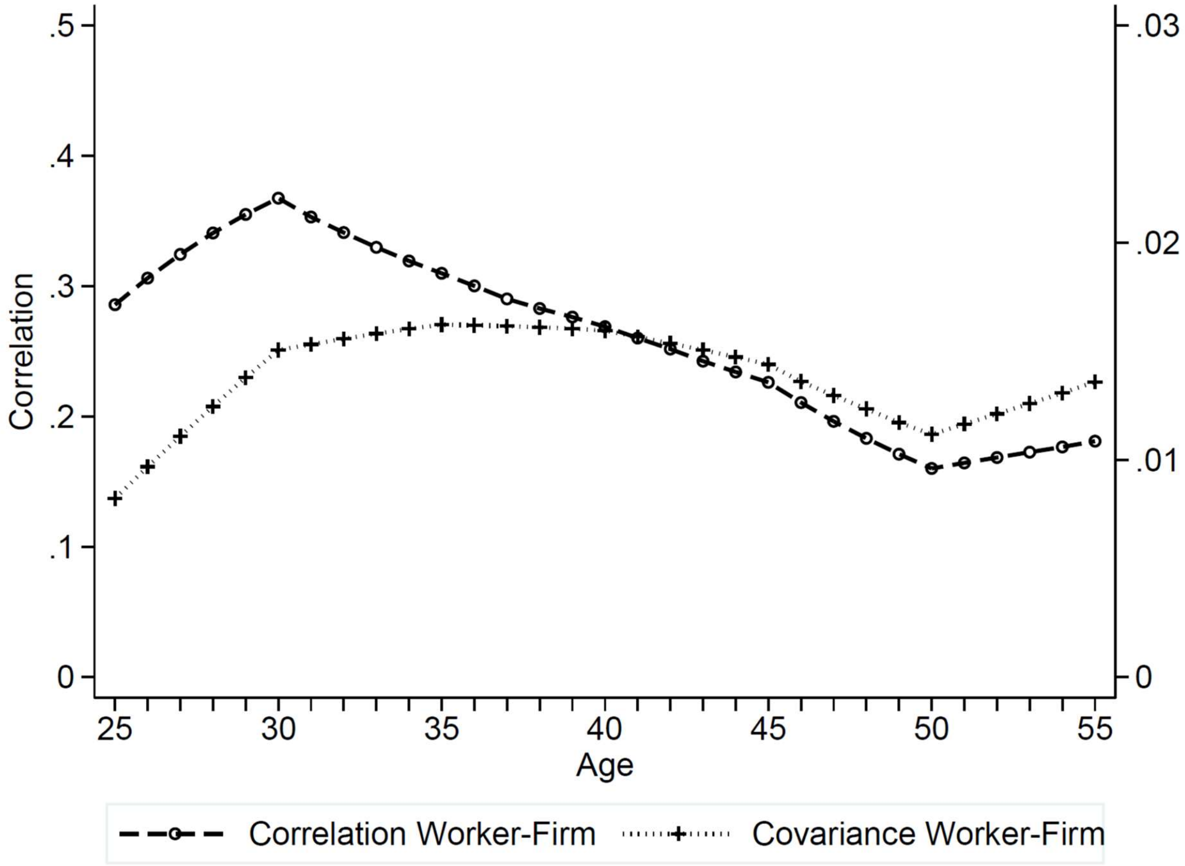
Notes: The figure reports the variance decomposition derived according to Equation (8). Variance components are predicted for any cohort-age combination that is present in the sample and then averaged across cohorts by age. Parameter estimates underlying the decomposition are reported in Table 1, Table 2 and Appendix Table A1.

Figure 6 – Decomposition of between-firms variance over the life cycle



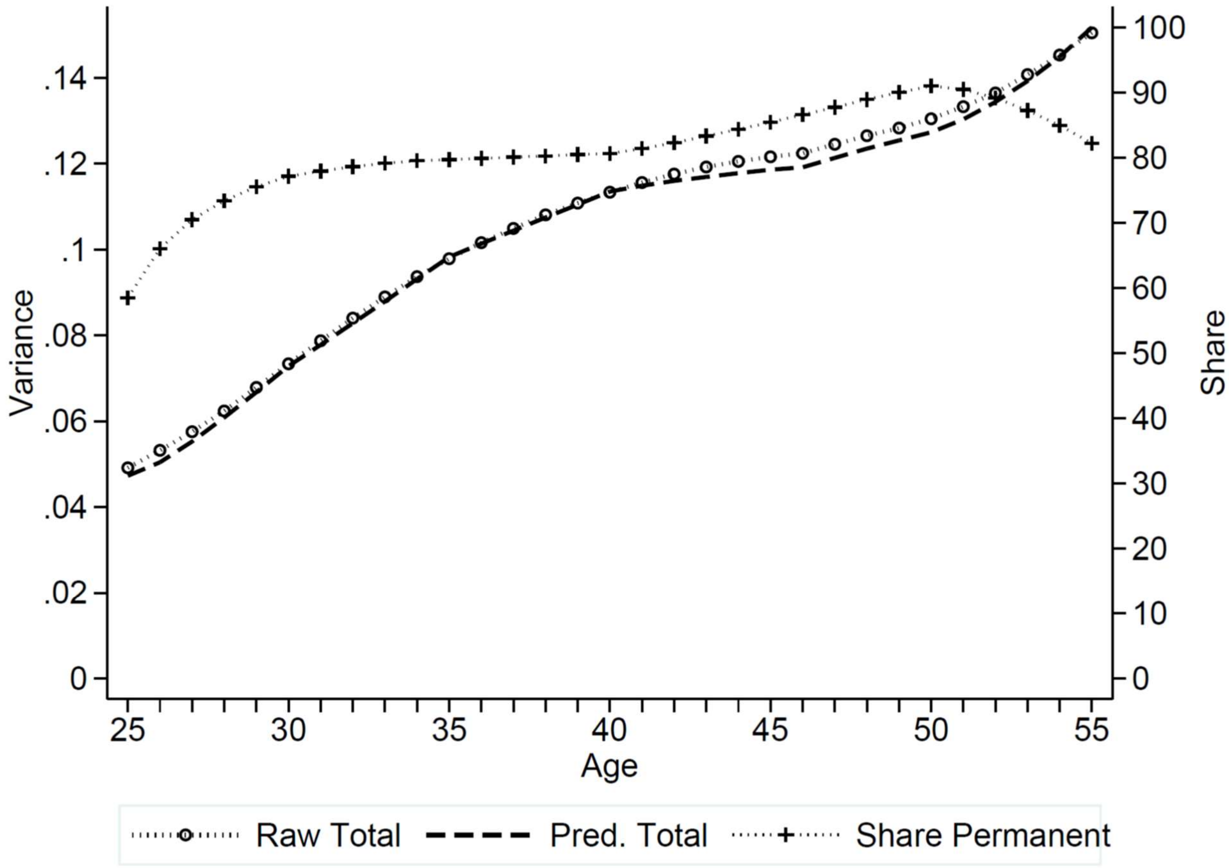
Notes: The figure reports the between-firms variance decomposition derived according to Equation (9). Variance components are predicted for any cohort-age combination that is present in the sample and then averaged across cohorts by age. Parameter estimates underlying the decomposition are reported in Table 1, Table 2 and Appendix Table A1.

Figure 7 – Worker-firm sorting over the life-cycle



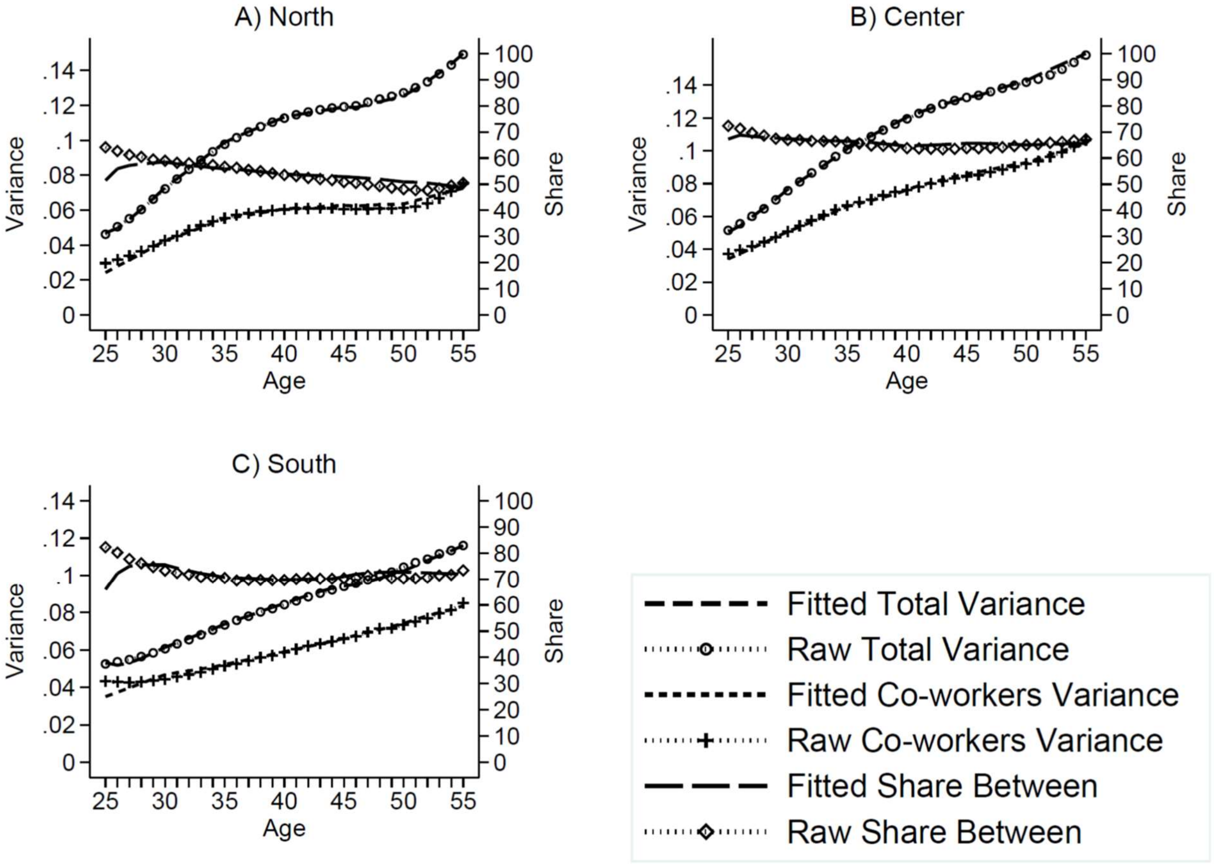
Notes: The figure reports sorting measures derived from the econometric model over the life cycle. The sorting covariance is obtained by applying Equation (5). Predictions are derived for any cohort-age-lag combination that is present in the data and then averaged across cohorts by age.

Figure 8 – Raw and predicted variances and permanent variance share over the life cycle – Standard earnings dynamics model



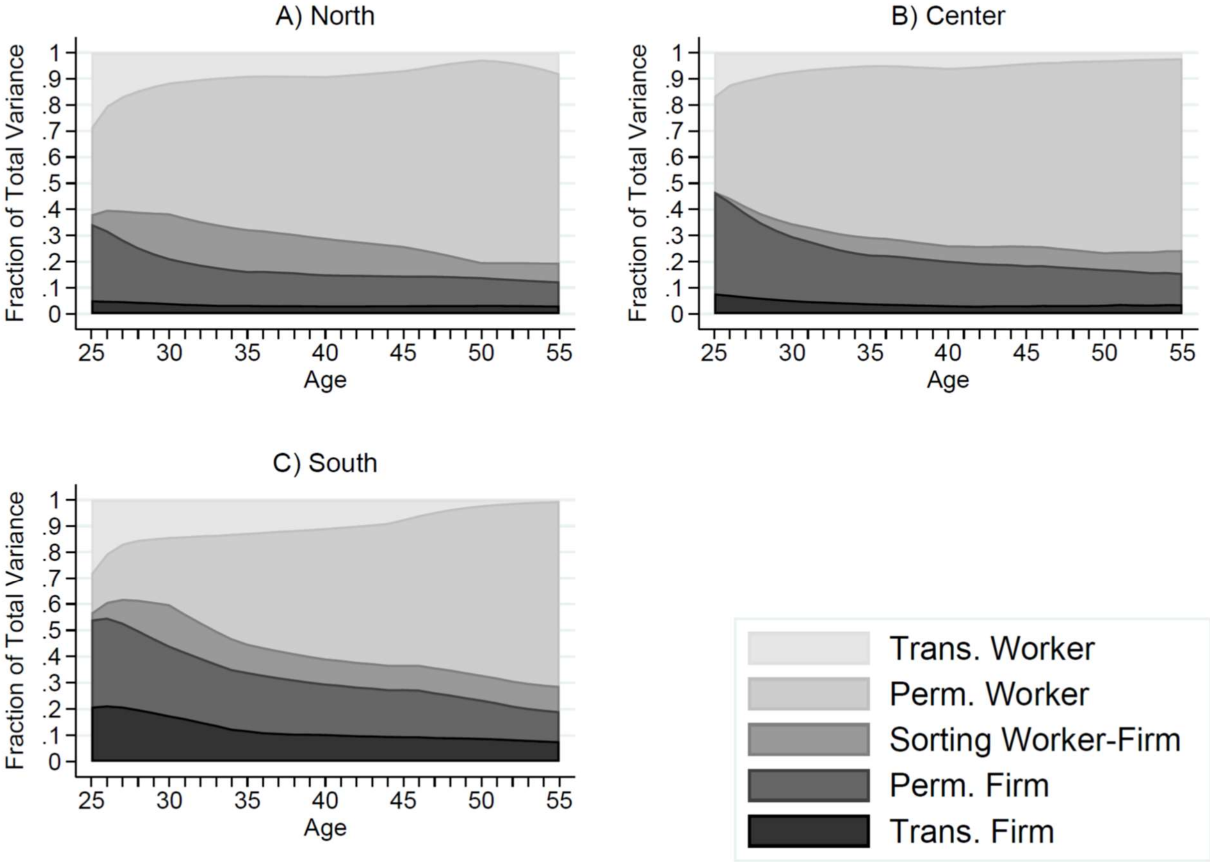
Notes: The figure reports raw empirical moments and their fitted counterparts derived from a standard earnings dynamics model without form effects. The fitted figures are predicted for each cohort-age combination that is present in the sample and then averaged across cohorts by age. Parameter estimates underlying the predictions are reported in Table 3 and Appendix Table A3.

Figure 9 – Raw and predicted variances and between-firms variance share over the life cycle, by geographical area



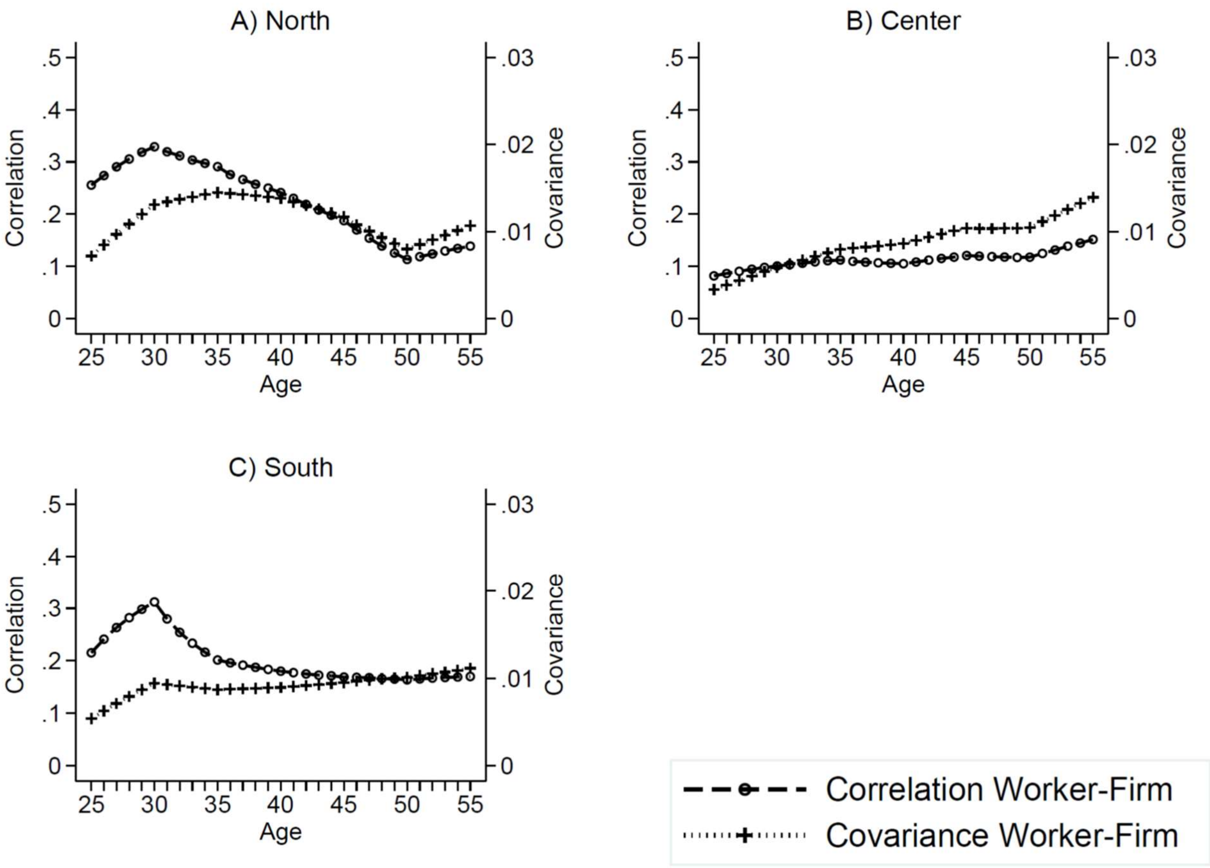
Notes: The figure reports raw empirical moments and their fitted counterparts derived from the earnings dynamics model estimated by geographical area. The fitted figures are predicted by area for each cohort-age combination that is present in the sample and then averaged across cohorts by age. Parameter estimates underlying the predictions are reported in Table 4, Table 5 and Appendix Table A4.

Figure 10 – Decomposition of total variance over the life cycle, by geographical area



Notes: The figure reports the variance decomposition derived according to Equation (8) by geographical area. Variance components are predicted by area for any cohort-age combination that is present in the sample and then averaged across cohorts by age. Parameter estimates underlying the decomposition are reported in Table 4, Table 5 and Appendix Table A4.

Figure 11 – Worker-firm sorting over the life-cycle, by geographical area



Notes: The figure reports sorting measures over the life cycle derived by area from the earnings dynamics model. The sorting covariance is obtained by applying Equation (5). Predictions are derived by area for any cohort-age-lag combination that is present in the data and then averaged across cohorts by age.

Table 1: Parameter estimates of permanent earnings components

	Coeff.	S.E.
A) Worker		
σ_{λ}^2	0.0077	0.00011
σ_{u26-30}^2	0.0019	0.00002
σ_{u31-35}^2	0.0021	0.00001
σ_{u36-40}^2	0.0013	0.00001
σ_{u41-45}^2	0.0011	0.00001
σ_{u46-50}^2	0.0012	0.00001
σ_{u51-55}^2	0.0010	0.00002
B) Firm		
$\sigma_{\phi q1}^2$	0.0148	0.00011
$\sigma_{\phi q2}^2$	0.0126	0.00013
$\sigma_{\phi q3}^2$	0.0148	0.00017
$\sigma_{\phi q4}^2$	0.0122	0.00017
$\sigma_{\phi q1q2}$	0.0124	0.00011
$\sigma_{\phi q1q3}$	0.0117	0.00012
$\sigma_{\phi q1q4}$	0.0111	0.00013
$\sigma_{\phi q2q3}$	0.0131	0.00014
$\sigma_{\phi q2q4}$	0.0106	0.00013
$\sigma_{\phi q3q4}$	0.0127	0.00015
C) Correlated effects		
C.1) Worker-firm sorting		
$\sigma_{\phi\lambda}$	0.0007	0.00002
$\sigma_{\phi u26-30}$	0.0009	0.00001
$\sigma_{\phi u31-35}$	0.0002	0.00001
$\sigma_{\phi u36-40}$	0.00003	0.00001
$\sigma_{\phi u41-45}$	-0.0001	0.00001
$\sigma_{\phi u46-50}$	-0.0004	0.00001
$\sigma_{\phi u51-55}$	0.0002	0.00001
C.2) Worker segregation		
μ	0.4609	0.00243
C.3) Firm connection		
π	0.3667	0.00901

Notes: Equally Weighted Minimum Distance (EWMD) estimates for the parameters of permanent earnings in the earnings dynamics model of Section 3. Number of observations 152,470,973; number of individuals 12,216,798; number of firms 3,067,753; number of empirical moments 21,164; overall number of model parameters 149; $\chi^2(21015)$= 311825.19. The parameter $\sigma_{\phi\lambda}$ is estimated based on the constraint described in Equation (10).

Table 2: Parameter estimates of transitory earnings components

	Coeff.	S.E.
	A) Worker	
$\sigma^2_{\varepsilon 26}$	0.0108	0.00017
κ_{27-30}	-0.0417	0.00388
κ_{31-35}	0.0281	0.00317
κ_{36-40}	0.0300	0.00264
κ_{41-45}	-0.0504	0.00310
κ_{46-50}	-0.2394	0.01038
κ_{51-55}	0.2600	0.01020
ρ	0.4731	0.00475
σ^2_{v1939}	0.0070	0.00069
σ^2_{v1940}	0.0071	0.00067
σ^2_{v1941}	0.0103	0.00070
σ^2_{v1942}	0.0115	0.00071
σ^2_{v1943}	0.0131	0.00069
σ^2_{v1944}	0.0116	0.00069
σ^2_{v1945}	0.0132	0.00070
σ^2_{v1946}	0.0116	0.00059
σ^2_{v1947}	0.0127	0.00060
σ^2_{v1948}	0.0111	0.00058
σ^2_{v1949}	0.0110	0.00058
σ^2_{v1950}	0.0127	0.00059
σ^2_{v1951}	0.0132	0.00058
σ^2_{v1952}	0.0145	0.00057
σ^2_{v1953}	0.0155	0.00056
σ^2_{v1954}	0.0172	0.00054
σ^2_{v1955}	0.0167	0.00051
σ^2_{v1956}	0.0171	0.00048
σ^2_{v1957}	0.0203	0.00047
σ^2_{v1958}	0.0216	0.00045
σ^2_{v1959}	0.0245	0.00043
$\sigma^2_{v1960-1982}$	0.0225	0.00027
	B) Firm	
$\sigma^2_{\xi q1}$	0.0060	0.00007
$\sigma^2_{\xi q2}$	0.0087	0.00012
$\sigma^2_{\xi q3}$	0.0085	0.00018
$\sigma^2_{\xi q4}$	0.0144	0.00024

Notes: Equally Weighted Minimum Distance (EWMD) estimates for the parameters of transitory earnings in the earnings dynamics model of Section 3. Number of observations 152,470,973; number of individuals 12,216,798; number of firms 3,067,753; number of empirical moments 21,164; overall number of model parameters; overall number of model parameters 149; χ^2(21015)= 311825.19.

Table 3: Parameter estimates from standard earnings dynamics model

	Coeff.	S.E.
	A) Permanent Earnings (RW)	
σ^2_{λ}	0.0170	0.00004
σ^2_{u26-30}	0.0033	0.00001
σ^2_{u31-35}	0.0025	0.00001
σ^2_{u36-40}	0.0016	0.00001
σ^2_{u41-45}	0.0012	0.00001
σ^2_{u46-50}	0.0011	0.00001
σ^2_{u51-55}	0.0005	0.00002
	B) Transitory Earnings (AR1)	
$\sigma^2_{\varepsilon 26}$	0.0113	0.00009
κ_{27-30}	0.0468	0.00178
κ_{31-35}	0.0513	0.00113
κ_{36-40}	0.0186	0.00100
κ_{41-45}	-0.0568	0.00118
κ_{46-50}	-0.0844	0.00220
κ_{51-55}	0.2165	0.00196
ρ	0.6500	0.00143
σ^2_{v1939}	0.0099	0.00085
σ^2_{v1940}	0.0119	0.00083
σ^2_{v1941}	0.0175	0.00087
σ^2_{v1942}	0.0195	0.00087
σ^2_{v1943}	0.0222	0.00086
σ^2_{v1944}	0.0201	0.00084
σ^2_{v1945}	0.0226	0.00086
σ^2_{v1946}	0.0213	0.00072
σ^2_{v1947}	0.0224	0.00072
σ^2_{v1948}	0.0217	0.00070
σ^2_{v1949}	0.0218	0.00069
σ^2_{v1950}	0.0252	0.00071
σ^2_{v1951}	0.0256	0.00069
σ^2_{v1952}	0.0278	0.00068
σ^2_{v1953}	0.0303	0.00067
σ^2_{v1954}	0.0322	0.00064
σ^2_{v1955}	0.0320	0.00060
σ^2_{v1956}	0.0332	0.00057
σ^2_{v1957}	0.0366	0.00055
σ^2_{v1958}	0.0378	0.00052
σ^2_{v1959}	0.0402	0.00048
$\sigma^2_{v1960-1982}$	0.0269	0.00013

Notes: Equally Weighted Minimum Distance (EWMD) estimates for the parameters of the permanent and transitory earnings components in a standard earnings dynamics model without firm effects. Number of observations 152,470,973; number of individuals 12,339,989; number of empirical moments 10,582; overall number of model parameters 97; $\chi^2(10,485)= 87381.3$.

Table 4: Parameter estimates of permanent earnings components by area

	(1) North		(2) Center		(3) South	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
A) Worker						
σ^2_{λ}	0.0080	0.00013	0.0114	0.00025	0.0037	0.00020
σ^2_{u26-30}	0.0020	0.00002	0.0030	0.00004	0.0007	0.00003
σ^2_{u31-35}	0.0020	0.00001	0.0025	0.00003	0.0014	0.00004
σ^2_{u36-40}	0.0012	0.00001	0.0018	0.00003	0.0010	0.00003
σ^2_{u41-45}	0.0010	0.00001	0.0012	0.00003	0.0009	0.00003
σ^2_{u46-50}	0.0011	0.00001	0.0009	0.00003	0.0009	0.00004
σ^2_{u51-55}	0.0006	0.00002	0.0012	0.00004	0.0011	0.00004
B) Firm						
$\sigma^2_{\phi q1}$	0.0115	0.00010	0.0182	0.00032	0.0334	0.00036
$\sigma^2_{\phi q2}$	0.0093	0.00012	0.0192	0.00037	0.0364	0.00053
$\sigma^2_{\phi q3}$	0.0119	0.00016	0.0242	0.00049	0.0334	0.00071
$\sigma^2_{\phi q4}$	0.0110	0.00017	0.0212	0.00050	0.0402	0.00099
$\sigma_{\phi q1q2}$	0.0097	0.00010	0.0176	0.00034	0.0336	0.00042
$\sigma_{\phi q1q3}$	0.0092	0.00011	0.0180	0.00035	0.0329	0.00045
$\sigma_{\phi q1q4}$	0.0080	0.00012	0.0191	0.00038	0.0329	0.00047
$\sigma_{\phi q2q3}$	0.0098	0.00013	0.0206	0.00040	0.0347	0.00055
$\sigma_{\phi q2q4}$	0.0071	0.00012	0.0196	0.00040	0.0332	0.00055
$\sigma_{\phi q3q4}$	0.0095	0.00014	0.0231	0.00048	0.0341	0.00066
C) Sorting						
C.1) Worker-firm shock covariance						
$\sigma_{\phi\lambda}$	0.0005	0.00001			0.0007	0.00002
$\sigma_{\phi u26-30}$	0.0007	0.00001	0.0003	0.00003	0.0009	0.00003
$\sigma_{\phi u31-35}$	0.0002	0.00001	0.0003	0.00002	-0.0002	0.00002
$\sigma_{\phi u36-40}$	0.0000	0.00001	0.0000	0.00001	0.0000	0.00002
$\sigma_{\phi u41-45}$	-0.0001	0.00001	0.0002	0.00001	0.0001	0.00002
$\sigma_{\phi u46-50}$	-0.0004	0.00001	-0.0001	0.00002	0.0001	0.00002
$\sigma_{\phi u51-55}$	0.0002	0.00001	0.0004	0.00002	0.0002	0.00002
C.2) Worker-worker correlation						
μ	0.3990	0.00269	0.5620	0.00377	0.6113	0.00481
C.3) Firm-firm correlation						
π	0.2827	0.01281	0.2151	0.01316	0.4738	0.01471

Notes: Equally Weighted Minimum Distance (EWMD) estimates for the parameters of permanent earnings in the earnings dynamics model of Section 3 estimated by geographical area. Number of observations: 89,131,587 (North), 34,498,864 (Center), 28,840,522 (South). Number of individuals: 6,574,646 (North), 2,899,923 (Center), 2,742,229 (South). Number of firms 1,685,499 (North), 952,386 (Center), 1,056,163 (South). Number of empirical moments 21,164 in each column; overall number of model parameters 149 in column 1, 147 in column 2 and 148 in column 3. $\chi^2(21015)$= in column 1; $\chi^2(21017)$= 123149.23 in column 2 and $\chi^2(21018)$= 1689379 in column 3. The parameter $\sigma_{\phi\lambda}$ in column 1 and 3 is estimated based on the constraint described in Equation (10), while it is set to 0 in column 2.

Table 5: Parameter estimates of transitory earnings components by area

	(1) North		(2) Center		(3) South	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
			A) Worker			
$\sigma^2_{\varepsilon 26}$	0.0104	0.00019	0.0083	0.00036	0.0047	0.00024
κ_{27-30}	0.0017	0.00411	-0.0541	0.01580	0.0676	0.01430
κ_{31-35}	0.0229	0.00300	-0.0439	0.01167	0.0159	0.00751
κ_{36-40}	0.0308	0.00259	0.1420	0.01079	0.0089	0.00693
κ_{41-45}	-0.0528	0.00302			-0.0331	0.00876
κ_{46-50}	-0.1754	0.00718	-0.1267	0.01050	-0.2506	0.02861
κ_{51-55}	0.2947	0.00717				
ρ	0.5057	0.00498	0.4509	0.01424	0.6536	0.00866
σ^2_{v1939}	0.0096	0.00079	0.0004	0.00170	0.0045	0.00240
σ^2_{v1940}	0.0093	0.00077	0.0015	0.00164	0.0076	0.00238
σ^2_{v1941}	0.0116	0.00080	0.0107	0.00177	0.0112	0.00240
σ^2_{v1942}	0.0123	0.00081	0.0124	0.00175	0.0152	0.00241
σ^2_{v1943}	0.0131	0.00080	0.0135	0.00167	0.0150	0.00234
σ^2_{v1944}	0.0116	0.00079	0.0129	0.00166	0.0148	0.00230
σ^2_{v1945}	0.0120	0.00082	0.0156	0.00163	0.0135	0.00216
σ^2_{v1946}	0.0115	0.00070	0.0131	0.00137	0.0107	0.00191
σ^2_{v1947}	0.0108	0.00069	0.0147	0.00139	0.0151	0.00191
σ^2_{v1948}	0.0108	0.00068	0.0099	0.00131	0.0132	0.00182
σ^2_{v1949}	0.0095	0.00068	0.0102	0.00130	0.0177	0.00184
σ^2_{v1950}	0.0105	0.00068	0.0126	0.00135	0.0217	0.00188
σ^2_{v1951}	0.0121	0.00069	0.0103	0.00125	0.0185	0.00180
σ^2_{v1952}	0.0124	0.00066	0.0122	0.00124	0.0228	0.00184
σ^2_{v1953}	0.0142	0.00065	0.0133	0.00125	0.0187	0.00175
σ^2_{v1954}	0.0161	0.00065	0.0118	0.00116	0.0205	0.00165
σ^2_{v1955}	0.0150	0.00060	0.0134	0.00112	0.0171	0.00156
σ^2_{v1956}	0.0157	0.00056	0.0108	0.00103	0.0178	0.00149
σ^2_{v1957}	0.0174	0.00053	0.0164	0.00106	0.0170	0.00142
σ^2_{v1958}	0.0193	0.00051	0.0181	0.00100	0.0146	0.00135
σ^2_{v1959}	0.0206	0.00047	0.0203	0.00098	0.0215	0.00128
$\sigma^2_{v1960-1982}$	0.0216	0.00029	0.0173	0.00062	0.0181	0.00047
			B) Firm			
$\sigma^2_{\xi q1}$	0.0033	0.00008	0.0070	0.00019	0.0135	0.00022
$\sigma^2_{\xi q2}$	0.0071	0.00012	0.0078	0.00030	0.0097	0.00019
$\sigma^2_{\xi q3}$	0.0070	0.00017	0.0069	0.00036	0.0115	0.00026
$\sigma^2_{\xi q4}$	0.0111	0.00022	0.0130	0.00055	0.0118	0.00029

Notes: Equally Weighted Minimum Distance (EWMD) estimates for the parameters of transitory earnings in the earnings dynamics model of Section 3 estimated by geographical area. Number of observations: 89,131,587 (North), 34,498,864 (Center), 28,840,522 (South). Number of individuals: 6,574,646 (North), 2,899,923 (Center), 2,742,229 (South). Number of firms 1,685,499 (North), 952,386 (Center), 1,056,163 (South). Number of empirical moments 21,164 in each column; overall number of model parameters 149 in column 1, 147 in column 2 and 148 in column 3. $\chi^2(21015)$= in column 1; $\chi^2(21017)$= 123149.23 in column 2 and $\chi^2(21018)$= 1689379 in column 3. Age splines for AR1 innovations after age 40 are reduced to 1 in column 2 and 2 in column 3.

Appendix Tables

Table A1: Estimates of time shifters (1985=1986=1)

	Individual (α)		Firm (δ)		Transitory (γ)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Year						
1987	1.1081	0.00175	1.1432	0.00408	0.8182	0.00395
1988	1.1736	0.00209	1.0962	0.00427	0.8319	0.00368
1989	1.2126	0.00246	1.0300	0.00441	0.8681	0.00366
1990	1.2572	0.00270	1.0455	0.00452	0.8795	0.00376
1991	1.3254	0.00308	1.0053	0.00453	0.8073	0.00371
1992	1.3827	0.00344	0.9515	0.00462	0.8041	0.00367
1993	1.3847	0.00355	0.9207	0.00474	0.7821	0.00372
1994	1.3873	0.00363	0.9165	0.00484	0.7927	0.00377
1995	1.4640	0.00386	0.9797	0.00521	0.7321	0.00394
1996	1.4456	0.00383	0.9740	0.00520	0.7512	0.00392
1997	1.4705	0.00393	1.0189	0.00543	0.7343	0.00390
1998	1.4667	0.00398	1.0133	0.00560	0.7704	0.00404
1999	1.4538	0.00395	1.1164	0.00589	0.7969	0.00422
2000	1.4753	0.00410	1.0851	0.00588	0.7583	0.00403
2001	1.4785	0.00414	1.1130	0.00600	0.7482	0.00403
2002	1.4874	0.00421	1.1282	0.00609	0.7377	0.00405
2003	1.4895	0.00434	1.0635	0.00609	0.7245	0.00395
2004	1.4811	0.00439	1.0371	0.00621	0.7269	0.00385
2005	1.5049	0.00456	1.0135	0.00638	0.6862	0.00377
2006	1.4977	0.00461	1.0176	0.00646	0.6650	0.00375
2007	1.5001	0.00476	0.9238	0.00640	0.7081	0.00370
2008	1.5273	0.00494	0.9576	0.00674	0.6961	0.00389
2009	1.5331	0.00517	0.8648	0.00677	0.6989	0.00401
2010	1.5313	0.00523	0.9034	0.00701	0.6484	0.00420
2011	1.5245	0.00524	0.9561	0.00725	0.6211	0.00446
2012	1.5261	0.00533	0.9208	0.00737	0.5936	0.00470
2013	1.5162	0.00530	0.9447	0.00756	0.5781	0.00498
2014	1.5125	0.00524	0.9925	0.00781	0.5840	0.00533
2015	1.4802	0.00500	1.0817	0.00811	0.6203	0.00562
2016	1.4685	0.00489	1.1226	0.00839	0.6394	0.00585

Notes: The table reports the estimates of the time shifters in the earnings dynamics model of Section 3. The point estimates of the shifters are represented graphically in Figure 4.

Table A2.1: Parameter estimates of permanent earnings components – Stayers data

	Coeff.	S.E.
	A) Worker	
σ^2_{λ}	0.0044	0.00021
σ^2_{u26-30}	0.0020	0.00003
σ^2_{u31-35}	0.0019	0.00002
σ^2_{u36-40}	0.0013	0.00002
σ^2_{u41-45}	0.0011	0.00002
σ^2_{u46-50}	0.0011	0.00002
σ^2_{u51-55}	0.0009	0.00003
	B) Firm	
$\sigma^2_{\phi q1}$	0.0198	0.00019
$\sigma^2_{\phi q2}$	0.0230	0.00025
$\sigma^2_{\phi q3}$	0.0284	0.00031
$\sigma^2_{\phi q4}$	0.0256	0.00032
$\sigma_{\phi q1q2}$	0.0194	0.00020
$\sigma_{\phi q1q3}$	0.0183	0.00020
$\sigma_{\phi q1q4}$	0.0183	0.00020
$\sigma_{\phi q2q3}$	0.0234	0.00026
$\sigma_{\phi q2q4}$	0.0197	0.00023
$\sigma_{\phi q3q4}$	0.0238	0.00027
	C) Sorting	
	C.1) Worker-firm shock covariance	
$\sigma_{\phi\lambda}$	0.0003	0.00001
$\sigma_{\phi u26-30}$	0.0006	0.00001
$\sigma_{\phi u31-35}$	0.0003	0.00001
$\sigma_{\phi u36-40}$	0.0000	0.00001
$\sigma_{\phi u41-45}$	-0.0001	0.00001
$\sigma_{\phi u46-50}$	-0.0004	0.00001
$\sigma_{\phi u51-55}$	0.0003	0.00001
	C.2) Worker-worker correlation	
μ	0.4339	0.00322

continues

Table A2.2: Parameter estimates of transitory earnings components – Stayers data

	Coeff.	S.E.
	A) Worker	
$\sigma^2_{\varepsilon 26-30}$	0.0036	0.00009
κ_{31-35}	0.1794	0.00482
κ_{36-40}	-0.0718	0.00410
κ_{41-45}	-0.1366	0.00690
κ_{46-50}	0.0869	0.01241
κ_{51-55}	0.5691	0.03664
ρ	0.6671	0.00664
$\sigma^2_{v1939-1942}$	0.0037	0.00094
σ^2_{v1943}	0.0057	0.00092
σ^2_{v1944}	0.0028	0.00090
σ^2_{v1945}	0.0047	0.00091
σ^2_{v1946}	0.0023	0.00077
σ^2_{v1947}	0.0027	0.00077
σ^2_{v1948}	0.0012	0.00075
σ^2_{v1949}	0.0005	0.00074
σ^2_{v1950}	0.0035	0.00075
σ^2_{v1951}	0.0037	0.00074
σ^2_{v1952}	0.0050	0.00072
σ^2_{v1953}	0.0070	0.00071
σ^2_{v1954}	0.0091	0.00069
σ^2_{v1955}	0.0083	0.00065
σ^2_{v1956}	0.0084	0.00062
σ^2_{v1957}	0.0114	0.00061
σ^2_{v1958}	0.0121	0.00058
σ^2_{v1959}	0.0142	0.00055
$\sigma^2_{v1960-1982}$	0.0076	0.00027
	B) Firm	
$\sigma^2_{\xi q1}$	0.0079	0.00010
$\sigma^2_{\xi q2}$	0.0049	0.00009
$\sigma^2_{\xi q3}$	0.0024	0.00010
$\sigma^2_{\xi q4}$	0.0075	0.00010

continues

Table A2.3: Estimates of time shifters – Stayers data

	Individual (α)		Firm (δ)		Transitory (γ)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Year (1985=1986=1)						
1987	1.0530	0.00345	1.1683	0.00412	0.6435	0.00812
1988	1.1191	0.00418	1.1477	0.00451	0.6341	0.00766
1989	1.1812	0.00492	1.0551	0.00456	0.7806	0.00583
1990	1.2171	0.00539	1.0769	0.00478	0.8197	0.00564
1991	1.3112	0.00620	1.0420	0.00490	0.7137	0.00582
1992	1.3656	0.00677	1.0156	0.00506	0.7437	0.00543
1993	1.3945	0.00719	0.9562	0.00515	0.7613	0.00531
1994	1.3976	0.00734	0.9431	0.00515	0.8108	0.00519
1995	1.4787	0.00784	0.9889	0.00543	0.7586	0.00572
1996	1.4469	0.00772	0.9801	0.00529	0.8431	0.00546
1997	1.4634	0.00785	1.0106	0.00538	0.8598	0.00568
1998	1.4267	0.00773	1.0136	0.00534	0.9858	0.00570
1999	1.4266	0.00774	1.0721	0.00551	0.9814	0.00583
2000	1.4569	0.00795	1.0600	0.00555	0.8958	0.00574
2001	1.4636	0.00807	1.0692	0.00561	0.9004	0.00566
2002	1.4686	0.00815	1.0819	0.00566	0.9172	0.00563
2003	1.4861	0.00838	1.0256	0.00562	0.8985	0.00556
2004	1.4795	0.00845	0.9991	0.00557	0.9170	0.00553
2005	1.5095	0.00873	0.9815	0.00564	0.8699	0.00559
2006	1.4930	0.00870	0.9937	0.00562	0.8571	0.00552
2007	1.4846	0.00877	0.9406	0.00559	0.9289	0.00543
2008	1.5095	0.00905	0.9675	0.00580	0.9309	0.00570
2009	1.5029	0.00922	0.9016	0.00584	0.9915	0.00596
2010	1.5081	0.00939	0.9233	0.00598	0.9378	0.00634
2011	1.5069	0.00946	0.9621	0.00611	0.8792	0.00692
2012	1.5204	0.00966	0.9219	0.00617	0.8400	0.00773
2013	1.5214	0.00971	0.9244	0.00626	0.7958	0.00871
2014	1.5253	0.00967	0.9485	0.00638	0.7764	0.00957
2015	1.5258	0.00960	0.9801	0.00652	0.7250	0.01109
2016	1.5299	0.00952	0.9940	0.00664	0.7036	0.01208

Notes: Equally Weighted Minimum Distance (EWMD) estimates for the parameters in the earnings dynamics model of Section 3. Estimates of intertemporal empirical moments are obtained after excluding from the calculation of intertemporal covariances wages of workers moving across firms. Number of observations 152,470,973; number of individuals 12,216,798; number of firms 3,067,753; number of empirical moments 21,164; overall number of model parameters 145; $\chi^2(21019)$= 369743.22. The parameter $\sigma_{\phi\lambda}$ is estimated based on the constraint described in Equation (10).

Table A3: Estimates of time shifters from standard earnings dynamics model

	Individual (α)		Transitory (γ)	
	Coeff.	S.E.	Coeff.	S.E.
Year (1985=1986=1)				
1987	1.1101	0.00071	0.9093	0.00200
1988	1.1465	0.00085	0.8927	0.00228
1989	1.1521	0.00095	0.8972	0.00245
1990	1.1898	0.00104	0.9097	0.00251
1991	1.2364	0.00114	0.8284	0.00247
1992	1.2653	0.00121	0.8319	0.00249
1993	1.2599	0.00124	0.8199	0.00249
1994	1.2565	0.00126	0.8367	0.00251
1995	1.3304	0.00136	0.8111	0.00257
1996	1.3134	0.00136	0.8387	0.00252
1997	1.3362	0.00142	0.8478	0.00254
1998	1.3343	0.00145	0.8576	0.00252
1999	1.3468	0.00149	0.8878	0.00257
2000	1.3620	0.00155	0.8428	0.00246
2001	1.3748	0.00160	0.8394	0.00246
2002	1.3867	0.00164	0.8381	0.00250
2003	1.3739	0.00166	0.8151	0.00252
2004	1.3617	0.00168	0.8091	0.00257
2005	1.3763	0.00173	0.7608	0.00278
2006	1.3744	0.00176	0.7436	0.00294
2007	1.3559	0.00178	0.7632	0.00297
2008	1.3841	0.00186	0.7667	0.00326
2009	1.3648	0.00188	0.7606	0.00351
2010	1.3703	0.00194	0.7436	0.00391
2011	1.3748	0.00199	0.7466	0.00421
2012	1.3669	0.00202	0.7271	0.00459
2013	1.3631	0.00206	0.7183	0.00493
2014	1.3706	0.00210	0.7238	0.00511
2015	1.3652	0.00208	0.7662	0.00486
2016	1.3666	0.00206	0.7986	0.00460

Notes: The table reports the estimates of the time shifters in a standard earnings dynamics model without firm effects.

Table A4.1: Estimates of time shifters by geographical area - North

	Individual (α)		Firm (δ)		Transitory (γ)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Year (1985=1986=1)						
1987	1.1137	0.00176	1.1622	0.00484	0.7913	0.00451
1988	1.1846	0.00219	1.0964	0.00506	0.8124	0.00409
1989	1.2171	0.00252	1.0747	0.00532	0.9017	0.00403
1990	1.2792	0.00300	1.0828	0.00539	0.8751	0.00393
1991	1.3406	0.00341	1.0711	0.00545	0.7798	0.00406
1992	1.3921	0.00383	1.0479	0.00560	0.7771	0.00412
1993	1.3992	0.00402	1.0179	0.00571	0.7587	0.00417
1994	1.4061	0.00421	0.9854	0.00577	0.7904	0.00415
1995	1.4662	0.00434	1.0863	0.00629	0.7221	0.00455
1996	1.4472	0.00428	1.0851	0.00633	0.7453	0.00453
1997	1.4542	0.00425	1.1483	0.00669	0.7498	0.00480
1998	1.4479	0.00425	1.1664	0.00695	0.7859	0.00483
1999	1.4592	0.00425	1.2622	0.00755	0.7848	0.00499
2000	1.4867	0.00444	1.2638	0.00769	0.7400	0.00501
2001	1.5011	0.00459	1.2630	0.00792	0.7470	0.00491
2002	1.5194	0.00470	1.2748	0.00803	0.7439	0.00483
2003	1.5194	0.00489	1.2048	0.00811	0.7306	0.00456
2004	1.5190	0.00503	1.1722	0.00823	0.7381	0.00436
2005	1.5467	0.00529	1.1441	0.00833	0.6797	0.00428
2006	1.5368	0.00535	1.1480	0.00845	0.6683	0.00426
2007	1.5545	0.00572	0.9942	0.00824	0.7058	0.00408
2008	1.5725	0.00588	1.0434	0.00865	0.6940	0.00431
2009	1.5769	0.00618	0.9436	0.00870	0.6952	0.00449
2010	1.5729	0.00622	0.9786	0.00899	0.6532	0.00477
2011	1.5791	0.00627	1.0133	0.00926	0.6318	0.00514
2012	1.5713	0.00632	0.9868	0.00931	0.6186	0.00553
2013	1.5563	0.00624	1.0091	0.00954	0.6209	0.00596
2014	1.5552	0.00616	1.0456	0.00981	0.6350	0.00642
2015	1.5305	0.00586	1.1101	0.01005	0.6887	0.00661
2016	1.5255	0.00568	1.1424	0.01031	0.7179	0.00673

continues

Table A4.2: Estimates of time shifters by geographical area - Center

	Individual (α)		Firm (δ)		Transitory (γ)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Year (1985=1986=1)						
1987	1.0808	0.00437	1.2355	0.01162	0.7319	0.01362
1988	1.1467	0.00479	1.1123	0.01106	0.7925	0.01044
1989	1.1890	0.00536	1.0472	0.01151	0.8485	0.01048
1990	1.2376	0.00578	1.0286	0.01156	0.8744	0.01039
1991	1.2910	0.00640	0.9703	0.01157	0.7751	0.01021
1992	1.3228	0.00689	0.9622	0.01204	0.7614	0.01031
1993	1.3040	0.00701	0.9920	0.01254	0.7263	0.01106
1994	1.2978	0.00706	0.9996	0.01259	0.7348	0.01116
1995	1.3758	0.00758	1.0158	0.01307	0.6024	0.01267
1996	1.3683	0.00748	0.9586	0.01247	0.6545	0.01100
1997	1.3826	0.00766	1.0071	0.01295	0.6885	0.01130
1998	1.3521	0.00753	1.0653	0.01320	0.6203	0.01259
1999	1.3130	0.00742	1.1701	0.01380	0.6235	0.01400
2000	1.2966	0.00741	1.1600	0.01368	0.6814	0.01261
2001	1.2943	0.00747	1.1666	0.01381	0.6715	0.01336
2002	1.2973	0.00759	1.1759	0.01407	0.6508	0.01369
2003	1.3184	0.00780	1.0640	0.01372	0.7160	0.01207
2004	1.2999	0.00778	1.0203	0.01366	0.7444	0.01174
2005	1.3297	0.00805	0.9778	0.01382	0.7284	0.01149
2006	1.3353	0.00821	0.9047	0.01374	0.7365	0.01113
2007	1.3433	0.00848	0.7753	0.01360	0.7888	0.01110
2008	1.3832	0.00883	0.7651	0.01421	0.7754	0.01157
2009	1.3834	0.00899	0.7032	0.01440	0.7911	0.01209
2010	1.3905	0.00917	0.6957	0.01480	0.7508	0.01231
2011	1.3672	0.00905	0.7303	0.01501	0.7180	0.01283
2012	1.3754	0.00922	0.6941	0.01521	0.6819	0.01314
2013	1.3697	0.00922	0.7033	0.01551	0.6490	0.01350
2014	1.3647	0.00913	0.7265	0.01569	0.6758	0.01400
2015	1.3507	0.00886	0.7920	0.01601	0.6974	0.01436
2016	1.3388	0.00868	0.8176	0.01630	0.7068	0.01450

continues

Table A4.3: Estimates of time shifters by geographical area - South

	Individual (α)		Firm (δ)		Transitory (γ)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Year (1985=1986=1)						
1987	1.1034	0.00844	1.0151	0.00661	0.9561	0.01008
1988	1.1440	0.00973	1.0302	0.00717	0.9344	0.01125
1989	1.2157	0.01184	0.8633	0.00653	0.9019	0.00988
1990	1.2192	0.01225	0.9109	0.00687	0.9696	0.01018
1991	1.4254	0.01619	0.8170	0.00673	0.9868	0.00933
1992	1.5196	0.01861	0.7279	0.00666	0.9761	0.00882
1993	1.5437	0.01992	0.6251	0.00659	0.9719	0.00844
1994	1.5215	0.01975	0.6555	0.00665	0.9519	0.00861
1995	1.6069	0.02117	0.7027	0.00723	0.9071	0.00898
1996	1.5784	0.02104	0.7019	0.00732	0.8918	0.00922
1997	1.6147	0.02196	0.6884	0.00749	0.8507	0.00941
1998	1.6644	0.02375	0.5515	0.00731	0.9441	0.00925
1999	1.6021	0.02260	0.6213	0.00748	1.0144	0.00956
2000	1.6500	0.02423	0.5229	0.00732	0.8863	0.00857
2001	1.6356	0.02408	0.5397	0.00743	0.8272	0.00832
2002	1.6245	0.02409	0.5444	0.00761	0.7887	0.00834
2003	1.5959	0.02398	0.5155	0.00768	0.7743	0.00815
2004	1.5775	0.02394	0.4944	0.00775	0.7816	0.00800
2005	1.5364	0.02299	0.5662	0.00794	0.8103	0.00827
2006	1.5596	0.02368	0.5452	0.00818	0.7995	0.00837
2007	1.4814	0.02243	0.5483	0.00816	0.9124	0.00867
2008	1.5429	0.02376	0.5540	0.00878	0.8834	0.00917
2009	1.5569	0.02454	0.4975	0.00916	0.9440	0.00961
2010	1.5276	0.02418	0.5373	0.00957	0.9143	0.01014
2011	1.4978	0.02392	0.5774	0.01009	0.8991	0.01078
2012	1.5077	0.02464	0.5207	0.01059	0.8995	0.01108
2013	1.5070	0.02491	0.5235	0.01124	0.8707	0.01186
2014	1.4984	0.02499	0.5510	0.01197	0.8434	0.01266
2015	1.4413	0.02391	0.5949	0.01222	0.8271	0.01295
2016	1.4374	0.02374	0.6011	0.01253	0.8063	0.01368

Notes: The table reports the estimates of the time shifters in the earnings dynamics model of Section 3 estimated by geographical area.

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