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 abstract from the life cycle. We study firm effects in individual earnings dynamics for the Italian private sector population, using the covariance structure of co-workers for identification. Our model allows for dynamics of both worker and firm effects, worker-firm sorting, worker segregation and correlation among connected firms. While firms explain most of the earnings variance 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 (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 individual earnings 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 firms in shaping earnings dynamics and inequality over the life cycle is still largely missing in the literature.[1]

We study the extent to which firms account for unequal earnings dynamics over working lives. Using data on the population of private sector Italian 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 both at the worker and firm levels. We allow for the sorting of workers across firms, as well as for co-worker segregation – the tendency of similar individuals to work together— and for the correlation of firm-specific shocks among firms connected by worker mobility. We identify earnings variance components exploiting the empirical auto-covariance

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

structure of earnings for both individuals and co-workers. While the covariance structure of individual earnings has been widely studied (see among others Baker and Solon, 2003, Moffitt and Gottschalk, 2012, and Hoffmann, 2019) we are the first to also exploit the intertemporal covariance of *co-worker* wages.

The literature on firm effects in individual wage dynamics is still scant and we are among the first to provide evidence on their interrelationship. Friedrich et al. (2019) use Swedish employer-employee wage data and balance sheet data to estimate a structural model linking life-cycle wage shocks and shocks to firm productivity, 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 that would be required with more processes. Furthermore, we distinguish between life-cycle shocks and calendar time shifts of the earnings distribution, both features that are harder to incorporate in a structural framework.

Our paper is 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 the existence of firm-related wage dispersion is usually interpreted as violation of the 'law of one price' (Card et al., 2018). A related question concerns the degree of sorting – the extent to which high (low) wage workers work for high (low) wage firms. 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 connected firms that are linked by worker mobility. Their results for France show that worker heterogeneity is more important than firm heterogeneity in explaining wage inequality, and that indeed high-wage workers sort into high-wage firms.

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.[2] Estimating the AKM model on various sub-periods, they show that in Germany the increase in wage inequality over the past 30 years has been driven by widening distributions of both worker- and firm-specific wage premia.[3] Song et. al (2019) applied the AKM framework to population data for the US, showing that much of the growth of firm-related inequality stems from worker sorting into firms, rather than from firm effects. They also found a growing role for worker segregation in shaping earnings dispersion between firms.

Recent studies have highlighted that AKM-type estimators fail to deliver a consistent decomposition of earnings dispersion due to limited mobility bias. In two-way FE models, firm effects are identified from workers mobility between firms and when there is limited mobility the estimated contribution of firms to the variance decomposition is upwardly biased, while the sorting correlation is biased downward, often becoming negative. Awareness of the issue is not new, but it is only recently that researchers have begun effectively taking it into account.[4] Kline, Saggio and Sølvsten (2020) introduce a bias-corrected estimator for the variance components showing that in the bias-corrected decomposition the weight of worker-firm sorting increases while the weight of the firm-specific component decreases compared with the AKM-based decomposition. Bonhomme et al. (2022) apply the bias correction to data for various countries and compare the results with those obtained from a Correlated Random Effect (CRE) estimator, showing that both methods succeed in overcoming the limited mobility bias that plagues AKM-based variance decompositions, although

[2] See also Card, Cardoso and Klein (2016).

[3] Card et al. (2018) discuss the parametric restrictions needed in two way fixed effects models when one wants to control for age effects in mean wages. Because fixed effects include year of birth, indicators for age and calendar time can be included among regressors to control for time-varying heterogeneity only through parametric restrictions, and results of variance decompositions turn out to be sensitive to the specific restrictions adopted.

[4] The importance of handling limited mobility bias when deriving variance decompositions from two-way FE models was first highlighted by Andrews et al. (2008), who proposed a bias correction derived under homoscedasticity assumptions.

using different assumptions.[6] Lachowska et al. (2021) apply the bias-corrected estimator while allowing for time varying firm effects, showing that firm effects are highly persistent. [7]

We introduce firm effects into a standard earnings dynamics model akin to those of Baker and Solon (2003), Moffitt and Gottschalk (2012) and Hoffmann (2019). We extend the Minimum Distance (MD) estimator typical in this literature to encompass firm heterogeneity. In this framework the parameters that form the object of estimation are the variance components themselves, rather than the fixed effects. For identification, our MD estimator relies on moment restrictions of individual and co-worker covariance structures that are defined irrespective of worker mobility and because of this feature our estimator is not subject to limited mobility bias.[8]

We use data from the Italian labor market. 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. Italy has been undergoing institutional changes over the last 20 years, mostly aimed at increasing employment flexibility through the diffusion of temporary work contracts and, more recently, relaxing firing restrictions for permanent contracts. Earlier reforms were focussed on wage flexibility. For example, during the 1970s an egalitarian system of wage indexation against inflation known as *Scala Mobile* caused a great compression of wage differentials between skill groups, a system that was reformed and eventually abolished only in the following decade (Erickson and Ichino, 1995; Manacorda, 2004). These changes formed the background for a re-opening of wage differentials throughout the 1990s and early 2000s (Hoffmann, Malacrino and Pistaferri, 2021).

We consider men aged 25 to 55 to limit issues of endogenous labour force participation and we follow the convention of earnings dynamics studies of estimating wage differentials by year of birth

[6] CRE estimators of variance components for worker and firm heterogeneity have been introduced in Woodcock (2008) and Bonhomme, Lamadon and Manresa (2019).
[7] While Lachowska et al. (2021) allow firm effects to vary, worker effects are assumed to be fixed.
[8] We show in the Appendix that our estimator can be applied to a dataset of only stayers.

to separate life-cycle shocks 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 purely transitory, and can be individual- or firm-specific. Individual-specific shocks accumulate during the life cycle. The life-cycle process may result from the accumulation of human capital, promotions within firms, or mobility between firms. Individual wages also evolve because of firm-specific shocks common to all co-workers. In studies using the AKM approach, these firm effects are fixed over time and are meant to capture firm-level factors affecting the whole workforce of the firm, and we further allow them to change with the age of the firm, because the firm's ability to impact wages may change as the firm ages. Firm effects are allowed to be correlated with individual-specific shocks to capture the possibility of worker-firm sorting. Moreover, worker-specific effects are allowed to be correlated among co-workers to allow for segregation, and firm effects are allowed to be correlated among connected firms. The model includes transitory earnings shocks both at the individual- and at the firm-specific levels. All types of shocks are allowed to impact on the earnings process through period-specific loading factors that capture cyclical or secular changes in the earnings distribution.

Results show that on average over the life cycle worker effects account for 60 percent of earnings inequality, while firm effects and worker-firm sorting each account for about 15 percent, with the remainder due to transitory wage shocks. However, these life-cycle averages mask tremendous variation over workers' careers. Among young workers, individual-specific and firm-specific factors are equally important in accounting for earnings dispersion, the contribution of each to total inequality being around 30 percent. Conversely, individual effects account for as much as 70 percent of earnings inequality for workers in their mid-50s, while firm effects account for as little as 8 percent at that age. The growing importance of worker-specific heterogeneity over the life cycle suggests that both human capital accumulation and the search for better matches require some time to impact wage inequality, and that firm heterogeneity is very relevant in the meantime. Our estimates of the stochastic earnings process show that the growth of life-cycle heterogeneity is non-linear, being faster in the late 20s and mid 30s than for middle-aged workers. This non-linear pattern is reflected in the sorting of workers across firms, which is strongest early in the career. We estimate a sorting correlation of about 0.3 on average, but estimates for younger workers are as high as 0.4, while for older workers the sorting correlation is below 0.2. We find that more than half of earnings dispersion is due to heterogeneity between firms, and mostly due to worker segregation. We measure worker segregation as the correlation of worker fixed effects for workers of the same age, and our estimates imply a substantial correlation of 0.46. Similarly, there is significant 0.37 correlation of firm effects for connected firms. Our model nests a standard earnings dynamics model without firm effects and we exploit this property to show that the standard model overstates the importance of individual earnings dynamics in explaining life-cycle inequality, in particular among young and prime age workers. Looking at regional variation, we find that firm effects and workers' segregation are weaker in the North than in the South, consistent with the idea of a better functioning labor market in the former.

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 fill in order to pay state pension contributions for their employees, which is available in digitalized form since 1983. In this form employers report the gross take home pay, which is the full net pay including all forms of monetary compensation, grossed up with labor income taxes and pension contributions levied on the employee. Besides the amount of gross pay, for each employment spell the data report total working days, start and end dates (start dates are recorded since February 1974) and broad occupational categories (apprentices, blue collar, white collar or manager). This is supplemented with employer-level information about industry, location, date of establishment and date of closure. Information is available at both the firm- and workplace-level and we maintain firms as the unit of analysis on the employer side.

Throughout the period, average firm size is about 9 employees, while the average firm age goes from 8 years in 1983 to 13 years in 2016. Demographic information on workers includes gender and year of birth, but not education. Focusing on men, for each man in each year, we determine the *prevalent employer* as the attachment with the most working weeks, excluding matches with prevalent employers of less than 8 full-time-equivalent weeks. In order to derive a precise measure of workplace tenure, we keep fresh spells in the years 1983-2016 and exclude men whose first observed job in that window started prior to 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 observations over the period.

We use data since 1985 because of incompleteness of digital records for 1983 and 1984. In keeping with much of the literature on individual wage dynamics we consider working careers between ages 25 and 55 to limit endogenous participation of men due to educational choices or early retirement. 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 number of working days, rescaled to full-time equivalents.

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 ease identification of life-cycle profiles, we require that each cohort is potentially observed for at least 10 years. In this way, cohorts participating in the analysis range from 1939 (aged 46 in 1985 and potentially observed ten times until age 55 in 1994) to 1982 (aged 25 in 2007 and potentially 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 potentially observed throughout the 25-55 age range, while the number of observations on 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 individuals in the sample, whereas each remaining cohort account for between 2 and 3 percent of individuals in the sample. Besides requiring

10 potential observations on individual wages based on birth year, we also require that individuals are actually observed for at least five consecutive years; we further winsorize the resulting wage distribution at the top and bottom 0.5 percent by year.

Applying the above selection rules gives a sub-population 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 sub-population under analysis 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, suggesting that wage-age patterns estimated from the sub-population are a good proxy for the overall population of men. We next compare hourly wages for the sub-population used in estimation with their counterparts in the full population of men aged 16-65.[9] Figure 1.C shows no substantial difference in average hourly wages between the two groups. Figure 1.D shows that similar trends between the selected sub-population and the full population emerge also considering the standard deviation of logs. There is a difference of about two percent of a standard deviation between the two plots (larger figures corresponding to the full population), which is roughly constant throughout the period.

3. Econometric model

We allow earnings to evolve over the individual worker life cycle through the arrival of individual-specific shocks and firm-specific shocks, the latter being 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 that reflect economic volatility.

[9] We reflate nominal values to 2015 using the CPI.

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 time-by-cohort means. 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., 2020; Lachowska et al., 2021). Note that although wages are indexed by calendar time, the couple (i,t) unambiguously identifies the age of person i in year t, such that our model will effectively capture life-cycle earnings dynamics.

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 shifters α, δ and γ allow for aggregate changes in the wage distribution over calendar time.

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 search and 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 since age 25, which is the first age at which workers are observed in our sample design:

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

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

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 the conventional starting point and will in effect also reflect the accumulation of shocks occurring up to that age. Permanent shocks u_{it} are drawn from age-specific distributions with variance $\sigma_{u(t-c)}^2$ to allow for the possibility that their impact in shaping earnings inequality changes with age. For example, there may be more scope for learning on-the-job or for promotions among younger workers compared with older workers. RW specifications for individual effects are standard in the life-cycle earnings literature (see e.g., Hoffmann, 2019), while studies of firm-based wage inequality typically assume that worker effects are constant.

Firm effects capture firm-specific wage policies common to all co-workers. These effects determine the average position in the earnings distribution for the employees of a given firm. Firm effects may originate from rent extraction, efficiency wages, or other frictions generating persistent heterogeneity among employers. However, monitoring technology or unions' ability to extract rents may vary over time. Lachowska et al. (2021) model time variation of firm effects by fully interacting with calendar year dummies. We allow for calendar time variation of firm effects through the period shifters δ_t of Equation (1). Moreover, we also allow for age-related variation by letting firm-specific effects to be drawn from a distribution that changes with the age of the firm, capturing the idea that a firm's ability to impact the wages of its employees may differ by firm age. We model firm effects ϕ_{jt} as Random Effects (RE) with age-specific variances and unrestricted intertemporal covariances:

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

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 the literature on individual earnings dynamics to include some form of autoregression in "transitory" wage shocks to accommodate non-instantaneous reversion to the mean. We also follow this approach and allow the individual-specific part of the shock to follow a non-stationary first-order autoregressive (AR(1)) process, with cohort-specific initial conditions and innovations drawn from age-specific distributions:

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

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

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 subsequent variation in the variance of innovations is allowed through the exponential spline function $g(t-c)$.[10]

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

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

3.2 Moment restrictions and identification

The model is estimated by Minimum Distance, matching empirical second moments of the earnings distribution across cohorts and time periods to their counterparts implied by the model. To separate

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

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. Since the individual-specific effects accumulates over the life-cycle through the arrival of persistent shocks after age 25, we allow for a similar structure also 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, papers on firm-based wage inequality highlight the relevance of worker *segregation* (or *worker-worker sorting*), the tendency of similar workers to be employed by the same firm (see Barth et al., 2016; Lopes de Melo, 2018; Song et al., 2019; Bonhomme et al., 2020). 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. But even if worker- and firm-specific effects were uncorrelated, worker segregation may still emerge as consequence of informal labour market networks or residential segregation, as both factors imply that similar individuals work together. This second form of sorting (among workers rather than between workers and firms) has received less attention in the literature on firm-related wage inequality, possibly because its assessment is not necessary for estimating the two-way fixed effects models predominant in that literature, and the segregation parameter can be calculated post-estimation.

We introduce segregation 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.[11] In contrast to two-way fixed effects, addressing segregation is necessary for Correlated Random Effects (CRE) estimators because they exploit cross-worker wage covariances to derive moment restrictions. Bonhomme et al. (2022) wipe out individual *fixed* effects through first-order differencing before estimating co-worker covariances, thus eliminating segregation from the moment restrictions of the CRE. Such a strategy would not be viable in our setting with life-cycle dynamics and calendar time effects, because differencing would not eliminate individual-specific effects, and, consequently, segregation. We therefore follow a different approach and model (rather than eliminate) the co-worker covariance. Specifically, we let the co-worker covariance be a fraction μ of the covariance of individual 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 $var(\lambda_{it}) = var(\lambda_{i't})$, such as μ is the cross-sectional correlation coefficient of person-specific effects among co-workers of the same age.

Besides worker segregation, another 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, informal networks and local firm agglomerations may contribute to such firm-firm correlations. We therefore allow firm-specific effects to be correlated among firms connected via workers mobility (*firm-firm sorting*).[12] The standard assumption for CRE estimators of worker-firm variance components is to assume no correlation. Bonhomme et al. (2022) assume zero

[11] Lopes de Melo (2018) illustrates the relevance of co-workers' segregation estimating the correlation of co-workers fixed effects after estimating the AKM model. Using estimates of the AKM model, Song et al. (2019) measure segregation as the variance over firms of firm-specific averages of workers' effects. Barth et al. (2016) estimate co-workers correlation in observable skill measures.

[12] The definition of connected firms that we require in order to identify firm-firm correlations is different from the definition required for identification of worker and firm effects in two-way fixed effect models. For a given firm, we connect to all other firms that workers at the given firm have ever worked for. Two-way fixed effect models continue this firm-firm connection process iteratively until no more connections can be made, estimating the model on the largest connected set of workers and firms.

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 to be a fraction π of the covariance of firm-specific effects among connected firms:

$$cov(\phi_{jt}, \phi_{kt'}) = \pi cov(\phi_{jt}, \phi_{jt'}) \; if \;\; k = J(i, t') \tag{7}$$

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 k 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 mobility for identification, all remaining parameters being estimable even in the absence of mobility.[13]

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

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

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

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

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

where $\mathbb{I}[\ ]$ is a binary indicator and $s = \max(1985, c+25)$. Note that the correlation of firm effects across connected firms (*firm-firm sorting*, 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 structure of *individual* wages, it does not depend on the segregation parameter

[13] In Appendix Table A2 we report the estimates of the model obtained from a sample of stayers.

μ, which only features in cross-workers moments. Thus, segregation does not affect overall wage inequality, but only its between/within firm decomposition (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, their initial conditions are identified as the intercept of the age-related trends, and separation of time and age effects is achieved by computing the empirical covariance by workers' 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 parameters related to workers' age, namely those related to the life-cycle accumulation of RW shocks (σ_u^2) and those related to the life-cycle accumulation of the sorting covariance ($\sigma_{\phi u}$). Also, there are three (sets of) permanent parameters that are constant with respect to workers' age, that is the initial condition of the random walk (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 $\sigma_{\phi\phi}$). Intuitively, a single piece of information (the intertemporal covariance of individual wages in Equation (8)) can identify at most one set of age-unrelated permanent parameters and one set of age-related permanent parameters. Thus Equation (8) alone does not provide sufficient information for identifying all parameters of the permanent component and for separating worker-specific effects from firm-related effects, additional information is needed.

The necessary information can be generated by considering the *wage covariance structure of co-workers*, 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 (permanent and transitory firm-specific effects, plus sorting) and the fact that similar workers may work at the same firm at some (not necessarily the same) point in time independently of the characteristics of the firm, i.e., there may be worker segregation on top of the sorting of workers into firms. The co-worker covariance structure is given by:

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

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

Equation (9) is the between-firm component of the wage covariance structure. Separation of time and age effects in Equation (9) is achieved by computing the empirical covariance by workers' birth cohort and by using all cohort-specific covariances simultaneously in estimation, as for Equation (8). Combining Equations (8) and (9) we have two sets of age-dependent moment restrictions, while the model includes two sets of age-related parameters (RW shocks and worker-firm sorting covariance), which are therefore identified. A similar identification argument does not apply for parameters that are not related to worker's age, because in this case there are three (sets of) parameters (RW initial condition, sorting initial condition and the variance of firm-specific effects) and two sets of moment restrictions.[14] We overcome the lack of identification by constraining one parameter. In particular, we project life-cycle sorting covariances back to age 25 using the ratio of life-cycle RW shocks to the RW initial condition, i.e., we impose that $\sigma_{\phi\lambda} = \sigma^2_\lambda \sum_{k=26}^{(t-c)}\sigma_{\phi uk}/\sum_{k=26}^{(t-c)}\sigma^2_{uk}$.[15]

[14] 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).

[15] Alternatively, we may simply exclude this parameter from estimation, i.e., fix it to 0. 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 former was 0, such as the estimate of the latter would effectively be a convolution of the two parameters. In our case, assuming 0 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

Equations (8) and (9) 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 that needs mobility for identification is segregation (π), defined as the correlation of firm effects among forms connected through workers mobility, for which stayers, per se, are uninformative. This aspect of our model is in common with the CRE estimator, and contrasts with AKM-type two-way FE estimators that require mobility for identification. To further illustrate the point, in the Appendix we estimate the earnings dynamics model based only on the sub-sample of stayers.

3.3 Estimation

Let the covariance of Equations (8) and (9) be a non-linear function $f(\beta)$ of all model parameters collected in the vector β. The Minimum Distance 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 Segall, 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

in the text or assuming a 0 initial condition does not alter the estimates of remaining model parameters, or the ability of the model to predict empirical moments.

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. Empirical moments of individual wages (denoted with *I*) are estimated by averaging across individuals the cross products of residualized log-wages:

$$m_{tt'}^{I} = \frac{\sum_i \omega_{ijt}\omega_{ij't'}}{\sum_i p_{ijt}p_{ij't'}} \tag{10}$$

where ω is the empirical counterpart of w in Equation (1), and p indicates whether person i is observed in period t, thus allowing for an unbalanced panel.[16] 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 201?; Hoffmann, 2019), and only require they are observed at least five consecutive times.

The co-worker covariance (indexed by *C*) is estimated by adapting the algorithm 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 weight. The weighting procedure attributes more weight to larger firms and makes inference person-representative. For a given cohort, the co-worker covariance is given by:

$$m_{tt'}^{C} = \sum_j \theta_j \frac{\sum_i \sum_{h>i} \omega_{ijt}\omega_{hjt'}}{\sum_i \sum_{h>i} p_{ijt}p_{hjt'}} \tag{11}$$

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

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, all co-workers are used in the estimation of (11), while for larger cohorts, a random sample of 200 co-workers stratified by occupation is used in estimation.

There are 21,164 empirical moments in total, 10,582 each for individuals (estimated with Equation 10) and co-workers (estimated with Equation 11). We report estimated empirical moments over the life-cycle in Figure 2. The plot labelled "Total Variance" is the overall wage variance estimated using deviations of individual wages from cohort-specific means, averaging cohort-specific 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. The growth appears to be faster in the 30s than in the early 40s; with an acceleration after age 45. Also, consistent with the greater job mobility of younger workers, the steeper growth of wage dispersion at the early stages of the career compared with mid-career. The late career acceleration could reflect greater labour market attachment at the tails of the wage distribution than in the middle, because from the middle of the distribution (partial) early retirement is more common. As discussed in the previous section, our earnings dynamics model features age-specific variances of shocks that can handle such changes in the nature of wage dispersion over the life-cycle.

Figure 2 also reports a plot labelled "Co-worker Variance" which is obtained using Equation (11) and which essentially provides a measure of how much co-workers *jointly* deviate from the overall (cohort-specific) mean due to the wage factors that are shared among co-workers. In other words, this plot documents 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 idiosyncratic individual 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 (11) to match employees *between firms* randomly extracted from the economy. There is only a negligible upward trend in dispersion among placebo co-workers, which reassures that the patterns recovered for true co-workers reflect exposure to a common firm effect, of the sorting process underlying firm-worker matches, or of worker-worker segregation, and not simply a statistical artefact due to linking individuals born in the same year.

Figure 2 also reports the share of variance between firms (right scale) derived as the ratio of co-worker variance to total variance. This share is obtained in a fully non parametric way, without specifying 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 about 70 percent of wage dispersion is due to between firm heterogeneity driven by factors that are shared among co-workers. As workers age, individual-specific heterogeneity becomes increasingly evident in wage dispersion, and consequently the fraction of between-firm wage inequality declines, to about 60 percent by age 55. On average over the life-cycle, about 65 percent of wage dispersion occurs between firms. At this stage of the analysis, we are unable to disentangle the components of between-firm dispersion, something that will be possible based on the model estimates presented in the next section.

5. Baseline results

We begin the discussion of results by providing an overview of model goodness-of-fit in Figure 3. We display the same sets of empirical moments of Figure 2 (without placebos), overlaid with the corresponding moments predicted by the model, and perform the same exercise for the between-firm share of earning inequality. The graph generally shows a close fit over the life cycle, both for total and for co-worker variances. 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, though fitted and actual values converge 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 assume that it equals the RW initial condition rescaled by the ratio of life-cycle sorting covariances to life-cycle RW shocks (i.e., $\sigma_{\phi\lambda} = \sigma_\lambda^2 \sum_{k=26}^{(t-c)} \sigma_{\phi uk} / \sum_{k=26}^{(t-c)} \sigma_{uk}^2$). The evidence from Figure 3 suggests that, if anything, lack of identification has a mild predictive impact at age 25, which becomes 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. Life-cycle variation in the distribution of permanent shocks is accounted for by allowing the variance of innovations to change at five-year intervals. The estimated life-cycle heterogeneity of earnings growth, captured by the age-specific variances of innovations ($\sigma_{u(t-c)}^2$), can be characterised by two phases. First, when workers are younger than 35, wage dispersion grows substantially each year, by about one quarter of the initial condition. Second, when workers enter their late 30's, the growth of earnings dispersion almost halves. This evidence of non-linearity is compatible 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 individual-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 presents the estimates of the RE process for firm-specific effects. We allow the variance of these effects to be drawn from a distribution that changes with the age of the firm. Empirical moments vary by the age of individuals and not of firms, but for each moment we know the average age of the firms employing the workers that contribute to that moment. We compute the quartiles of these firm ages across all empirical moments, and let the variance of firm effects vary by quartile ($\sigma^2_{\phi q}$). We model long-term persistence of firm-specific shocks through a set of cross-quartile covariances ($\sigma_{\phi qq}$). The estimates for the 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 (i.e., $\sigma^2_{\lambda} + 3\sigma^2_{u26-30} = 0.0134$). Also, the cross-period covariances of the firm-specific REs are sizeable, implying a mean intertemporal correlation of 0.88.[18]

Panel C of Table 1 reports the parameters for the sorting components, between workers and firms (Panel C.1), between workers through segregation (Panel C.2) and between connected firms (Panel C.3). Starting from the worker-firm sorting components of Panel C.1, these are estimated as covariances between life-cycle shocks and the firm-specific effect ($\sigma_{\phi u(t-c)}$). The life-cycle pattern of worker-firm sorting reflects the pattern of 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. [19] The negative covariance innovations can be interpreted as a slowing down of the sorting process with age. For example, the probability that high-wage workers leave one high-wage firm to be hired by 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.

[18] Lachowska et al (2021) report intertemporal correlations of firm-specific effects of similar size.

[19] 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. Indeed, accumulation of innovations of covariances implies that worker-firm sorting remains positive throughout, as we show later in this Section, when we will discuss the implications of these estimates in terms of sorting covariances and correlations.

The instantaneous worker-firm sorting covariance become positive again for ages 51-55. As noted in the previous section, in that age range the growth of the empirical variance accelerates and selective survival in the labour market due to e.g., early retirement, could explain the pattern. The result of increasing sorting suggests this selectivity may come primarily from workers that are negatively sorted into firms, for example high age workers (mis-)matched to low wage firms.

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 numbers. 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. This firm-firm segregation is smaller in magnitude than worker-worker segregation, but still substantial, with a point estimate of 0.36 and highly statistically significant. This estimate of firm-firm segregation 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 other estimates of this parameter in the literature.

5.2 Transitory wages

Table 2 reports in Panel A the estimates for the parameters of the worker-specific transitory wage component, 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, fluctuating 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 Hoffman (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 persistence. 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.[20].

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 the estimated factor loadings for the worker effects, firm effects, and the transitory components. Following Hoffmann (2019), we set the first two factor loadings in each of the three groups equal to unity for identification. Loadings on the individual components show a pronounced widening of permanent wage differentials between the mid-1980s and mid-1990s, which levels off thereafter. The trend over the 1980s and 1990s resembles that of overall wage dispersion shown in Figure 1, 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

[20] Baker and Solon (2003) report a similar pattern of initial conditions in Canadian social security records.

productivity growth, which effectively stops around 2000 (see Figure 1 in Hoffmann, Malacrino and Pistaferri, 2021), 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 those 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-cyclicality of firm heterogeneity is consistent with the pattern of firm entry and exit over the business cycle.

The last set of factor loadings in Figure 1 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 produced estimates of loading factors for the transitory components that were more stable over time than those depicted in Figure 4. This difference suggests that part of the wage instability estimated from standard earnings dynamics models is in fact due to fluctuations of the firm-related wage component.

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, worker-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 worker-specific transitory shocks. In contrast, at age 25 firm specific transitory shocks explain less than 10 percent of the total variation, and even less (three percent) is due to sorting. We show at the beginning of this section that worker-firm sorting is underestimated at age 25, but the fit quickly improves as sorting covariances accumulate over the life-cycle. For example, at age 30, the sorting component accounts for about 20 percent of earnings dispersion, another 20 percent is explained by permanent firm heterogeneity, while transitory firm heterogeneity explains about five 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. 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 shock account for 4 percent; finally, the remaining 15 percent is due to sorting. Our estimates of the variance decomposition are in the range of these by Bonhomme et al. (2022) using bias corrected FE or CRE estimators. In particular, for Italy using a sub-sample of the data we use for two medium sized provinces in the Veneto region over 1996-2001, they attribute about 15 percent of the total variance to both firm-specific effects and worker-firm sorting.

We already know from Figures 2 and 3 that about 60 percent of earnings inequality stems from between-firm heterogeneity and that this share is rather stable over the life cycle. 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-specific heterogeneity, coupled with the fact that similar workers tend to work together. The life-cycle variation of between-firm inequality share due to worker-worker segregation grows remarkably 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. [21] All covariances and correlations are positive. The covariances (right scale) indicate that sorting grows at a relatively fast pace in the initial years, reflecting both the underestimation of sorting at 25 and the fact that instantaneous sorting covariances between ages 26 and 30 are relatively large (the corresponding parameter in Table 1 is the largest of the instantaneous sorting covariances). The growth of sorting covariance levels-off and even becomes negative mid-career, which, we have argued, could reflect that the probability that high-wage workers leaving high-wage firms to be hired at other high-wage firms may decline with age. Figure 7 also shows the increase of sorting covariances over the final part of the life cycle, which as we have discussed above could reflect selective early retirement from the labour market.

To put our findings into perspective, Figure 7 also provides the evolution of sorting correlations, which are more informative than covariances about the strength of sorting, and also offers a metric for comparison with other studies. Sorting correlations follow similar pattern to covariances in the initial years, after which correlations immediately start declining (rather than slowing down like the covariances), and increase from age 50. The reason for the earlier decline of correlations compared to covariances is due to the fact that 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 Table1. On average

[21] Since worker-firm sorting affects not only cross-sectional dispersion but also intertemporal wage persistence, at each age covariances and correlations are computed averaging variances and covariances over any lead and lag of the data that include that particular age level.

throughout the life cycle there is a sorting correlation of 0.28 that is in the range of estimates reported by other papers in the literature. This 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 earnings dynamics model with RW permanent shocks, AR transitory shocks and period-specific loading factors on each. 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. We provide evidence on this point by estimating the standard earnings dynamics model using only the individual-level covariance structure. Results on the permanent component are reported in Panel A of Table 3 and they show that RW parameters are substantially larger than in the baseline estimates, but only for the initial part of the life-cycle, that is when firm heterogeneity matters most for explaining earnings dispersion. Also, the serial correlation of mean reverting shocks is larger in the standard model compared with the baseline (0.65 vs 0.47, see Panel B of Table 3), reaching a level that is common with other individual earnings dynamics studies.

Figure 8 summarizes the findings from the standard model, showing the variance predictions over the life cycle. The overall prediction is very close to that from the baseline model shown in Figure 3. What differs from the baseline is the share of earnings dispersion that can be imputed to the permanent and transitory components. In the baseline, this share went from about 30 percent at the beginning of the life cycle to about 75 percent at age 55. On the other hand, the share due to individual transitory shocks went from 25 percent to less than 5 percent over the life cycle. In the standard specification underlying Figure 8, the model predicts that at age 25 about 60 percent of inequality is due to individual-specific permanent earnings, and reaches 80 percent by age 55. From these comparisons we conclude that the standard earnings dynamics specification that omits firm effects overestimates the relative importance of both the permanent and transitory individual components and that such overestimation is more pronounced at young ages, 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 life cycle, before the influence of individual heterogeneity comes to dominate. Mechanisms behind this change in relative importance are human capital accumulation and worker turnover, and it is conceivable that their effectiveness depends 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 across different economic environments 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 are among the most productive in Europe, with 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 production, and by relatively high unemployment especially among the youth. In terms of these contrasts, central regions fall somewhat 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 based on the province of work. 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 most prevalent area being due to temporary migrations to the North. The number of firms in the regional sub-samples is 1,685,499 (North), 952,386 (Center), 1,056,163 (South); a sum exceeding the count for the overall sample due to multi-plant firms 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 by Minimum Distance. [22]

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 Appendix Table A4. Comparing estimates of the individual-specific RW process, the South is very distinctive, especially at the beginning of the career. In the south individual-specific earnings dynamics among young workers are less important than the rest of the country, with corresponding parameter estimates being approximately between one half and a third 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. Another major difference by area is the level of firm-specific heterogeneity, which is three times higher in the South than the North. Greater firm-specific dispersion may reflect less worker reallocation/turnover and in general greater labour market rigidity, making firm-specific wage premia less likely to be competed away by worker mobility across firms. This possibility is supported also by the evidence on worker segregation and correlation of firm effects among connected firms, both parameters being larger in the South than elsewhere. Considering estimates of the transitory shocks in Table 5, we can see that shocks are more persistent in the South, again indicating greater labor market rigidity. Also, the dispersion of firm-specific shocks increases with the firm age in the North and Center but not in the South. In Section 5 we have noted that the overall age pattern is consistent with greater exposure to stock market volatility among older firms, and evidence from Table 5 suggests that there may be more limited access to the stock market among southern firm than in the rest of the country.

Figure 9 illustrates the implications of the estimates in terms in terms of life-cycle variance profiles and between firm variance shares, where they are contrasted to the corresponding empirical

[22] 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 AR1 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 Section 3.2 resulted in convergence issues in the case of the Center, which we overcome by constraining the initial condition to 0.

moments and between shares derived from the data. Both in the North and Center, overall earnings dispersion displays stronger growth before age 40 than after, replicating the pattern that we have already observed for the country as a whole, consistent with greater worker turnover, promotions, or human capital accumulation prior to age 40. The pattern from the South is strikingly different in that there is little change in the growth of earnings dispersion over the life cycle, and the lifetime age gradient in the South resembles that for older workers in the North and Center. The other remarkable difference across areas is the share of variance between firms, rangingfrom 55 percent in the North to 70 percent in the Center and South. Overall, Figure 9 illustrates how much greater scope for individual heterogeneity to shape earnings trajectories exists in the North than elsewhere. The 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 first at age 40 in the South. Conversely, firm related wage components are more relevant throughout the life cycle in the Center and especially in the South than in the North. Finally Figure 11 illustrates that worker-firm sorting is greater in the North then in the rest of the country.

7. Conclusion

Using data on the population of Italian employers and employees, we have modelled the life-cycle earnings dynamics of men allowing wages to depend on firm-specific and individual-specific shocks. We have developed an identification strategy for variance components based on the covariance structure of co-worker earnings.

The results indicate that firm-related heterogeneity is a dominant factor for explaining earnings differences among young workers. Worker-specific heterogeneity is the dominant factor of wage dispersion in the long-run, but it takes time for it to display its inequality-enhancing effects. The growth of worker-specific heterogeneity is faster among young workers than for older ones consistently with a reduction in human capital investments and reduced worker mobility. The sorting of workers into firms is sizeable and characterised by life-cycle variation that reflects the evolution individual heterogeneity, being stronger for young workers. We also find that there is relevant workers' segregation and that firm-specific wage premia are correlated among connected firms. Overall, about 60 percent of earnings inequality is due to wage differences between forms and the bulk of it stems from segregation. Both segregation and firm-specific earnings dispersion are stronger in high unemployment regions.

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Figure 1 – Sample descriptives

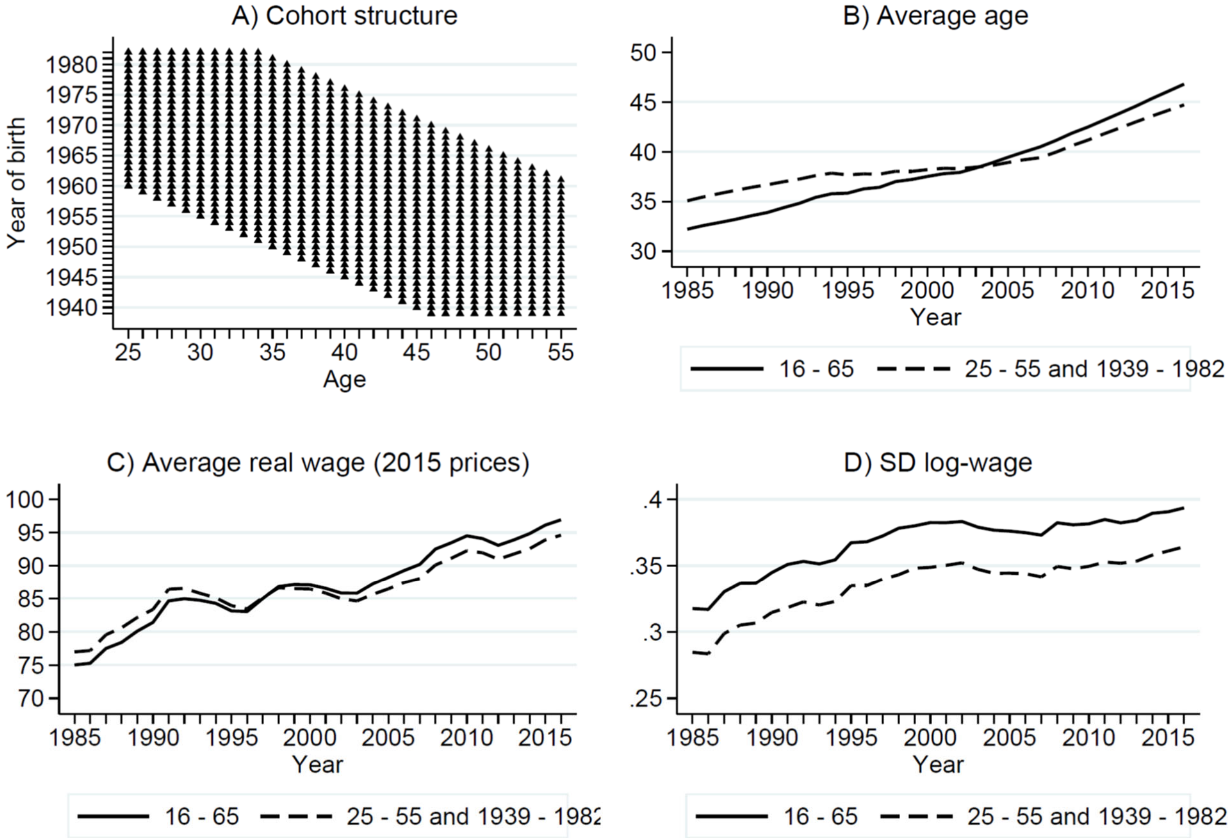
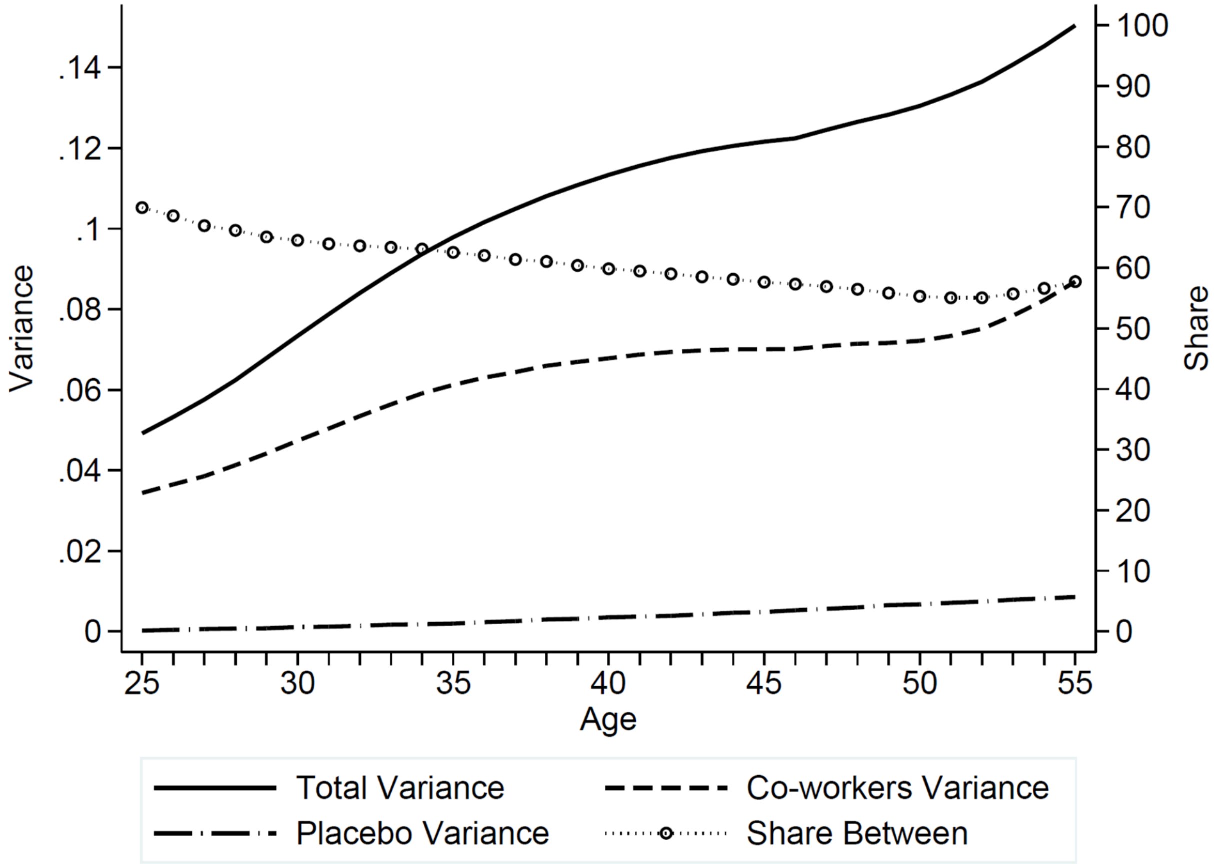
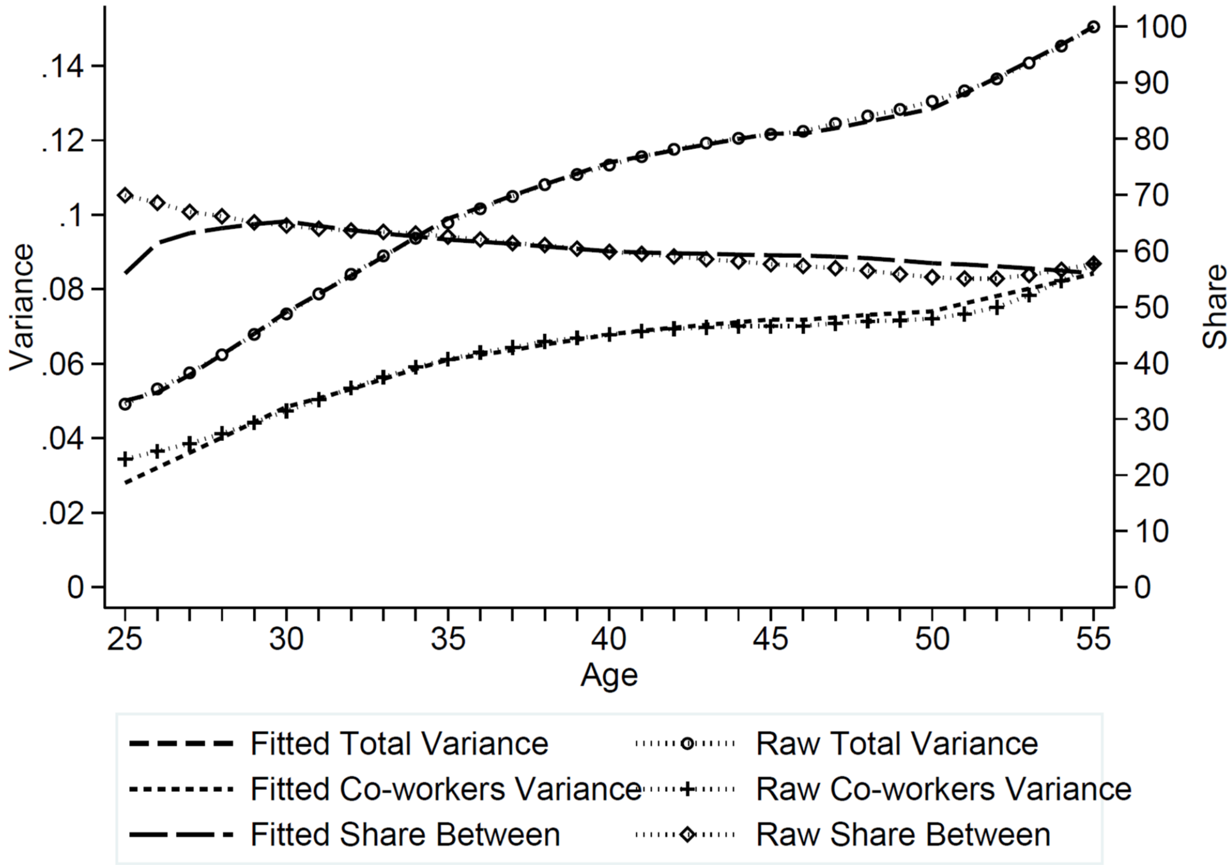


Figure 2 – Raw variances and between-firms variance share over the life cycle



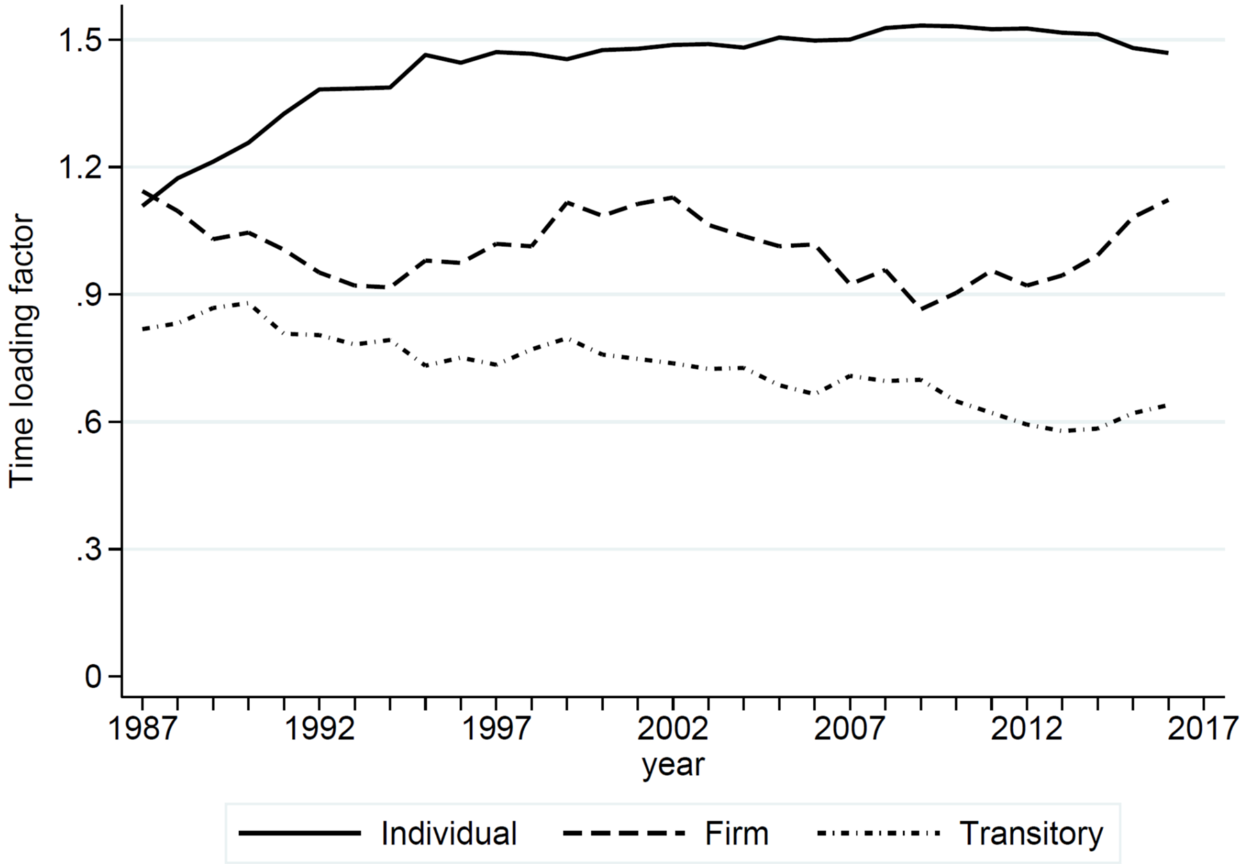
Notes: The figure reports the life-cycle evolution of the variance and of its between-firms component. Empirical moments are estimated by birth cohort and averaged across cohorts by age. Total Variance is the variance derived from the empirical second moments of individual wages. Co-workers Variance 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



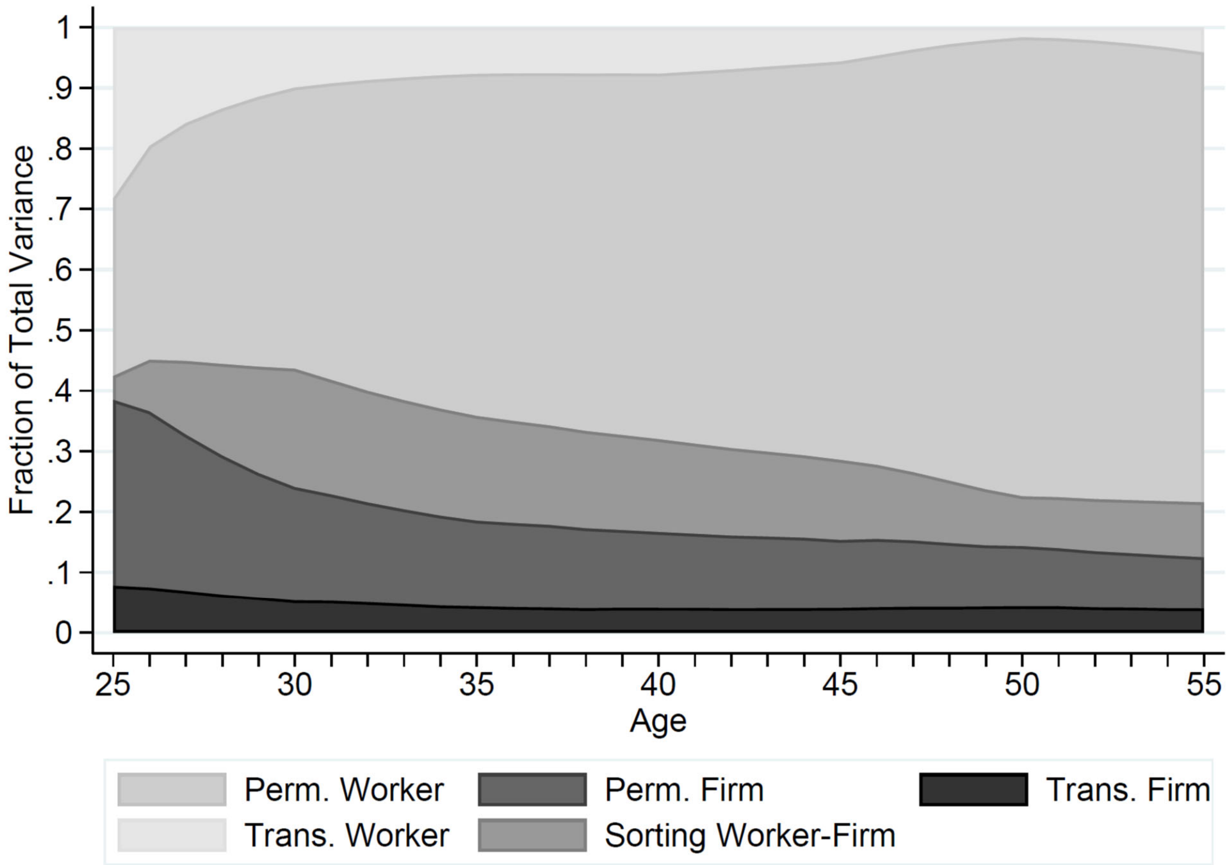
Notes: The figure reports raw empirical moments and their fitted counterparts derived from the econometric model. The raw figures are as in Figure 2. The fitted figures are predicted for each cohort-age combination that is present in the sample and then averaged across cohorts by age. Parameter estimates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

Figure 4 – Estimates of time loading factors



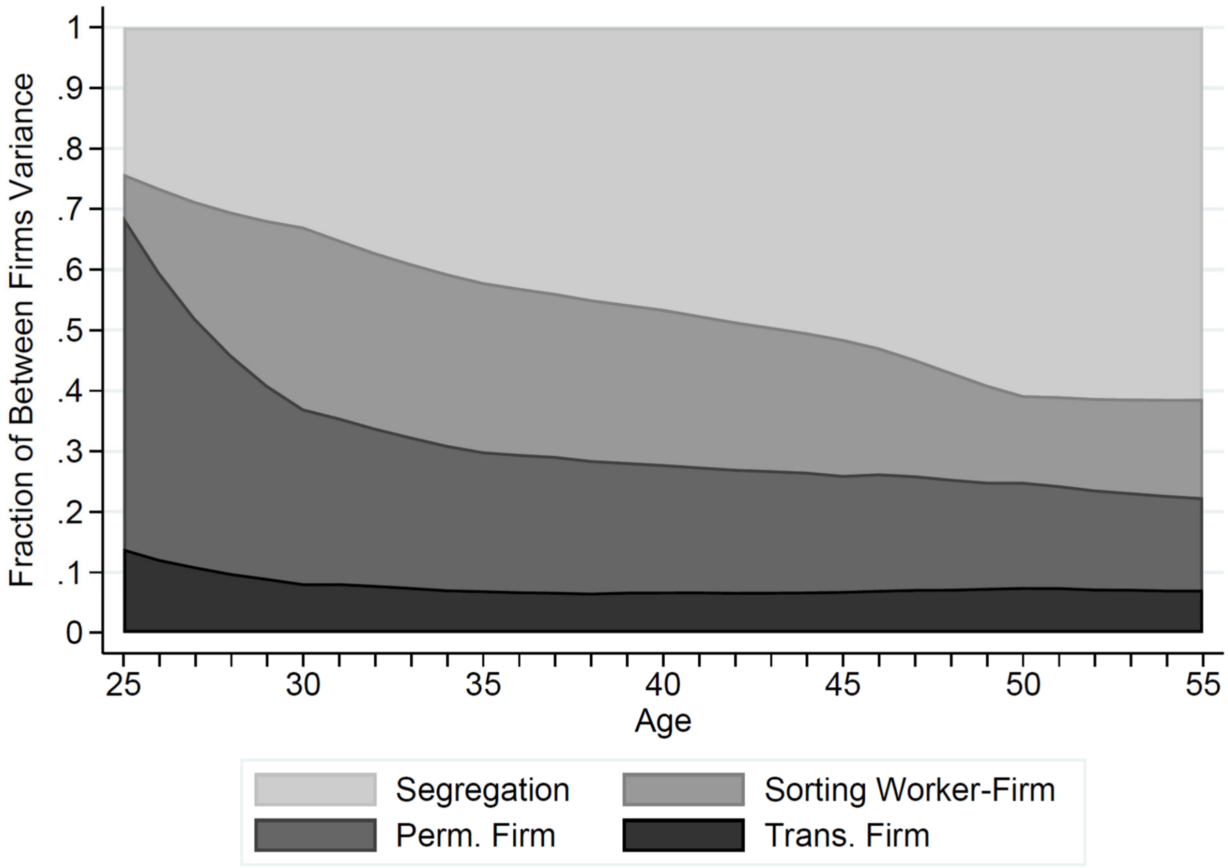
Notes: The figure reports the point estimates of the time loading factors for the individual permanent component, the firm permanent component and the transitory component, denoted α, δ and γ , respectively, in the earnings model of Equation (1). The loading factors are normalised to 1 in 1985 and 1986. 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



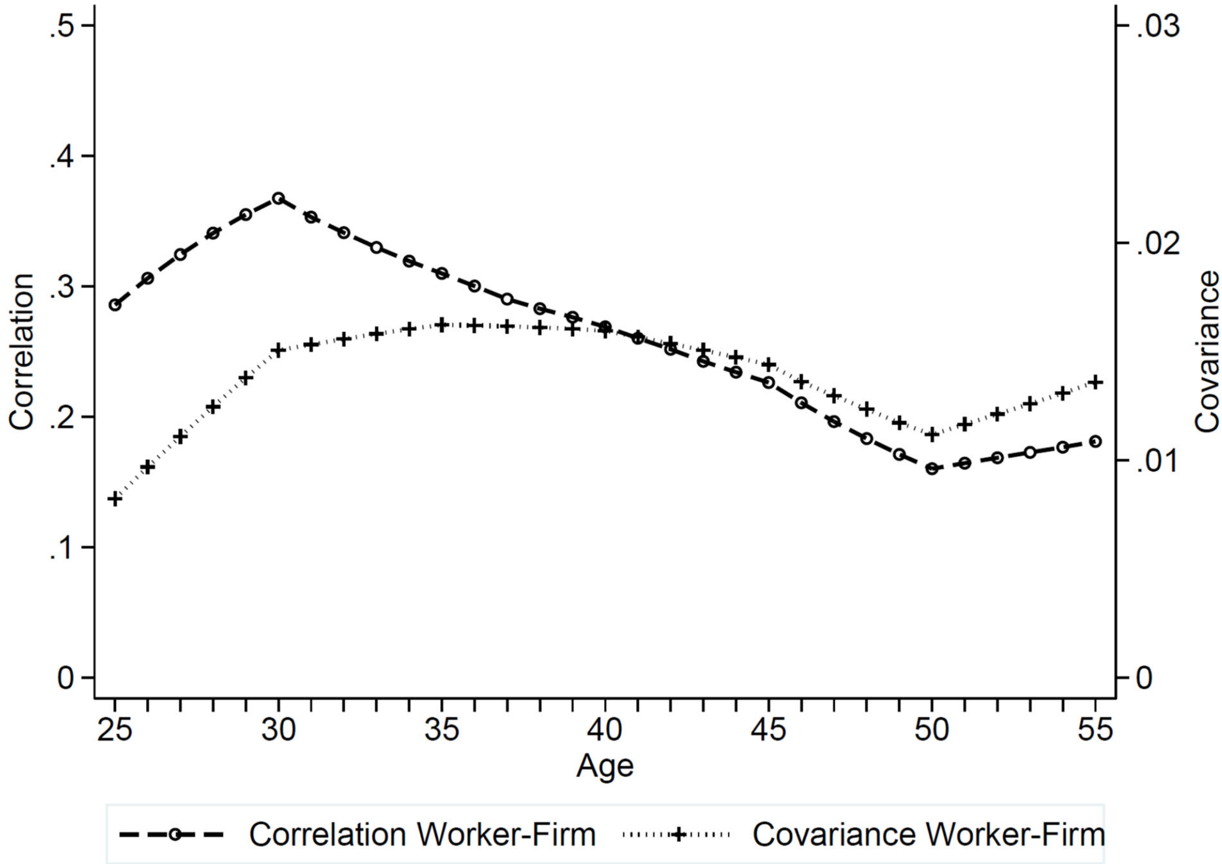
Notes: The figure reports the variance decomposition derived according to Equation (8). Variance components are predicted for any cohort-age combination that is present in the sample and then averaged across cohorts by age. Parameter estimates underlying the decomposition are reported in Table 1, Table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

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



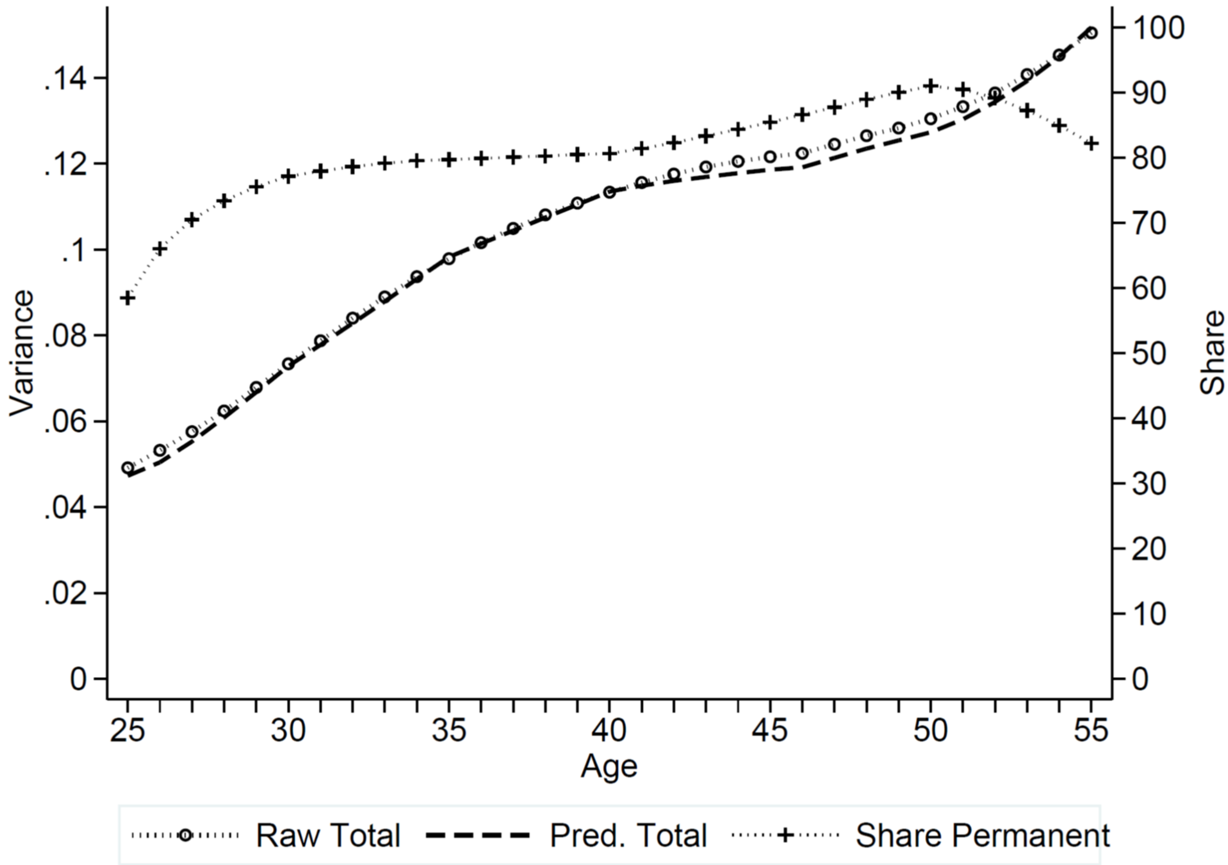
Notes: The figure reports the between-firms variance decomposition derived according to Equation (9). Variance components are predicted for any cohort-age combination that is present in the sample and then averaged across cohorts by age. Parameter estimates underlying the decomposition are reported in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

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



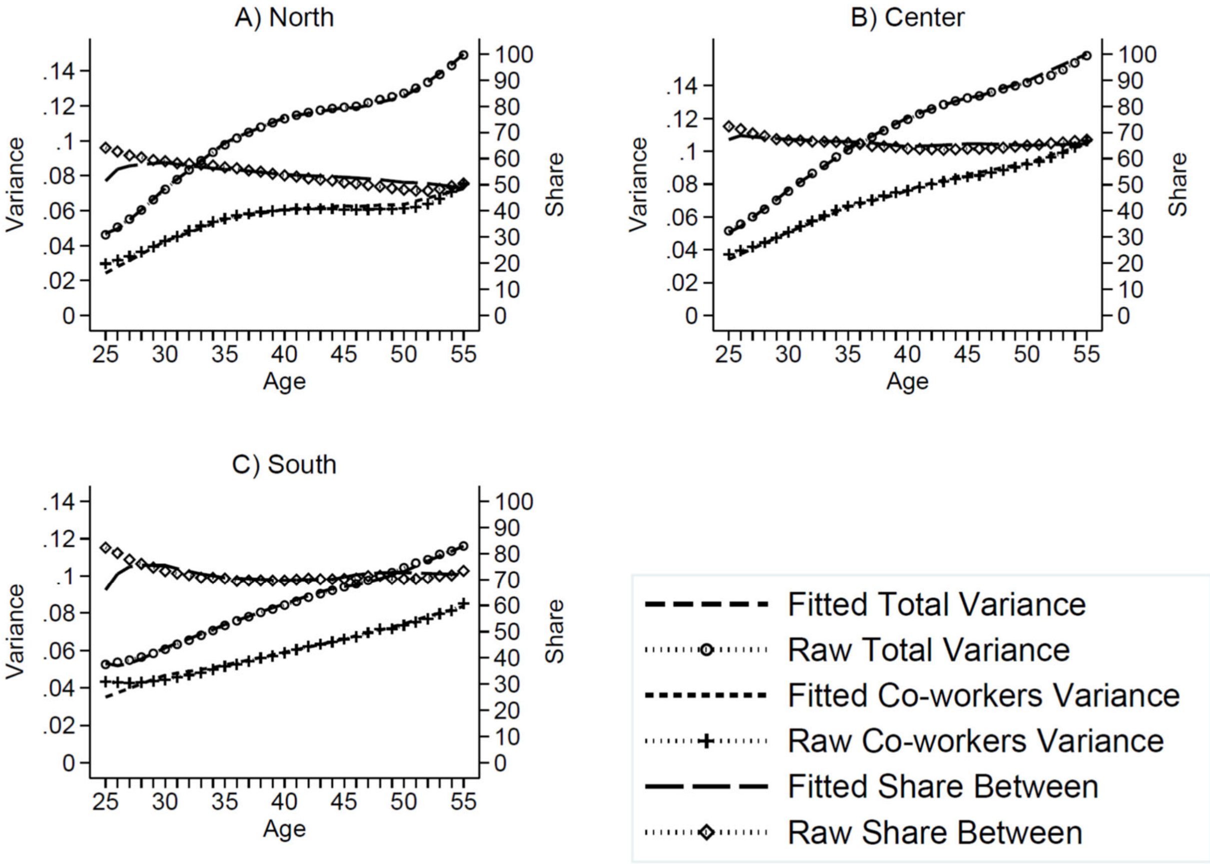
Notes: The figure reports sorting measures derived from the econometric model over the life cycle. The sorting covariance is obtained by applying Equation (5). Predictions are derived for any cohort-age-lag combination that is present in the data and then averaged across cohorts by age.

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



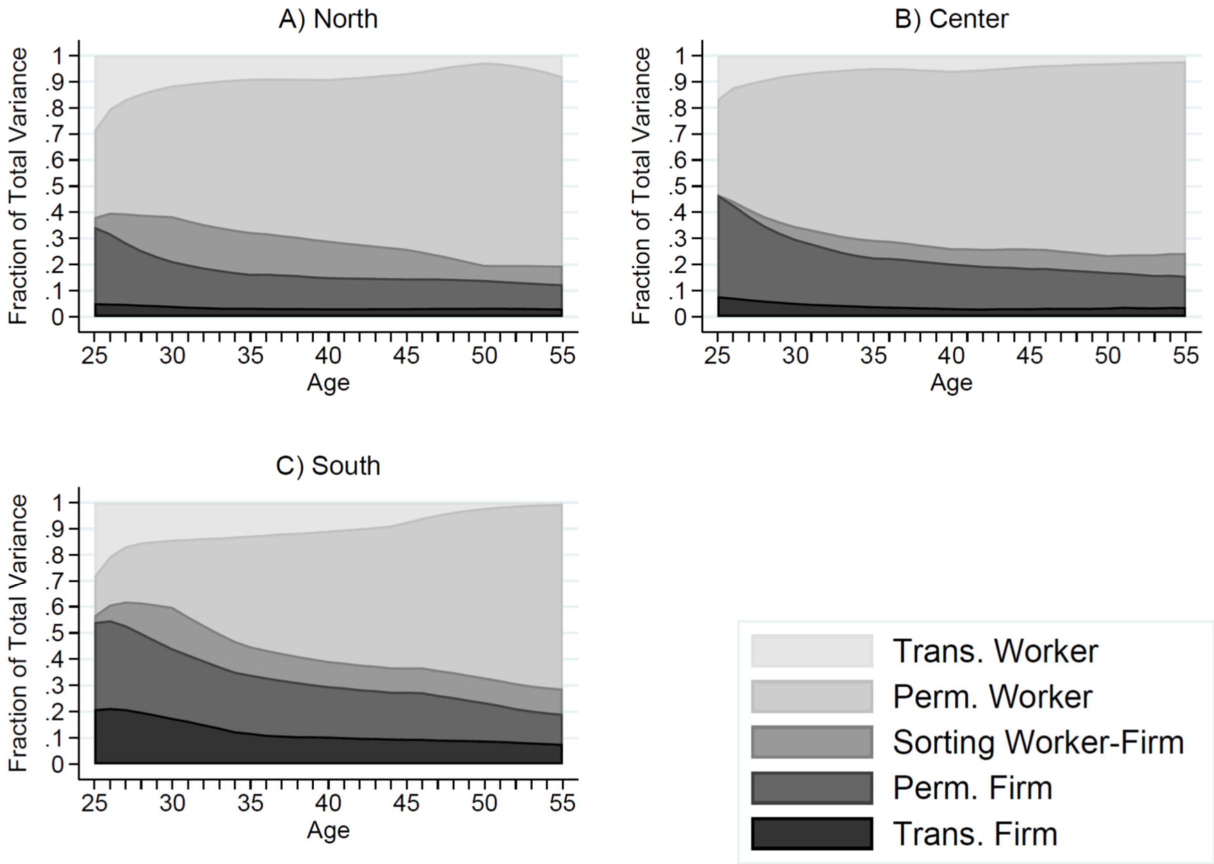
Notes: The figure reports raw empirical moments and their fitted counterparts derived from a standard earnings dynamics model without form effects. The fitted figures are predicted for each cohort-age combination that is present in the sample and then averaged across cohorts by age. Parameter estimates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



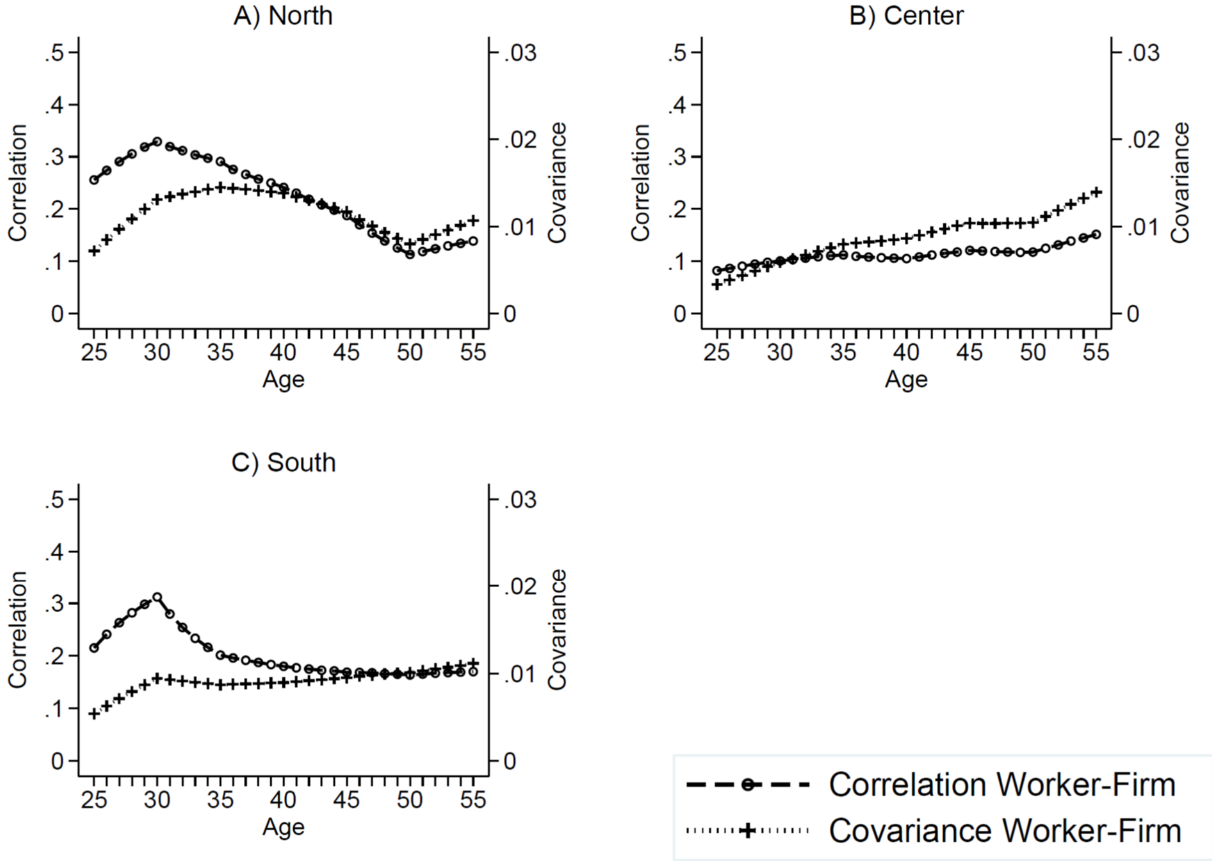
Notes: The figure reports raw empirical moments and their fitted counterparts derived from the earnings dynamics model estimated by geographical area. The fitted figures are predicted by area for each cohort-age combination that is present in the sample and then averaged across cohorts by age. Parameter 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^2_{λ}	0.0077	0.00011
σ^2_{u26-30}	0.0019	0.00002
σ^2_{u31-35}	0.0021	0.00001
σ^2_{u36-40}	0.0013	0.00001
σ^2_{u41-45}	0.0011	0.00001
σ^2_{u46-50}	0.0012	0.00001
σ^2_{u51-55}	0.0010	0.00002
B) Firm		
$\sigma^2_{\phi q1}$	0.0148	0.00011
$\sigma^2_{\phi q2}$	0.0126	0.00013
$\sigma^2_{\phi q3}$	0.0148	0.00017
$\sigma^2_{\phi q4}$	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) Sorting		
C.1) Worker-firm shock covariance		
$\sigma_{\phi\lambda}$	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-worker correlation		
μ	0.4609	0.00243
C.3) Firm-firm correlation		
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 Section 3.

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

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; $\chi^2(21015)$= 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

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		0.0114	0.00025	0.0037	0.00020
σ^2_{u26-30}	0.0020		0.0030	0.00004	0.0007	0.00003
σ^2_{u31-35}	0.0020		0.0025	0.00003	0.0014	0.00004
σ^2_{u36-40}	0.0012		0.0018	0.00003	0.0010	0.00003
σ^2_{u41-45}	0.0010		0.0012	0.00003	0.0009	0.00003
σ^2_{u46-50}	0.0011		0.0009	0.00003	0.0009	0.00004
σ^2_{u51-55}	0.0006		0.0012	0.00004	0.0011	0.00004
			B) Firm			
$\sigma^2_{\phi q1}$	0.0115		0.0182	0.00032	0.0334	0.00036
$\sigma^2_{\phi q2}$	0.0093		0.0192	0.00037	0.0364	0.00053
$\sigma^2_{\phi q3}$	0.0119		0.0242	0.00049	0.0334	0.00071
$\sigma^2_{\phi q4}$	0.0110		0.0212	0.00050	0.0402	0.00099
$\sigma_{\phi q1q2}$	0.0097		0.0176	0.00034	0.0336	0.00042
$\sigma_{\phi q1q3}$	0.0092		0.0180	0.00035	0.0329	0.00045
$\sigma_{\phi q1q4}$	0.0080		0.0191	0.00038	0.0329	0.00047
$\sigma_{\phi q2q3}$	0.0098		0.0206	0.00040	0.0347	0.00055
$\sigma_{\phi q2q4}$	0.0071		0.0196	0.00040	0.0332	0.00055
$\sigma_{\phi q3q4}$	0.0095		0.0231	0.00048	0.0341	0.00066
			C) Sorting			
			C.1) Worker-firm shock covariance			
$\sigma_{\phi\lambda}$	0.0005				0.0007	0.00002
$\sigma_{\phi u26-30}$	0.0007		0.0003	0.00003	0.0009	0.00003
$\sigma_{\phi u31-35}$	0.0002		0.0003	0.00002	-0.0002	0.00002
$\sigma_{\phi u36-40}$	0.0000		0.0000	0.00001	0.0000	0.00002
$\sigma_{\phi u41-45}$	-0.0001		0.0002	0.00001	0.0001	0.00002
$\sigma_{\phi u46-50}$	-0.0004		-0.0001	0.00002	0.0001	0.00002
$\sigma_{\phi u51-55}$	0.0002		0.0004	0.00002	0.0002	0.00002
			C.2) Worker-worker correlation			
μ	0.3990		0.5620	0.00377	0.6113	0.00481
			C.3) Firm-firm correlation			
π	0.2827		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 Section 3, while it is fixed 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		0.0083	0.00036	0.0047	0.00024
κ_{27-30}	0.0017		-0.0541	0.01580	0.0676	0.01430
κ_{31-35}	0.0229		-0.0439	0.01167	0.0159	0.00751
κ_{36-40}	0.0308		0.1420	0.01079	0.0089	0.00693
κ_{41-45}	-0.0528				-0.0331	0.00876
κ_{46-50}	-0.1754		-0.1267	0.01050	-0.2506	0.02861
κ_{51-55}	0.2947					
ρ	0.5057		0.4509	0.01424	0.6536	0.00866
σ^2_{v1939}	0.0096		0.0004	0.00170	0.0045	0.00240
σ^2_{v1940}	0.0093		0.0015	0.00164	0.0076	0.00238
σ^2_{v1941}	0.0116		0.0107	0.00177	0.0112	0.00240
σ^2_{v1942}	0.0123		0.0124	0.00175	0.0152	0.00241
σ^2_{v1943}	0.0131		0.0135	0.00167	0.0150	0.00234
σ^2_{v1944}	0.0116		0.0129	0.00166	0.0148	0.00230
σ^2_{v1945}	0.0120		0.0156	0.00163	0.0135	0.00216
σ^2_{v1946}	0.0115		0.0131	0.00137	0.0107	0.00191
σ^2_{v1947}	0.0108		0.0147	0.00139	0.0151	0.00191
σ^2_{v1948}	0.0108		0.0099	0.00131	0.0132	0.00182
σ^2_{v1949}	0.0095		0.0102	0.00130	0.0177	0.00184
σ^2_{v1950}	0.0105		0.0126	0.00135	0.0217	0.00188
σ^2_{v1951}	0.0121		0.0103	0.00125	0.0185	0.00180
σ^2_{v1952}	0.0124		0.0122	0.00124	0.0228	0.00184
σ^2_{v1953}	0.0142		0.0133	0.00125	0.0187	0.00175
σ^2_{v1954}	0.0161		0.0118	0.00116	0.0205	0.00165
σ^2_{v1955}	0.0150		0.0134	0.00112	0.0171	0.00156
σ^2_{v1956}	0.0157		0.0108	0.00103	0.0178	0.00149
σ^2_{v1957}	0.0174		0.0164	0.00106	0.0170	0.00142
σ^2_{v1958}	0.0193		0.0181	0.00100	0.0146	0.00135
σ^2_{v1959}	0.0206		0.0203	0.00098	0.0215	0.00128
$\sigma^2_{v1960-1982}$	0.0216		0.0173	0.00062	0.0181	0.00047
			B) Firm			
$\sigma^2_{\xi q1}$	0.0033		0.0070	0.00019	0.0135	0.00022
$\sigma^2_{\xi q2}$	0.0071		0.0078	0.00030	0.0097	0.00019
$\sigma^2_{\xi q3}$	0.0070		0.0069	0.00036	0.0115	0.00026
$\sigma^2_{\xi q4}$	0.0111		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. The parameter $\sigma_{\phi\lambda}$ in column 1 and 3 is estimated based on the constraint described in Section 3, while it is fixed to 0 in column 2. Age splines for AR1 innovations after age 40 are reduced to 1 in column 2 and 2 in column 3.