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Earnings Dynamics, Inequality, and Firm Heterogeneity

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ABSTRACT

Studies of individual earnings dynamics typically overlook firm heterogeneity, while worker and firm decompositions of earnings inequality often neglect the life cycle. We study firm effects in individual earnings dynamics for the Italian private sector population, using the covariance structure of co-worker earnings for identification. We allow for dynamics of both worker and firm effects, as well as worker-firm sorting and worker segregation. When workers are young, firm and worker heterogeneity explain similar shares of earnings inequality; however, over the life cycle, workers account for most of the inequality. Sorting is substantial, especially among younger workers. Segregation accounts for most of the earnings inequality between firms.

JEL Classification: J24, J31

1 | Introduction

Individual earnings dynamics have been extensively studied to understand earnings inequality and instability. Labor economists have explored the earnings process, identifying that long-term inequality stems from differences in human capital investments and returns, while instability is linked to labor market deregulation (Baker and Solon 2003; Moffitt and Gottschalk 2012; Blundell et al. 2015; Magnac et al. 2018; Hoffmann 2019). Public economists and macroeconomists have analyzed the statistical properties of labor earnings to understand consumption patterns and evaluate the effectiveness of alternative policies for insuring income risk (Meghir and Pistaferri 2004, 2011; Huggett et al. 2011; Blundell 2014).

Studies of earnings dynamics often acknowledge the relevance of firm heterogeneity. The interaction between workers and firms affects life-cycle earnings through several mechanisms: Employer learning leads to wage adjustments as firms update their beliefs about worker productivity; firms may provide informal insurance, smoothing earnings in response to temporary shocks; and workers accumulate firm-specific human capital, which can increase wages with tenure. Wage changes also arise from worker mobility, as both employers and employees search for better matches. 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 from the literature.[1]

By explicitly incorporating firm heterogeneity into the standard model of earnings dynamics, we provide a framework to analyze how differences between firms contribute to unequal earnings trajectories throughout individuals' working lives. Using data on the population of Italian private sector firms and workers, we estimate the stochastic process governing earnings across the life cycle. Our approach separately identifies the effects of both individual- and firm-specific shocks, distinguishing between permanent and transitory components at each level. This framework allows us to capture how persistent and short-lived shocks, originating from either workers or firms, shape earnings trajectories and contribute to wage inequality over time.

We account for the dynamics of firm effects and the sorting of workers across firms, where high- and low-wage workers tend to cluster in high- and low-wage firms. Additionally, our framework captures worker segregation, reflecting the tendency of similar individuals to work together. We identify the components of the earnings variance by exploiting the empirical autocovariance structure of earnings for both individuals and their co-workers. Although the covariance of individual earnings has been extensively studied in the literature (see, among others, Baker and Solon 2003; Moffitt and Gottschalk 2012; and Hoffmann 2019), our approach is novel in that we analyze earnings dynamics by utilizing the intertemporal covariance of co-worker wages.

The literature examining firm effects in life-cycle earnings dynamics remains relatively sparse, and our study is among the few that provide evidence of this relationship. Friedrich et al. (2024) use Swedish employer–employee wage and balance sheet data within a structural framework that links life-cycle wage shocks to firm productivity shocks, while explicitly modeling endogenous worker mobility between firms and worker-firm match effects. Their findings indicate that match effects play only a minor role in shaping life-cycle earnings dynamics. In contrast, our approach relies solely on earnings data and does not model match effects or require worker mobility. Instead, we account for non-idiosyncratic heterogeneity by allowing for correlation between workers and firms (sorting) and among co-workers (segregation). These two features capture important dimensions of earnings inequality that are often difficult to incorporate into structural models.

Our paper also closely relates to the literature that decomposes wage inequality into worker- and firm-specific components, abstracting from life-cycle dynamics. In theory, under a perfectly competitive labor market, firm-specific wage premia should be absent; their empirical presence is often interpreted as a violation of the "law of one price" (Card et al. 2018). Abowd, Kramarz, and Margolis (1999, hereafter AKM) pioneered the empirical estimation of worker and firm effects, overcoming identification challenges by employing two-way fixed effects (FE) models when the data include firms connected through chains of worker mobility. Their analysis for France indicates that worker heterogeneity accounts for a larger share of wage inequality than firm heterogeneity. Furthermore, they were able to quantify the extent of sorting between workers and firms, finding positive, albeit modest, correlations.

Card et al. (2013) sparked a resurgence of interest in questions of worker and firm effects in wage determination by adapting the AKM framework to examine secular changes in wage inequality. Estimating the AKM model on various sub-periods, they show that the rise in wage inequality in Germany from 1985 to 2009 is attributable to increasing dispersion in both worker- and firm-specific wage premia, alongside a growing degree of sorting between workers and firms.

Building on this approach, Card et al. (2016) explored the impact of firm-specific wage premia and sorting on gender wage disparities in Portugal. They show that women are disproportionately sorted into lower-paying firms relative to men, and that the combined effects of sorting and bargaining account for one-fifth of the observed gender pay gap.[2] Similarly, Song et al. (2019) applied the AKM framework to US population data, dividing the data into 7-year intervals. Their findings indicate that differences between firms explain an increasing proportion of overall earnings inequality. Further decomposition shows that the rise in firm-related inequality is driven equally by increased sorting of workers into firms and by greater segregation among workers.

Recent research has highlighted that AKM-type estimators produce inconsistent decompositions of earnings dispersion due to limited-mobility bias. In two-way FE models, firm effects are identified through worker mobility between firms; when mobility is infrequent, estimation noise is inflated, distorting the decomposition of wage variance (see, e.g., Kline 2024). The conventional plug-in estimator for the variance of firm effects is particularly sensitive to this noise, leading to an overestimate of the firm component in earnings variance and an underestimate of the correlation between worker and firm effects, sometimes even producing spurious negative correlations.

Although the existence of such biases has long been recognized, researchers have only recently developed effective correction methods.[3] Kline et al. (2020) propose a bias-corrected estimator for the variance components, demonstrating that, relative to the standard AKM approach, their correction increases the estimated role of worker-firm sorting while reducing the attributed importance of firm-specific effects.

Expanding on these advances, Bonhomme et al. (2023) systematically compare conventional AKM decompositions with bias-robust estimates across several countries. Their findings reveal that adjusting for limited-mobility bias reduces the estimated share of wage variance due to firm effects from approximately 20% to 10%, while the share attributable to sorting rises from 8% to 15%.[4] They also show that a correlated random effect (CRE) framework produces similar bias-robust results without requiring post hoc correction.[5] Lachowska et al. (2023) apply the bias-corrected estimator to data from Washington State, allowing for time-varying firm effects while holding worker effects fixed over time, thereby extending the applicability of these improved methods to more dynamic labor market settings.

We extend the standard earnings dynamics framework, building on the approaches of Baker and Solon (2003), Moffitt and Gottschalk (2012), and Hoffmann (2019), by explicitly incorporating firm heterogeneity. Identification in our model is achieved through moment restrictions derived from the covariances of individual earnings and those of co-workers. Unlike traditional approaches that estimate worker- or firm-specific effects, our methodology directly targets the variance components as the primary parameters of interest. This approach circumvents the biases inherent in plug-in variance decompositions.[6] Our estimation strategy uses moment restrictions that remain valid even when there is no worker mobility across firms.

We apply our model to wages from the Italian private sector between 1985 and 2016. Italian wage-setting features national contracts negotiated at the industry level, which cover approximately 80% of workers. In addition to these national contracts, firm-level bargaining allows for supplementary wage adjustments tailored to local economic conditions. Italy does not have a statutory national minimum wage; instead, wage floors are set through sectoral collective agreements, which are legally binding for employers within each sector.

During the 1970s, an egalitarian system of wage indexation for inflation, known as Scala Mobile (literally, “escalator”), led to a pronounced compression of wage differentials between skill groups. This system was reformed and eventually abolished in the 1980s and early 1990s (Erickson and Ichino 1995; Manacorda 2004). The dismantling of Scala Mobile paved the way for the gradual appearance of wage differentials during the 1990s and early 2000s (Hoffmann et al. 2022). Over the past two decades, labor market reforms have primarily aimed at increasing employment flexibility. The expansion of temporary work contracts and the relaxation of dismissal protections for employees with permanent contracts have been central policy shifts.

We consider men aged 25 to 55 in order to minimize concerns related to endogenous labor force participation. This focus is motivated by the fact that, within our cohorts, many women are outside the labor force with caring responsibilities, young individuals are typically engaged in education or training, and older individuals may qualify for early retirement benefits. Following the practice used in the earnings dynamics literature, we estimate empirical wage covariances by year of birth, which allows us to distinguish life-cycle variation from calendar time effects. In our framework, individual wages evolve over the life cycle through the arrival of various shocks. These shocks may be persistent or transitory and can originate from both person- and firm-specific sources. Person-specific shocks accumulate throughout the life cycle, reflecting processes such as human capital accumulation, promotions, or job-search activities. Individual wages are also influenced by firm-specific shocks that are common to all co-workers.

The model incorporates transitory earnings shocks at both the individual and firm levels. While the conventional AKM approach typically assumes that firm effects are constant over time, recent research has begun to relax this assumption, allowing for time-varying firm effects (Lachowska et al. 2023). We allow firm-specific effects to evolve with firm age, reflecting the idea that a firm's ability to influence wages may change as it matures. Additionally, we account for life-cycle variation in both worker-firm sorting and worker segregation. All shocks can impact the earnings process through period-specific loading factors, which account for calendar time variation in the earnings distribution in a flexible manner.

We find that, on average, worker-specific effects account for 60% of wage inequality over the life cycle. Firm effects and worker-firm sorting each contribute about 15%, with the remaining variation attributable to transitory shocks. However, these average figures conceal substantial heterogeneity over the working career. Among young workers, person- and firm-specific factors are of comparable importance, each accounting for roughly 30% of total earnings dispersion. In contrast, among workers in their mid-50s, person effects become more dominant, explaining about 70% of earnings inequality, while the contribution of firm effects declines to just 8%.

The increasing prominence of worker heterogeneity over the life cycle indicates that factors contributing to persistent wage differentials, such as human capital accumulation or job-search dynamics, take time to manifest their effects fully. In the early stages of a career, firm-specific influences play a comparatively larger role in wage dispersion. Over the life cycle, wage variance growth is nonlinear, expanding more rapidly for young workers than for middle-aged workers. This pattern is reflected in the dynamics of worker-firm sorting: Sorting is most pronounced at the outset of workers' careers and diminishes with age. Specifically, while the average worker-firm sorting correlation is 0.3, this correlation declines from 0.4 for younger workers to 0.2 for those later in their working lives.

We find that differences between firms explain more than half of the overall earnings dispersion. This between-firm component includes the variance in permanent and transitory firm effects, worker-firm sorting, and worker segregation; among these, segregation accounts for the largest share. Measuring segregation as the correlation of individual effects for co-workers of the same age, we find a substantial correlation of 0.46 on average, with only modest variation observed over the life cycle. Importantly, we demonstrate that neglecting segregation severely biases the decomposition of wage inequality: Specifically, the share of total wage inequality attributed to worker-firm sorting is overstated by a factor of two, 33% compared to 15% when segregation is properly accounted for.

Our model nests standard individual earnings dynamics models without firm effects. Leveraging this feature, we show that standard models tend to overstate the importance of individual earnings dynamics in explaining life-cycle inequality, especially among young and prime-age workers. Finally, we analyze regional disparities, finding that both firm effects and worker segregation contribute less to inequality in Northern Italy compared to the South. This finding aligns with the interpretation that labor markets in the North operate more efficiently, limiting the influence of firm-level factors and segregation on earnings inequality.

The rest of the paper is organized as follows. The next section describes the population-based linked employer–employee data we use. Section 3 outlines the econometric framework. Section 4 presents descriptive statistics on the intertemporal covariance of individual and co-worker earnings. In Section 5, we discuss the baseline empirical results, followed by an examination of geographical variation in Section 6. Section 7 offers concluding remarks.

2 | Data

We use administrative data from the archives of the Italian Social Security Institute (*Istituto Nazionale di Previdenza Sociale*, INPS), which encompasses the population of firms and workers in the private, nonagricultural sector. The primary source of information is the mandatory employer filing required for the payment of state pension contributions for their employees, which has been digitized since 1983. These records contain information on gross pay, covering all forms of monetary compensation, including employee pension contributions, as well as labor income taxes.

For each employment spell, the data also includes the total number of working days, the start and end dates of employment (with start dates censored before February 1974), and a broad occupational classification that distinguishes between apprentices, blue-collar workers, white-collar workers, and managers. In addition to these spell-level variables, the dataset is supplemented with firm-level characteristics, including geographic location, year of establishment, and closure status. Although the employment spell data contain workplace identifiers, we maintain firms as the unit of analysis on the employer side.

Demographic information on workers in our dataset includes gender and year of birth; however, data on educational attainment are not recorded. Our inability to condition on education is a limitation, given that wage dynamics are well documented to vary systematically across education groups. In the earnings dynamics literature, a common approach to address this heterogeneity is to estimate separate models by education group (see, for example, Blundell et al. 2015; Hoffmann 2019). This strategy, however, is not feasible in our framework because identifying firm and sorting effects depends on the covariance structure among co-workers within firms. Partitioning the data by education group would reduce the variation among co-workers, which is essential for identifying these components. Consequently, in our analysis, persistent differences in earnings associated with education are likely absorbed into the worker effect. At the same time, the sorting component captures the extent of educational sorting across firms.

We restrict our analysis to male workers to mitigate concerns related to endogenous labor force participation. For each man in each year, we define the *prevalent employer* as the firm where he accumulates the highest number of working weeks, excluding instances in which the prevalent employment amounts to fewer than eight full-time-equivalent weeks. Employment spells are further restricted by excluding left-censored cases, i.e., those in which the prevalent employment observed in January 1983 began before February 1974. The resulting dataset provides a comprehensive match between all private sector employers and male employees in Italy from 1983 to 2016, encompassing 3,493,326 firms and 14,021,258 workers, and yielding a total of 192,112,742 person-year observations.

We restrict our analysis to data from 1985 onward, as digital records for 1983 and 1984 are incomplete. Consistent with standard practice in the literature on individual wage dynamics, we focus on working careers between ages 25 and 55 to minimize selection bias arising from labor market entry and exit. We exclude apprentices and managers, who represent 0.5% and 1.5% of the observations, respectively. Gross daily wages are computed as the ratio of gross annual earnings with the prevalent employer to the corresponding number of full-time equivalent working days.

We focus on life-cycle dynamics by selecting individuals based on year of birth, allowing us to observe specific segments of the life cycle for each cohort and to reconstruct the complete profiles from ages 25 to 55 through overlapping cohorts. To help identify life-cycle profiles, we require that each cohort be observed for a minimum of 10 years. As a result, the analytical sample includes cohorts born between 1939 (who were aged 46 in 1985 and observed 10 times until age 55 in 1994) and 1982 (who entered the sample at age 25 in 2007 and were observed 10 times until age 34 in 2016). The structure of cohort coverage is depicted in Figure 1A.

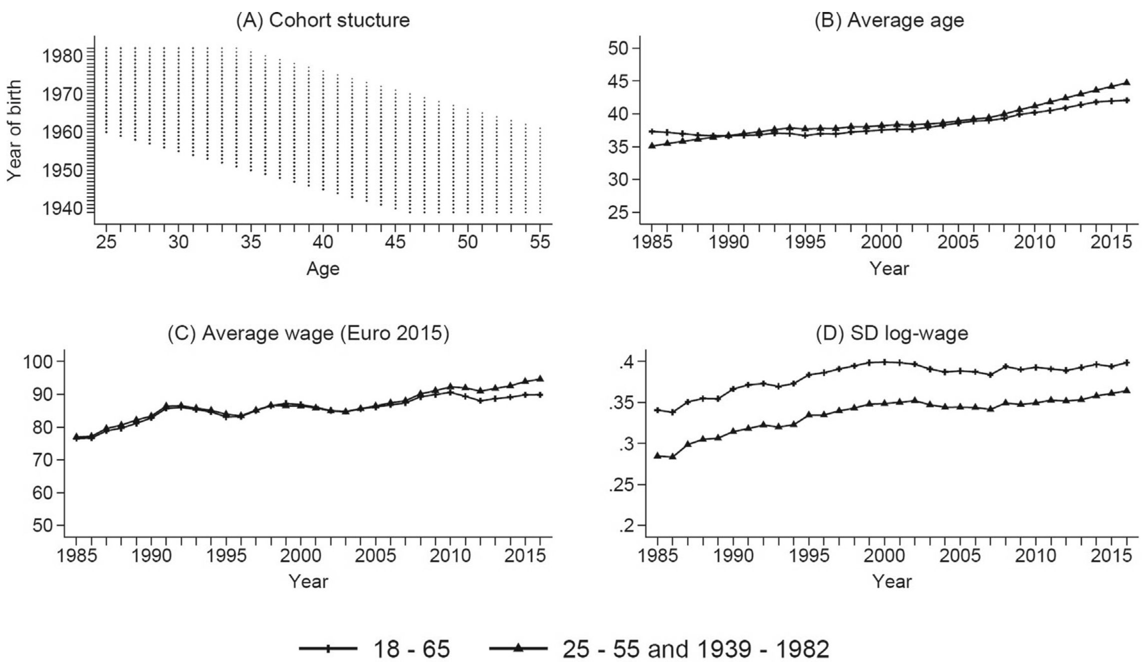

FIGURE 1 | Sample descriptives. *Note:* In Panel A, each marker denotes a cohort-age combination that is present in the estimation sample. Panels B–D compare the time evolution of average age, average real daily wages, and standard deviation of the logs of real daily wages (respectively) between the estimation sample and the population of working men aged 18–65. Real wages are in Euros at 2015 prices.

The 1959 and 1960 birth cohorts are observed continuously across the 25–55 age span, while the number of observations per cohort diminishes as one moves away from these central cohorts. Cohorts born before 1954 or after 1979 each represent between 1.5% and 2% of individuals in the sample, whereas all other cohorts account for between 2% and 3% of individuals. We also require that individuals appear in the data for at least five consecutive years.[7] Finally, to mitigate the influence of outliers, we winsorize the wage distribution at the top and bottom 0.5% within each year.

Applying these selection criteria yields an estimation sample comprising 12,339,989 men and 3,067,752 firms observed between 1985 and 2016, resulting in a total of 152,470,973 person-year earnings records. Figure 1B compares the average age in the estimation sample to that of the broader population of men aged 18–65. Although the estimation sample is somewhat younger before the early 2000s and slightly older thereafter, reflecting the revolving cohort structure of the data, especially after 2007, these differences are relatively minor.

To assess the representativeness of the estimation sample in terms of earnings, we compare average daily wages with those of the total population of men aged 18–65.[8] As illustrated in Figure 1C, there is no meaningful difference in average daily wages between the two groups, except for a modest difference that appears towards the end of the observation period. Figure 1D further demonstrates that the standard deviation of log daily wages follows similar trends in both the estimation sample and the full population, with the estimation sample exhibiting consistently lower dispersion.

3 | Econometric Model

We model earnings as a dynamic process that evolves throughout an individual's working life, incorporating both person- and firm-specific shocks that are shared by all workers employed by the same firm in a given year. These earnings shocks can be either persistent or mean-reverting. Persistent shocks capture the influence of enduring or gradually changing wage determinants, while mean-reverting shocks represent transitory fluctuations associated with economic volatility.

3.1 | Model Specification

Let w_{ijt} denote the residualized log of daily earnings for worker i in year t, where $j = J(i,t)$ identifies the firm employing worker i in year t. To obtain these residuals, we regress the raw log earnings on a set of time dummies through cohort-specific regressions, thereby centering the residuals on calendar year by cohort means. This residualization approach is standard in the earnings dynamics literature and is analytically equivalent to including age and calendar year dummies as controls in wage regressions, consistent with the AKM framework (see Baker and Solon 2003; Bonhomme et al. 2023; Lachowska et al. 2023). Although wages are indexed by calendar year, the pair (i,t) uniquely determines the age of individual i in year t, ensuring that our notation effectively represents the individual life cycle.

We model residualized earnings using the following specification:

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

In this formulation, λ_{it}, ϕ_{jt}, and ψ_{ijt} represent the components of earnings heterogeneity attributable to individual, firm, and transitory factors, respectively, each assumed to have an unconditional mean of zero. The time-varying loading factors α_t, δ_t, and γ_t capture aggregate changes over calendar time in the distributions of worker effects, firm effects, and transitory shocks. For identification, following Hoffmann (2019), we impose the restriction that the first two loading factors, corresponding to 1985 and 1986, are set to unity for each of the three components.

The first term on the right-hand side of Equation (1) represents the persistent component of wages, which arises from shocks experienced over the life cycle. These shocks reflect the accumulation of, and returns to, human capital, as well as other sources of enduring wage changes, such as those resulting from job search. Life-cycle shocks have a permanent effect on the age-wage profile, regardless of the firm at which individual i is employed in a given year. To accommodate the long-lasting impact of shocks, we model this component as a unit root process (Random Walk, RW).

Specifically, over the life cycle, the RW specification allows for the accumulation of shocks beginning at age 25, which is the earliest age at which we observe workers in our sample:

$$\begin{aligned} \lambda_{it} &= \lambda_{i(t-1)} + u_{it} = \lambda_{i(c+25)} + \sum\nolimits_{k=c+26}^{t} u_{ik} \\ var\left(\lambda_{i(c+25)}\right) &= \sigma_\lambda^2 \\ var\left(u_{it}\right) &= \sigma_{u(t-c)}^2 \end{aligned} \tag{2}$$

where $c = c(i)$ denotes the year of birth of individual i, so that $c + 25$ is the calendar year when the earnings trajectory of person i conventionally begins, and $(t - c)$ represents the age of individual i in year t.

The variance of the initial condition σ_λ^2 measures idiosyncratic wage dispersion at age 25, capturing both the accumulation of shocks before age 25 and unobserved heterogeneity predating labor market entry, such as differences in educational attainment not observed in our data. The innovations u_{it} represent long-lasting shocks, and to allow the impact of permanent shocks on earnings inequality to evolve with age, these are drawn from age-specific distributions with variance $\sigma_{u(t-c)}^2$. For example, younger workers may experience greater wage variability due to a broader range of opportunities for learning and promotion compared to older workers. While studies of firm-based wage inequality often assume that worker effects are fixed, the RW specification for individual effects is standard in the life-cycle earnings literature, as it more accurately reflects the dynamic accumulation of persistent shocks over the working life.

The Random Growth or Heterogeneous Income Profile (RG/HIP) model offers an alternative to the RW specification by modeling the life-cycle evolution of earnings as an individual-specific trend, as discussed by Guvenen (2007). In contrast, Baker and Solon (2003) adopt a mixed approach that incorporates both RW and RG components. Hoffmann (2019) demonstrates that when age-specific variances in RW innovations are permitted, the life-cycle profile of wage covariances ceases to be informative for detecting the presence of an RG/HIP component. In this context, identification of the RG/HIP model relies exclusively on the presence of convexities in the autocovariance profiles at long lags.

Hoffmann (2019) proposes a practical diagnostic, an "eyeball test," for the RG/HIP, which involves visually inspecting the shape of the autocovariance profiles at extended lags. His analysis of German administrative data reveals that these profiles remain flat at long lags, indicating the absence of convexity and thus providing evidence against the RG/HIP model. Consistent with these findings, Figure A1 in the Supporting Information in our study shows that autocovariance profiles in our dataset also exhibit no convexity at long lags. Based on this evidence, we adopt the RW model with age-specific innovation variances as the foundation for our analysis.

The second term in Equation (1) captures firm effects, representing wage-setting policies that are common across all employees within the same firm. These firm-specific effects determine the average placement of a firm's workforce in the broader earnings distribution. Sources of firm effects include mechanisms such as rent extraction, efficiency wages, and other labor market frictions that generate persistent wage disparities among otherwise identical workers employed at different firms (Card et al. 2018). The influence of factors like monitoring technologies or the bargaining power of unions may also evolve, further shaping wage heterogeneity.

Lachowska et al. (2023) incorporate time variation in firm effects by interacting them with calendar year indicators, thereby capturing temporal shifts in firm wage policies. In our approach, we allow for time variation of firm effects through two distinct channels. First, we capture secular changes in the distribution of firm effects via the period-specific loadings δ_t of Equation (1). Second, we introduce age-related variation by modeling firm-specific effects as draws from a distribution that evolves with the firm's age, acknowledging that the degree of firm heterogeneity may differ between younger and older firms.

Formally, we specify firm effects ϕ_{jt} as a random effect (RE) with age-specific variances and unrestricted intertemporal covariances:

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

where $d = d(j)$ denotes the establishment year of firm j, so that $(t-d)$ represents the firm's age in year t. This specification allows for both the magnitude and persistence of firm effects to vary flexibly with firm age, accommodating the possibility that wage-setting practices and their impact on earnings dispersion evolve as firms mature.

The third random component of Equation (1), ψ_{ijt}, represents the effect of mean-reverting shocks that have transitory, short-lived impacts on wages. We model these mean-reverting shocks as the sum of individual- and firm-specific components:

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

In line with standard practice in the earnings dynamics literature, we incorporate an autoregressive structure into the transitory wage shocks to reflect gradual reversion to the mean (see, for example, Baker and Solon 2003). Specifically, the individual-specific component, v_{it}, follows a nonstationary first-order autoregressive process (AR(1)), with cohort-specific initial conditions whose variance is allowed to vary flexibly with age:

$$\begin{aligned} v_{it} &= \rho v_{i(t-1)} + \varepsilon_{it} \\ var(\varepsilon_{it}) &= \sigma^2_{\varepsilon 26} g(t-c) \\ var(v_{i(c+25)}) &= \sigma^2_{vc} \end{aligned} \tag{3}$$

Here, $v_{i(c+25)}$ denotes the initial condition for individual i at age 25, $\sigma^2_{\varepsilon 26}$ is the variance of innovations at age 26, and $g(t-c)$ is an exponential spline function that governs the evolution of innovation variance with age.[9]

For the firm-specific transitory shocks, ξ_{jt}, we assume a white noise (WN) process, with innovations drawn from distributions whose variance depends on the age of the firm:

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

The earnings model specified in Equation (1) does not incorporate a match effect, i.e., it omits a wage component that is unique to each firm–worker pair and would capture the idiosyncratic productivity arising from specific matches, beyond the separate contributions of worker and firm effects.[10] The literature provides mixed evidence regarding the significance of match quality. Card et al. (2013) show that saturating the AKM model with match-specific effects yields only marginal improvements in model fit, indicating that match effects play a limited role in explaining overall wage dispersion. Similarly, Friedrich et al. (2024) develop a structural model with endogenous mobility and match-specific productivity, concluding that match effects have a limited impact on the evolution of earnings inequality over time, even in the absence of sorting. In contrast, Carneiro et al. (2023) and Woodcock (2023) find a more substantial influence of match heterogeneity; although in their analyses, the structure of unobserved heterogeneity is assumed to be time-invariant, unlike the approach taken in our model. A notable advantage of excluding match components from our specification is that it does not condition on workers' mobility decisions, thereby reducing the risk of biases in parameter estimates that could arise from endogenous mobility.[11]

A limitation of our approach is that it does not explicitly model the mechanisms governing the formation and persistence of worker-firm matches over time. Rather, the distribution of matches, including the covariance between worker and firm effects, is treated as exogenous in our framework. In practice, however, matches that fail to generate sufficient joint surplus are unlikely to form or persist, introducing a selection bias into the observed data. As a result, the observed covariance between worker and firm effects is estimated from a truncated distribution, reflecting only those matches with sufficiently high joint surplus.

This selection mechanism implies that our estimates of the sorting parameter may be downward biased, since matches with lower surplus are systematically underrepresented in the data. Addressing this selection issue would necessitate a fundamentally different modeling strategy, such as the adoption of a structural model of worker mobility and match formation (see Lentz et al. 2023; Friedrich et al. 2024). Although such extensions are beyond the scope of this paper, it is important to interpret our findings regarding the magnitude of worker-firm sorting with this limitation in mind.

3.2 | Moment Restrictions and Identification

We assume that transitory shocks are uncorrelated both with each other and with permanent shocks:

$$\begin{aligned} cov\left(\varepsilon_{it}, \xi_{jt'}\right) &= cov\left(\varepsilon_{it}, \lambda_{it'}\right) = cov\left(\varepsilon_{it}, \phi_{jt'}\right) \\ &= cov\left(\xi_{jt}, \lambda_{it'}\right) = cov\left(\xi_{jt}, \phi_{jt'}\right) = 0, \forall t, t' \end{aligned} \tag{4}$$

This orthogonality assumption between permanent and transitory components is standard in the earnings dynamics literature employing moment-based estimators, which can be broadly understood as a form of RE modeling of variance components (see, for example, Baker and Solon 2003; Hoffmann 2019). It is crucial for distinguishing persistent from transitory variation in wage processes and is fundamental to identifying life-cycle accumulation dynamics.

In contrast, FE estimators in the AKM framework do not require this orthogonality, as they allow for unrestricted correlation between persistent unobserved heterogeneity and transitory shocks. Our RE approach, however, relies on this assumption for identification. The distinction between RE and FE frameworks also extends to the treatment of covariates: FE models permit arbitrary correlation between regressors and unobserved effects, whereas RE models assume mean independence. In our case, since the covariance structure is specified after conditioning on year dummies by birth cohort, no additional covariates are included, rendering the mean independence assumption less of a concern.

Given these differences, comparisons between RE- and FE-based estimates of variance components should be interpreted with caution. However, recent evidence indicates that, after correcting for limited-mobility bias, variance component estimates from FE models closely align with those produced by RE approaches (Bonhomme et al. 2023).

A central finding in the literature examining worker and firm wage effects is that these two components are interdependent, as workers are systematically sorted into particular firms. We capture worker sorting by modeling the covariance between individual- and firm-specific effects. Since individual-specific effects evolve through the life cycle, primarily due to the accumulation of persistent shocks occurring after age 25, a parallel structure is incorporated into the covariance that characterizes worker-firm sorting:

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

Beyond sorting, worker segregation constitutes an additional form of cross-unit dependence. Although the standard approach in the earnings dynamics literature assumes that individual-specific effects are independent across individuals, recent studies of firm-based wage inequality underscore the importance of segregation (Barth et al. 2016; Lopes de Melo 2018; Song et al. 2019). It is important to distinguish between sorting and segregation, as they are related but distinct mechanisms. Sorting inherently leads to segregation; for instance, when high-wage workers are concentrated in high-wage firms, these workers inevitably work alongside one another. In contrast, segregation can exist independently of sorting. Even in the absence of a correlation between worker- and firm-specific effects, and thus without sorting, segregation may still arise through processes unrelated to firm heterogeneity.

Informal job-search networks constitute a significant mechanism contributing to workplace segregation. When network homophily is present—that is, when individuals are more likely to form social ties with others who share similar characteristics—people with comparable backgrounds often become concentrated within the same workplaces. This concentration occurs because they tend to access employment opportunities through shared referral channels or participate in overlapping information networks.[12] As a result, co-worker segregation can emerge independently of any direct association between worker and firm heterogeneity.

Segregation processes are particularly relevant in the Italian context, where informal social connections have long been integral to job matching, especially among younger individuals and in local labor markets. The widespread use of referrals promotes homophilous hiring practices, thereby increasing similarity among employees within firms and fostering segregation, even in the absence of sorting mechanisms. Italy's pronounced contractual dualism amplifies this segregation mechanism. Workers on temporary contracts are subject to higher job turnover, face diminished prospects for skill development, and encounter restricted access to formal recruitment channels. Consequently, these workers are more dependent on distinct and often less robust informal networks than their peers holding permanent contracts. This resulting variation in network quality, determined by contract status, produces divergent patterns of job access and shapes the composition of co-worker groups, thereby reinforcing segregation between employment types independently of systematic differences in firm-level characteristics.

It is essential to formally characterize segregation, as our empirical strategy relies on co-worker wage covariances to derive moment restrictions. In our framework, segregation is captured by allowing persistent individual-specific effects to covary among co-workers, defined as individuals employed by the same firm, regardless of whether their tenures overlap. Segregation is parameterized as a worker age-specific proportion, denoted $\mu_{(t-c)}$, of the covariance of individual worker effects. Specifically, we express this relationship as follows:

$$cov\left(\lambda_{it}, \lambda_{i't'}\right) = \mu_{(t-c)} cov\left(\lambda_{it}, \lambda_{it'}\right) \quad if\, J(i,t) = J\left(i', t'\right) \tag{6}$$

where the equality of $J(i,t)$ and $J\left(i',t'\right)$ indicates that individuals i and i' are co-workers by virtue of being observed at the same firm, albeit in possibly different time periods t and t'. When $t = t'$, the covariance $cov(\lambda_{it}, \lambda_{it'})$ reduces to the variance $var(\lambda_{it})$, and for individuals of the same age, $var(\lambda_{it}) = var(\lambda_{i't})$. Consequently, $\mu_{(t-c)}$ represents the cross-sectional correlation coefficient of person-specific effects among co-workers of age $(t-c)$.[13]

Under the assumptions (4) through (6), the covariance of residualized individual log wages between year t and $t' \geq t$ can be expressed as follows:

$(\sigma_{\phi\lambda})$, and the variances and intertemporal covariances of the firm effects (σ^2_{ϕ} and σ_{ϕ}).[14]

Intuitively, the intertemporal covariance of individual wages described in Equation (7) can identify, at most, one set of age-related parameters and one set of age-invariant parameters. As a result, Equation (7) alone is insufficient for the identification of all parameters of the permanent earnings component, necessitating additional information to disentangle worker-specific effects from those attributable to firms.

$$
\begin{aligned}
cov(w_{ijt}w_{ij't'}) = {} & \underbrace{\alpha_t\alpha_{t'}\left(\sigma^2_{\lambda} + \sum_{k=26}^{(t-c)}\sigma^2_{uk}\right)}_{\text{worker permanent}} + \underbrace{\delta_t\delta_{t'}\mathbb{I}[j = j']\left(\sigma^2_{\phi(t-d)}\mathbb{I}[t = t'] + \sigma_{\phi(t-d)(t'-d)}\mathbb{I}[t \neq t']\right)}_{\text{firm permanent}} \\
& + \underbrace{(\alpha_t\delta_{t'} + \alpha_{t'}\delta_t)\left(\sigma_{\phi\lambda} + \sum_{k=26}^{(t-c)}\sigma_{\phi uk}\right)}_{\text{worker-firm sorting}} + \underbrace{\gamma_t\gamma_{t'}\mathbb{I}[t = t']\sigma^2_{\xi(t-d)}}_{\text{firm transitory}} \\
& + \underbrace{\gamma_t\gamma_{t'}\left(\mathbb{I}[t = t' = s]\sigma^2_{vc} + \mathbb{I}[t = t' > s]\left(\sigma^2_{\varepsilon 26}g(t-c) + var(v_{i(t-1)})\rho^2\right) + \mathbb{I}[t \neq t']cov(v_{i(t-1)}v_{it'})\rho\right)}_{\text{worker transitory}}
\end{aligned}
\tag{7}
$$

Here, $\mathbb{I}[]$ denotes a binary indicator, and $s = \max(1985, c + 25)$. It is important to note that, since Equation (7) describes the covariance of *individual* wages, it is independent of the segregation parameter $\mu_{(t-c)}$, which only appears in cross-worker moments (see Equation 8 below). Therefore, unlike sorting, segregation does not influence overall wage inequality but instead only affects the decomposition of inequality between and within firms (Song et al. 2019).

Permanent shocks have a lasting impact on the wage covariance structure at all time intervals. In contrast, transitory shocks diminish quickly, either dissipating rapidly in the case of individual-specific transitory shocks or affecting only the contemporaneous wage variance when they are firm-specific. The distinction between shocks that exhibit persistent effects over extended periods and those that decay swiftly is crucial for empirically distinguishing permanent components from transitory components in wage dynamics.

To distinguish the effects of calendar time from those of age, the empirical covariance is computed separately for each birth cohort, and all cohort-specific covariances are jointly incorporated into the estimation procedure. In models of individual earnings dynamics that do not account for firm effects, permanent shocks occurring over the life cycle are identified through age-related variations in the wage covariance function, with their initial conditions corresponding to the intercepts of these age trends.

Equation (7) reveals the presence of two broad sets of permanent earnings parameters that vary with worker age: One group pertains to the life-cycle accumulation of RW shocks (σ^2_u), while the other is associated with the accumulation of the sorting covariance ($\sigma_{\phi u}$). In addition, three sets of permanent earnings parameters are constant with respect to worker age: the initial condition of the RW (σ^2_{λ}), the initial condition of the sorting covariance

Additional information can be obtained by considering the *covariance of co-worker wages*; specifically, individuals i and i' who have been employed by the same firm at any point in their careers, i.e., for some t and t', $J(i,t) = J(i',t')$. This co-worker wage covariance encapsulates all the firm-related sources of wage variation, including both permanent and transitory firm-specific effects, as well as the impact of worker-firm sorting. Additionally, it accounts for the possibility that workers with similar characteristics may be employed at the same firm, reflecting potential segregation. The formal expression for the co-worker covariance is as follows:

$$
\begin{aligned}
cov(w_{ijt}w_{i'jt'}) = {} & \underbrace{\delta_t\delta_{t'}\left(\sigma^2_{\phi(t-d)}\mathbb{I}[t = t'] + \sigma_{\phi(t-d)(t'-d)}\mathbb{I}[t \neq t']\right)}_{\text{firm permanent}} \\
& + \underbrace{(\alpha_t\delta_{t'} + \alpha_{t'}\delta_t)\left(\sigma_{\phi\lambda} + \sum_{k=26}^{(t-c)}\sigma_{\phi uk}\right)}_{\text{worker-firm sorting}} \\
& + \underbrace{\mu_{(t-c)}\alpha_t\alpha_{t'}\left(\sigma^2_{\lambda} + \sum_{k=26}^{(t-c)}\sigma^2_{uk}\right)}_{\text{co-worker segregation}} \\
& + \underbrace{\mathbb{I}[t = t']\gamma^2_t\sigma^2_{\xi(t-d)}}_{\text{firm transitory}}
\end{aligned}
\tag{8}
$$

Equation (8) represents the between-firm component of the wage covariance. As with Equation (7), the distinction between calendar time and age effects in Equation (8) is achieved by calculating the empirical covariance for each birth cohort and incorporating all cohort-specific covariances simultaneously in the estimation process. The combination of Equations (7) and (8) yields two sets of age-dependent moment restrictions, which serve to identify the two corresponding sets of age-related parameters: those associated with RW shocks and those linked to the worker-firm sorting covariance.

For parameters unrelated to worker age, this identification argument is not applicable. In this context, there are three sets of parameters: the initial condition for the RW, the initial condition for the sorting covariance, and the variance–covariance of firm-specific effects, but only two sets of moment restrictions. To resolve this identification issue, we constrain the initial condition of the sorting covariance to equal the initial condition of the RW, scaled by the ratio of the sum of cumulated life-cycle sorting covariances and the sum of the cumulated RW life-cycle shocks:[15]

$$\sigma_{\phi\lambda} = \sigma_{\lambda}^{2} \sum\nolimits_{k=26}^{55} \sigma_{\phi uk} / \sum\nolimits_{k=26}^{55} \sigma_{uk}^{2}. \tag{9}$$

Equations (7)–(9), along with the unit restrictions on the initial time loading factors, collectively provide a full set of restrictions on the second moments of individual and co-worker earnings. These restrictions are sufficient to ensure identification of the model parameters.

A key advantage of these moment restrictions is that they facilitate the identification and direct estimation of variance components. Unlike AKM-type approaches, which involve a two-step procedure—first estimating worker- and firm-specific effects from a wage regression and then calculating plug-in estimates of their variances—our moment-based approach circumvents the biases of the plug-in method. Specifically, when worker mobility is limited, estimation noise tends to inflate the variance attributed to firm effects. It leads to a substantial upward bias in the firm component while simultaneously producing a downward bias in the sorting component. By modeling the variance and covariance structure of observed earnings directly without relying on intermediate estimates of worker- or firm-specific effects, the proposed method effectively eliminates the limited-mobility bias in the variance decomposition.

The identification strategy in our model is anchored in two sets of moment restrictions: the individual covariance structure and the co-worker covariance structure. These restrictions remain applicable even when there is no worker mobility across firms. In contrast, identification in AKM-type models is inherently dependent on worker mobility. For example, in a scenario where no workers move between firms, the two-way FE model becomes unidentifiable because firm effects are perfectly collinear with the sum of their employees' FEs. By contrast, our approach maintains its validity under such conditions. The individual covariance structure, derived from the expectation of intertemporal cross-products of individual wages, and the co-worker covariance structure, based on the expectation of intertemporal cross-products of co-worker wages, both remain well-defined and informative. These moment conditions continue to allow the separate identification of the variances associated with worker and firm effects, regardless of the presence of worker mobility.[16]

In sum, the identification of model parameters is grounded in a comprehensive set of moment conditions constructed from both individual and co-worker wage covariances. By incorporating data from multiple birth cohorts, the analysis effectively separates calendar time effects from those related to the life cycle. Transitory components are identified through the rapid attenuation of empirical covariances over short time intervals, whereas permanent components are identified through their enduring influence on wage dynamics.

Variation in the individual covariance structure over the life cycle identifies the accumulation pattern of persistent, individual-specific shocks. In parallel, changes in the co-worker covariance structure across the life course identify the development of worker-firm sorting. Parameters that remain constant with respect to worker age are identified from the level component of the empirical moments: The baseline of the individual covariance structure identifies the initial condition of the RW, while the baseline of the co-worker covariance structure identifies the variance components specific to firms.

Given that only two sets of moment conditions are available to identify the three sets of parameters that are constant with respect to worker age—the initial condition of the RW, firm-specific effects, and sorting initial condition—we impose a parametric restriction on the initial sorting to achieve identification. The variance components associated with firms also exhibit dependence on firm age, which is identified by exploiting differences in average firm age across the empirical moments. Segregation is identified by loading persistent individual heterogeneity into the co-worker covariance structure.

3.3 | Estimation

To estimate the model parameters, we employ the Minimum Distance approach by matching empirical second moments of the earnings distribution, measured across cohorts and time periods, with their model-implied counterparts. The earnings covariance, as defined by Equations (7)–(9), is expressed as a nonlinear function $f(\beta)$ of the parameters vector β. The Minimum Distance estimator is obtained by minimizing the quadratic distance between $f(\beta)$ and its empirical counterpart m:

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

where W is a weighting matrix. In this framework, the model comprises 154 parameters, with one parameter constrained by Equation (9), leaving 153 free parameters to be estimated (see Table A3 in the Supporting Information). In contrast, the empirical analysis utilizes more than 20,000 moment conditions, as detailed in the following section. Consistent with standard practice in the literature, we set W equal to the identity matrix to mitigate biases arising from sampling error, thereby implementing the Equally Weighted Minimum Distance estimator (Altonji and Segal 1996).

For inference, we use a robust variance estimator given by:

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

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

4 | Empirical Covariance Structures

We estimate cohort-specific wage covariances, which we match to the set of moments described in the previous section, to estimate the model's parameters. The analysis focuses on two primary sets of moments: those pertaining to individual wages and those related to co-workers' wages. Empirical moments of individual wages (denoted with I) are calculated by averaging the cross-products of residualized log wages across individuals:

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

In this formulation, ω represents the empirical counterpart of w from Equation (1), and p is an indicator variable that denotes whether individual i has a recorded wage in period t, thereby accommodating an unbalanced panel.[17] Consistent with standard practice in the earnings dynamics literature, it is assumed that individuals entering or leaving the panel do so at random, ensuring that missing data are missing at random.[18]

We estimate the co-worker covariance by adapting the weighting scheme introduced by Page and Solon (2003) for neighborhood covariances in outcomes. The procedure begins by calculating the firm-specific covariance, which is obtained by averaging the cross-products of log-wage residuals across all possible pairs of co-workers within each firm. Following this, the firm-specific covariances are averaged across firms, with each firm weighted by the square root of the number of pairwise matches it contributes. The weighting scheme ensures that larger firms, which provide more information, receive greater emphasis, thereby rendering the inference representative at the individual level.

Formally, the co-worker covariance (denoted as C) is defined as follows:

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

where the firm-specific weight θ_j is given by $\theta_j = \sqrt{\sum_i \sum_{h>i} p_{ijt}p_{hjt'}} / \sum_l \sqrt{\sum_i \sum_{h>i} p_{ilt}p_{hlt'}}$. For cohorts comprising up to 200 co-workers, all available co-workers are included in the estimation. For larger cohorts, we select a random sample of 200 co-workers stratified by occupation to ensure computational tractability.

A total of 21,164 empirical moments are used in the analysis, with 10,582 moments estimated for individuals (using Equation 10) and an equal number for co-workers (using Equation 11). The number of empirical moments varies over cohorts, ranging from 110 moments for the 1939 and 1982 cohorts to 992 moments for the 1960 and 1961 cohorts. Estimated empirical moments across the life cycle are presented in Figure 2. The curve labeled "Total Variance" represents the overall wage variance, which is calculated by measuring deviations of individual wages from their respective cohort means and then averaging these cohort variances across all cohorts.

The observed pattern of rising wage inequality across the life cycle aligns with the presence of heterogeneous wage dynamics among workers. Wage dispersion expands most rapidly during the early stages of the career, a pattern that is consistent with the higher job mobility and greater returns to training typically observed among younger workers. This initial phase of accelerated dispersion is followed by a period of slower growth during mid-career, reflecting relative stability in earnings trajectories. Notably, after age 45, there is a renewed acceleration in the growth of dispersion. This late career increase could reflect stronger labor market attachment among workers at both the lower and upper ends of the wage distribution, while those in the middle are more likely to exit the labor force through early or partial retirement. Such compositional changes at older ages contribute to the observed widening of wage inequality. Our earnings dynamics model incorporates age-specific variances, enabling it to capture these shifts in the nature and magnitude of wage dispersion over the life cycle.

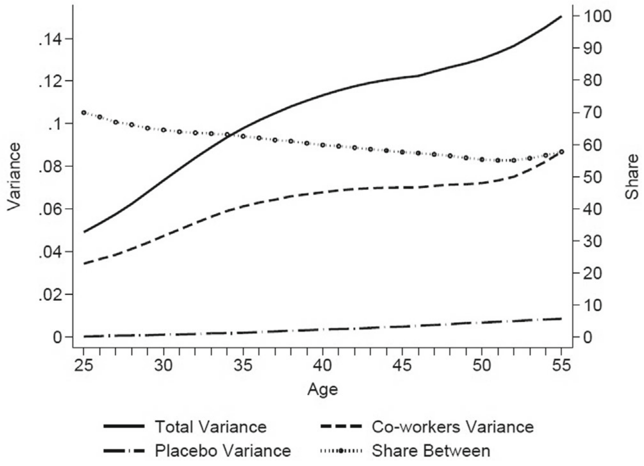

FIGURE 2 | Raw variances and between-firms variance share over the life cycle. *Note:* The figure reports the life-cycle evolution of the variance and of its between-firm component. Empirical moments are estimated by birth cohort and averaged across cohorts by age. Total Variance is the variance derived 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.

The "Co-worker Variance" line in Figure 2, derived from Equation (11), quantifies the extent to which co-workers *collectively* diverge from the cohort mean wage as a result of shared factors. This measure captures the evolution of wage dispersion between firms, reflecting both idiosyncratic firm effects and the influence of shared wage-generating characteristics among co-workers. Such similarities arise from the sorting of workers into firms and segregation. Importantly, the co-worker covariance excludes wage differences attributable solely to individual-specific characteristics. The pattern of dispersion between groups of co-workers closely mirrors the age profile of overall wage dispersion. This similarity arises because the heterogeneity in individual effects across workers, when concentrated within firms, contributes to the observed firm-level wage dispersion through segregation.

To address the concern that the similar evolution of total and co-worker variances might be a statistical artifact of aging, Figure 2 displays the life-cycle evolution of a "Placebo Variance." This placebo measure is constructed using Equation (11) to match individuals of the same age from firms drawn randomly from the economy, pretending that they were co-workers. The resulting placebo variance shows only a negligible upward trend in dispersion, suggesting that the variance observed among actual co-workers is attributable to a genuine shared effect within firms, rather than merely reflecting the grouping of individuals by birth cohort.

The right axis of Figure 2 presents the proportion of wage variance attributable to differences between firms, calculated as the ratio of co-worker variance to total variance. This measure is constructed in a fully nonparametric manner, without the need to estimate models of worker or firm heterogeneity. The data reveal a clear decline in the importance of between-firm wage dispersion over the life cycle. At age 25, between-firm heterogeneity accounts for 70% of total wage variance. As workers age, this share falls to 60% by age 55, reflecting the increasing importance of individual-specific heterogeneity in shaping wage outcomes. On average, between-firm differences explain 65% of wage dispersion across the working life. The subsequent section provides a detailed decomposition of individual-specific heterogeneity and the various components contributing to between-firm dispersion.

5 | Results

This section presents parameter estimates for the stochastic components of the earnings dynamics model and examines the resulting variance decompositions.[19] The analysis begins by evaluating the model's goodness-of-fit, as shown in Panel A of Figure 3. Here, the empirical moments of Figure 2 (excluding placebo measures) are displayed alongside the corresponding moments predicted by the model, including the between-firm share of earnings inequality. The model demonstrates a satisfactory overall fit, with the predicted total variance aligning closely with empirical values across the life cycle.

At the start of working life, there is a slight discrepancy in the co-worker variance, where the model underestimates the empirical value around age 25. This gap diminishes rapidly, and by age 29, the modeled and observed series are nearly indistinguishable. A similar mismatch is observed when comparing the raw and fitted "Share Between" lines. This divergence emerges mechanically from the discrepancy in the co-worker variance: Because the between share is calculated as the ratio of co-worker to total

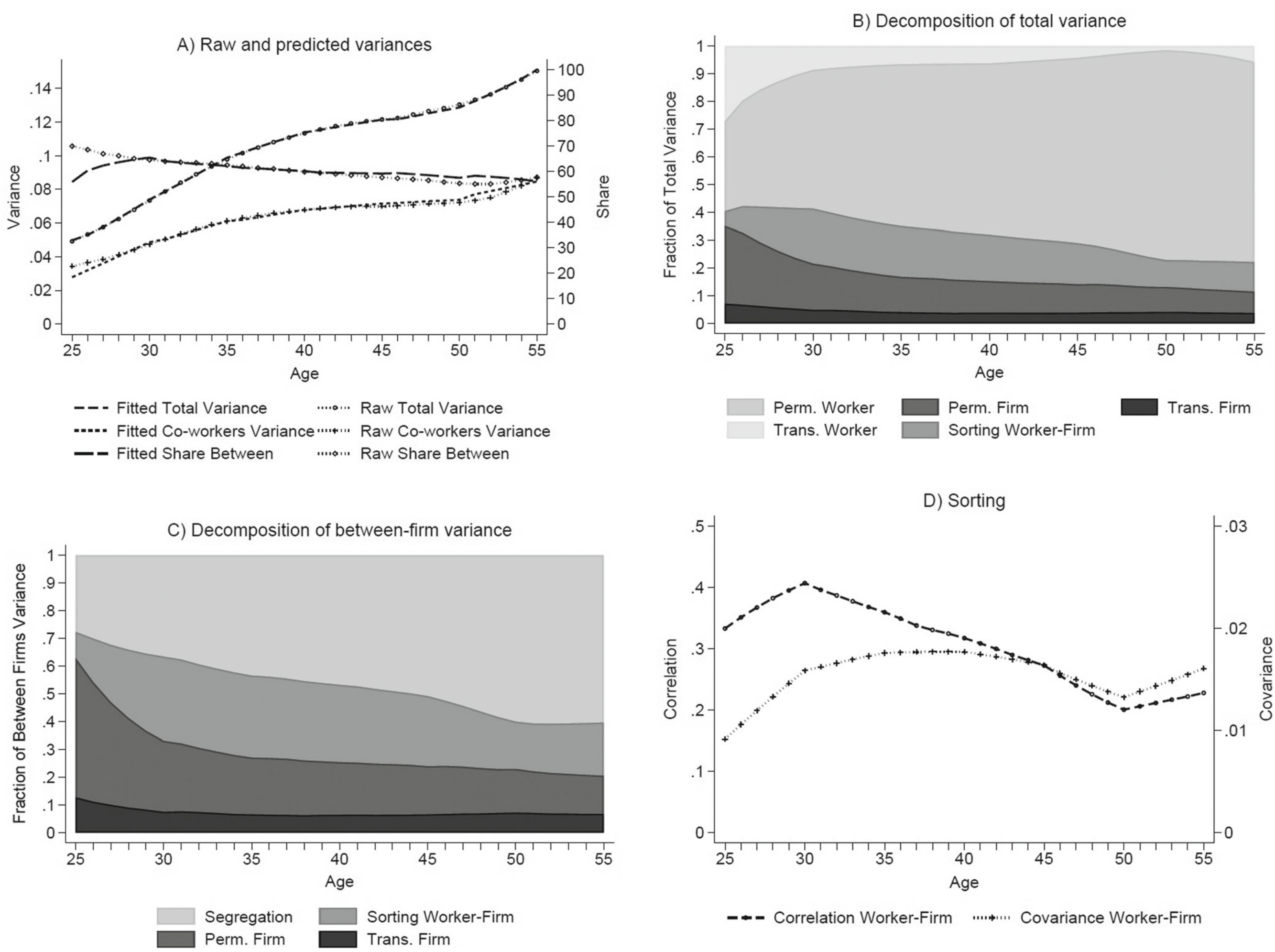

FIGURE 3 | Predictions and variance decompositions—main model. *Note:* Parameter estimates underlying the predictions and decompositions are reported in Tables 1 and 2 and Table A1 in the Supporting Information. The fitted figures are generated for each cohort-age combination that is present in the sample and then averaged across cohorts by age.

variance, even minor differences in the numerator can be magnified when the denominator is accurately predicted and remains below one.

exhibiting larger values for younger workers and declining with age. Indeed, the covariances between *innovations* of the individual-specific RW and the firm-specific RE become negative between ages 40 and 50.

5.1 | Permanent Wages

Table 1 reports estimates for the permanent component of the earnings dynamics model. Panel A presents the estimated parameters for the variance of worker-specific effects, as modeled by the RW process. The variance of the initial condition (σ^2_λ) captures not only the heterogeneity of individual-specific effects at age 25 but also reflects the variation of individual wage histories up to that age, as well as differences established before labor market entry, such as those arising from educational attainment.

To accommodate life-cycle variation in the distribution of permanent shocks, the model allows the variance of innovations to change at 5-year intervals. The results indicate that the evolution of life-cycle heterogeneity in earnings growth, as measured by the age-specific variances of innovations ($\sigma^2_{u(t-c)}$), evolves in two distinct phases. During the first phase, wage dispersion grows markedly up to age 35, rising by approximately one-quarter of the initial condition each year. In the second phase, beginning in the late 30s, the growth rate of earnings dispersion almost halves. This observed nonlinearity is consistent with a deceleration in human capital accumulation and reduced job mobility among older workers. Overall, the accumulation of person-specific wage dispersion over the life cycle is substantial. By age 40, the variance of the RW component exceeds four times its initial level, and by age 55, it surpasses six times the initial variance.

Panel B of Table 1 reports the estimated parameters of the RE process governing firm-specific effects. The variances of these effects are modeled as functions of firm age, with distributions that change across the firm age spectrum. Although the empirical moments are indexed by the age of individuals rather than firms, the average age of the firms employing the workers is known for each year. By calculating the quartiles of firm age across all empirical moments, we allow the variance of firm effects ($\sigma^2_{\phi q}$) to differ by firm age quartile.[20]

We model long-term persistence in firm-specific shocks through a set of intertemporal cross-quartile covariances ($\sigma_{\phi qq}$). The estimated variances are substantial and exhibit relative stability across the distribution of firm ages. For context, the average variance of the firm effect (0.0124) is approximately equal to the variance of individual effects at the beginning of a worker's career. For example, for a worker aged 27, the RW variance ($\sigma^2_\lambda + 2\sigma^2_{u26-30}$) is 0.0129. In addition, the estimated cross-period covariances of the firm-specific REs are large, yielding an average intertemporal correlation of 0.82.[21]

Panel C of Table 1 reports the parameters capturing non-idiosyncratic heterogeneity, specifically worker-firm sorting (Panel C.1) and co-worker segregation (Panel C.2). The life-cycle sorting parameters of Panel C.1 ($\sigma_{\phi u(t-c)}$) are estimated as covariances between RW shocks and the firm-specific effect, while the sorting initial condition ($\sigma_{\phi\lambda}$) is estimated based on Equation (9). The estimated life-cycle profile of worker-firm sorting reflects the evolution of individual life-cycle shocks,

TABLE 1 | Parameter estimates of permanent earnings components—main model.

	Coeff.	S.E.
	(A) Worker	
σ^2_λ	0.0087	0.00010
σ^2_{u26-30}	0.0021	0.00001
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}	0.0011	0.00001
σ^2_{u51-55}	0.0008	0.00002
	(B) Firm	
$\sigma^2_{\phi q1}$	0.0135	0.00011
$\sigma^2_{\phi q2}$	0.0112	0.00013
$\sigma^2_{\phi q3}$	0.0137	0.00017
$\sigma^2_{\phi q4}$	0.0112	0.00018
$\sigma_{\phi q1q2}$	0.0107	0.00011
$\sigma_{\phi q1q3}$	0.0098	0.00012
$\sigma_{\phi q1q4}$	0.0088	0.00013
$\sigma_{\phi q2q3}$	0.0117	0.00014
$\sigma_{\phi q2q4}$	0.0086	0.00013
$\sigma_{\phi q3q4}$	0.0112	0.00015
	(C) Correlated effects	
	(C.1) Worker-firm sorting	
$\sigma_{\phi\lambda}$	0.0009	0.00002
$\sigma_{\phi u26-30}$	0.0009	0.00001
$\sigma_{\phi u31-35}$	0.0002	0.00001
$\sigma_{\phi u36-40}$	0.0001	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) Co-worker segregation	
μ_{25-30}	0.4769	0.00322
μ_{31-35}	0.4618	0.00280
μ_{36-40}	0.4546	0.00266
μ_{41-45}	0.4476	0.00254
μ_{46-50}	0.4542	0.00234
μ_{51-55}	0.4680	0.00234

Note: Equally Weighted Minimum Distance estimates for the parameters of permanent earnings in the earnings dynamics model of Section 3. Number of observations: 152,470,973; number of individuals: 12,339,989; number of firms: 3,067,752; number of empirical moments: 21,164; overall number of model parameters: 154. The parameter $\sigma_{\phi\lambda}$ is estimated based on the constraint described in Equation (9). $\chi^2(21011) = 297190.7$.

TABLE 2 | Parameter estimates of transitory earnings components—main model.

	Coeff.	S.E.
	(A) Worker	
$\sigma^2_{\varepsilon 26}$	0.0132	0.0002
κ_{27-30}	−0.1017	0.0036
κ_{31-35}	0.0293	0.0031
κ_{36-40}	0.0204	0.0028
κ_{41-45}	−0.0654	0.0035
κ_{46-50}	−0.1880	0.0087
κ_{51-55}	0.3337	0.0088
ρ	0.4269	0.0048
$\sigma^2_{\upsilon 1939}$	0.0053	0.0007
$\sigma^2_{\upsilon 1940}$	0.0054	0.0006
$\sigma^2_{\upsilon 1941}$	0.0085	0.0007
$\sigma^2_{\upsilon 1942}$	0.0099	0.0007
$\sigma^2_{\upsilon 1943}$	0.0113	0.0007
$\sigma^2_{\upsilon 1944}$	0.0101	0.0007
$\sigma^2_{\upsilon 1945}$	0.0116	0.0007
$\sigma^2_{\upsilon 1946}$	0.0102	0.0006
$\sigma^2_{\upsilon 1947}$	0.0113	0.0006
$\sigma^2_{\upsilon 1948}$	0.0099	0.0005
$\sigma^2_{\upsilon 1949}$	0.0100	0.0006
$\sigma^2_{\upsilon 1950}$	0.0117	0.0006
$\sigma^2_{\upsilon 1951}$	0.0124	0.0006
$\sigma^2_{\upsilon 1952}$	0.0138	0.0005
$\sigma^2_{\upsilon 1953}$	0.0147	0.0005
$\sigma^2_{\upsilon 1954}$	0.0166	0.0005
$\sigma^2_{\upsilon 1955}$	0.0164	0.0005
$\sigma^2_{\upsilon 1956}$	0.0170	0.0005
$\sigma^2_{\upsilon 1957}$	0.0204	0.0005
$\sigma^2_{\upsilon 1958}$	0.0219	0.0004
$\sigma^2_{\upsilon 1959}$	0.0249	0.0004
$\sigma^2_{\upsilon 1960-1982}$	0.0229	0.0002
	(B) Firm	
$\sigma^2_{\xi q1}$	0.0057	0.0001
$\sigma^2_{\xi q2}$	0.0089	0.0001
$\sigma^2_{\xi q3}$	0.0087	0.0002
$\sigma^2_{\xi q4}$	0.0150	0.0003

Note: Equally Weighted Minimum Distance estimates for the parameters of transitory earnings in the earnings dynamics model of Section 3. Number of observations: 152,470,973; number of individuals: 12,339,989; number of firms: 3,067,752; number of empirical moments: 21,164; overall number of model parameters: 154; $\chi^2(21011) = 297190.7$.

It is important to note that negative covariances between innovations do not imply that overall sorting is negative, as the sorting component of the wage covariance at any given age reflects the accumulation of all worker-firm sorting covariances up to that age, owing to the persistence of RW shocks. Our estimates imply that worker-firm sorting remains positive throughout the life cycle, a point elaborated further later in this section. The emergence of negative covariances of innovations can be interpreted as a deceleration in the sorting process with age. For example, the likelihood that a high-wage worker departing from a high-wage firm will secure employment at another high-wage firm may decrease as workers grow older.[22]

The instantaneous worker-firm sorting covariance returns to positive values in the 51–55 age range. As discussed previously, this period is characterized by an acceleration in the growth of the empirical earnings variance. One plausible explanation for this pattern is selective survival in the labor market due to, e.g., early retirement of certain worker groups. The observed increase in worker-firm sorting after age 50 aligns with the notion that workers who are negatively sorted into firms, for example, high-wage workers employed in low-wage firms, are more likely to exit the labor force through early retirement, thereby raising the observed sorting covariance among those who remain.

Panel C.2 presents the estimated worker segregation parameters ($\mu_{(c-t)}$), which represent the extent to which the covariance of individual effects is incorporated into the co-worker covariance structure, as specified in Equation (8). These parameters quantify the correlation of worker effects among co-workers of the same age. The results indicate that worker segregation is substantial, with an average correlation coefficient of 0.46 observed over the life cycle. The estimates do not display pronounced life-cycle variation, showing a slight decline except in the final age group; a trend that mirrors the pattern observed for worker-firm sorting.

Comparable magnitudes of worker segregation have been documented in other studies employing correlation coefficients. For example, Barth et al. (2016) report a segregation correlation of approximately 0.35 in the United States based on observed workers' skills, which is consistent with our larger estimate that encompasses both observed and unobserved sources of worker heterogeneity. Similarly, Lopes de Melo (2018) find a correlation of 0.52 for worker FEs in Brazil using an AKM model.

5.2 | Transitory Wages

Table 2 reports estimates for the parameters of transitory wage components. Panel A focuses on the worker-specific transitory component, modeled as a nonstationary AR(1) process with age-dependent innovations.[23] The estimated spline coefficients describing the age profile of the variance of AR(1) innovations indicate that volatility declines sharply in the earliest years of the working career, fluctuates during mid-career, and then increases again at older ages. This broadly decreasing volatility pattern, particularly in the early career, is consistent with findings in the literature, such as those reported by Baker and Solon (2003).

The estimated serial correlation in the AR(1) process is moderate, with a value of 0.43. This value suggests that the impact of past shocks decays quickly, such that only approximately 2% of an initial shock persists after 5 years. The estimated serial correlation is lower than those reported in previous studies. Baker and Solon (2003) and Hoffmann (2019) report values of

TABLE 3 | Parameter estimates of permanent earnings—model without segregation.

	Coeff.	S.E.
	(A) Worker	
σ^2_{λ}	0.0019	0.00004
σ^2_{u26-30}	0.0016	0.00001
σ^2_{u31-35}	0.0012	0.00001
σ^2_{u36-40}	0.0008	0.00001
σ^2_{u41-45}	0.0007	0.00001
σ^2_{u46-50}	0.0008	0.00002
σ^2_{u51-55}	0.0005	0.00003
	(B) Firm	
$\sigma^2_{\phi q1}$	0.0110	0.00008
$\sigma^2_{\phi q2}$	0.0082	0.00008
$\sigma^2_{\phi q3}$	0.0079	0.00010
$\sigma^2_{\phi q4}$	0.0080	0.00012
$\sigma_{\phi q1q2}$	0.0086	0.00007
$\sigma_{\phi q1q3}$	0.0070	0.00007
$\sigma_{\phi q1q4}$	0.0032	0.00006
$\sigma_{\phi q2q3}$	0.0071	0.00008
$\sigma_{\phi q2q4}$	0.0032	0.00006
$\sigma_{\phi q3q4}$	0.0056	0.00009
	(C) Correlated effects	
	(C.1) Worker-firm sorting	
$\sigma_{\phi\lambda}$	0.0008	0.00001
$\sigma_{\phi u26-30}$	0.0010	0.00001
$\sigma_{\phi u31-35}$	0.0008	0.00001
$\sigma_{\phi u36-40}$	0.0003	0.00001
$\sigma_{\phi u41-45}$	0.0001	0.000005
$\sigma_{\phi u46-50}$	−0.0002	0.00001
$\sigma_{\phi u51-55}$	0.0003	0.00001

Note: Equally Weighted Minimum Distance estimates for the parameters of permanent earnings in an earnings dynamics model without segregation. Number of observations: 152,470,973; number of individuals: 12,339,989; number of firms: 3,067,752; number of empirical moments: 21,164; overall number of model parameters: 148. The parameter $\sigma_{\phi\lambda}$ is estimated based on the constraint described in Equation (9). $\chi^2(21017) = 417523.42$.

0.7 and 0.8, respectively; however, neither study incorporates firm-specific effects into the wage process. As demonstrated later in this section, omitting firm effects or co-worker segregation leads to higher estimates of serial correlation. Panel A also presents the AR(1) initial conditions, which are cohort-specific for left-censored cohorts (those born from 1939 to 1959). The results indicate greater dispersion of initial conditions for uncensored cohorts, with a gradual decline in dispersion observed for earlier cohorts.[24]

Panel B of Table 2 reports estimated parameters for firm-specific transitory shocks, indicating that their dispersion increases with firm age. This finding implies that employees in older firms are subject to greater volatility in firm-specific wage components than those in younger firms. This pattern may reflect older firms' enhanced access to debt and equity markets, which can lead to increased exposure to fluctuations in financial markets as firms mature.

5.3 | Variance Decompositions

Panel B of Figure 3 presents the variance decomposition implied by the model, corresponding to the variance components outlined in Equation (7) and averaged by age across birth cohorts and time periods. At age 25, permanent shocks attributable to both person- and firm-specific sources each account for 30% of the observed earnings dispersion. Individual-specific transitory shocks contribute a slightly smaller proportion, representing 27% of the total variance at this age. In contrast, firm-specific transitory shocks explain less than 10% of the overall variation at age 25, a share that is comparable to the contribution of the sorting component.

At age 30, the sorting component contributes 20% of the overall earnings dispersion, with permanent firm heterogeneity accounting for an additional 20% and transitory firm heterogeneity explaining 5% of overall dispersion. In contrast, the influence of individual-specific transitory shocks diminishes with age, representing approximately 10% of earnings inequality at age 30. Meanwhile, individual-specific permanent inequality grows in importance, accounting for over 45% of total earnings inequality at this age. As the life cycle progresses, the share of earnings inequality attributable to the individual-specific permanent component continues to rise, ultimately becoming the dominant source of wage dispersion, while the relative importance of transitory shocks, firm effects, and worker-firm sorting declines.

Firm-related factors, including permanent and transitory firm effects as well as worker-firm sorting, play a more prominent role in shaping earnings among younger workers compared to their older counterparts. At age 25, these firm-related components account for 40% of total inequality, whereas by age 55, their contribution declines to just over 20%. On average, over the life cycle, the permanent individual-specific component emerges as the dominant source of wage dispersion, explaining 61% of total variance. Firm-specific permanent effects contribute 13%, while individual-specific transitory shocks account for an additional 7% of overall inequality. Firm-specific transitory shocks represent 4% of the total, and worker-firm sorting is responsible for the remaining 15%. These variance decomposition estimates are in line with the findings reported by Bonhomme et al. (2023) using bias-corrected FE or CRE approaches.

Figure 2 indicates that approximately 60% of earnings inequality stems from between-firm heterogeneity, with this proportion exhibiting a modest decline as individuals progress through their careers.[25] In contrast, Panel B of Figure 3 reveals that the relative contributions of different earnings components to the overall wage dispersion shift markedly over the life cycle. This pattern suggests that the composition of between-firm inequality is also likely to evolve with age. Panel C of Figure 3 provides a direct assessment of how the sources of between-firm earnings inequality change over the life cycle. The graph shows that, as workers age, segregation emerges as the predominant driver of between-firm dispersion. This pattern reflects the increasing importance of worker heterogeneity and the tendency for individuals with similar characteristics to work together. The share of between-firm inequality attributable to worker segregation rises steadily from 25% at age 25 to 60% by age 55.[26]

TABLE 4 | Parameter estimates of transitory earnings components—model without segregation.

	Coeff.	S.E.
	(A) Worker	
$\sigma^2_{\varepsilon 26}$	0.0049	0.0002
κ_{27-30}	0.0132	0.0067
κ_{31-35}	0.0101	0.0047
κ_{36-40}	0.0227	0.0043
κ_{41-45}	−0.1018	0.0065
κ_{46-50}	−0.2164	0.0249
κ_{51-55}	0.3644	0.0198
ρ	0.8154	0.0026
$\sigma^2_{\upsilon 1939}$	0.0022	0.0011
$\sigma^2_{\upsilon 1940}$	0.0041	0.0011
$\sigma^2_{\upsilon 1941}$	0.0078	0.0012
$\sigma^2_{\upsilon 1942}$	0.0091	0.0012
$\sigma^2_{\upsilon 1943}$	0.0115	0.0012
$\sigma^2_{\upsilon 1944}$	0.0073	0.0012
$\sigma^2_{\upsilon 1945}$	0.0071	0.0012
$\sigma^2_{\upsilon 1946}$	0.0065	0.0010
$\sigma^2_{\upsilon 1947}$	0.0052	0.0010
$\sigma^2_{\upsilon 1948}$	0.0056	0.0010
$\sigma^2_{\upsilon 1949}$	0.0028	0.0010
$\sigma^2_{\upsilon 1950}$	0.0062	0.0010
$\sigma^2_{\upsilon 1951}$	0.0082	0.0010
$\sigma^2_{\upsilon 1952}$	0.0087	0.0010
$\sigma^2_{\upsilon 1953}$	0.0129	0.0010
$\sigma^2_{\upsilon 1954}$	0.0148	0.0010
$\sigma^2_{\upsilon 1955}$	0.0147	0.0009
$\sigma^2_{\upsilon 1956}$	0.0184	0.0008
$\sigma^2_{\upsilon 1957}$	0.0222	0.0008
$\sigma^2_{\upsilon 1958}$	0.0249	0.0007
$\sigma^2_{\upsilon 1959}$	0.0272	0.0007
$\sigma^2_{\upsilon 1960-1982}$	0.0293	0.0003
	(B) Firm	
$\sigma^2_{\xi q1}$	0.0059	0.0001
$\sigma^2_{\xi q2}$	0.0096	0.0001
$\sigma^2_{\xi q3}$	0.0107	0.0002
$\sigma^2_{\xi q4}$	0.0105	0.0002

Note: Equally Weighted Minimum Distance estimates for the parameters of transitory earnings in an earnings dynamics model without segregation. Number of observations: 152,470,973; number of individuals: 12,339,989; number of firms: 3,067,752; number of empirical moments: 21,164; overall number of model parameters: 148; $\chi^2(21017) = 417523.42$.

5.4 | Sorting

Panel D of Figure 3 depicts the evolution of sorting covariances and correlations across the life cycle, as implied by the estimated model parameters. We calculate these measures by averaging the sorting component on the right-hand side of Equation (7), standardized in the case of correlations, over cohorts and periods for each age. The results indicate that both covariances and correlations remain positive throughout the life cycle. The sorting covariances, shown on the right axis, increase rapidly early in the career, driven by the relatively large covariances between RW innovations and firm effects for workers aged 26 to 30. The initial growth of sorting covariances subsequently stabilizes and even turns negative during mid-career, which may reflect a reduced likelihood that high-wage workers who, as they age, leave high-wage firms, are subsequently rehired at other high-wage firms. In the later stages of the life cycle, sorting covariances rise again, a pattern that may be attributable to selective early retirement from the labor force, as previously discussed.

Figure 3 also presents, on the left axis, the evolution of sorting correlations, which offer a more precise measure of the strength of worker-firm sorting and facilitate direct comparison with findings from other studies. In the early stages of the career, sorting correlations exhibit a similar pattern to that of covariances. However, while covariances increase gradually before declining, correlations begin to decrease earlier. Both measures show an uptick after age 50. The earlier decline in correlations relative to covariances can be attributed to the dynamics between ages 26 and 45, when the growth of sorting covariances slows, while the individual-specific variances in the denominator of the correlation continue to rise, albeit at a slower pace. This relationship is evident in the variance decomposition presented in Panel B of the figure and is supported by the parameter estimates in Table 1. On average, the worker-firm sorting correlation across the life cycle is 0.30, which aligns with the range of estimates reported by Bonhomme et al. (2023) using bias-corrected FE or CRE approaches. The average correlation reflects relatively high values of approximately 0.4 at age 30 and lower values, below 0.2, around age 50.

5.5 | The Relevance of Segregation

Segregation plays a pivotal role in the model, rendering worker-specific heterogeneity essential for explaining the covariance structure of co-worker earnings. To demonstrate the importance of segregation, we re-estimate the model under the assumption of no segregation, thereby restricting the co-worker moment condition to depend solely on firm-related components, i.e., the variances of permanent and transitory firm effects, as well as the worker-firm sorting covariance. The parameter estimates for permanent earnings, presented in Table 3, reveal an increase in the magnitude of the sorting components relative to the baseline model that incorporates segregation. Furthermore, Table 4 reports the estimates for transitory earnings, showing a substantial rise in the serial correlation parameter of the AR(1) process, which reaches 0.81. This value is comparable to those obtained from earnings dynamics models that do not account for firm effects.[27]

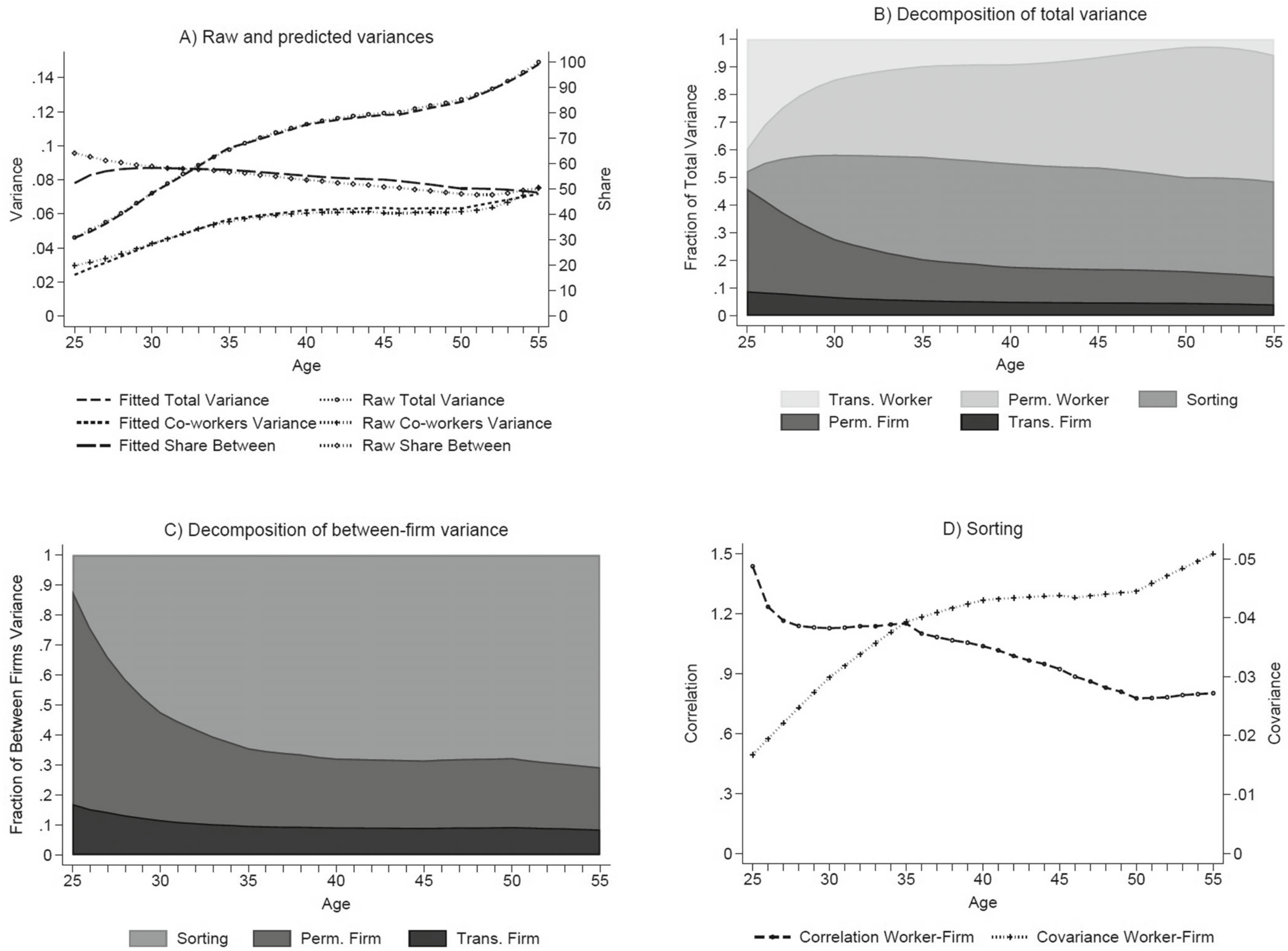

FIGURE 4 | Predictions and variance decompositions—model without segregation. *Note:* The figure reports predictions and decomposition results from a model that does not account for segregation, that is, the correlation of worker effects among co-workers. The co-worker moment restrictions for this model are given by Equation (8) after setting the parameters $\mu_{(t-c)}$ equal to zero. The underlying parameter estimates are reported in Tables 3 and 4 and Table A4 in the Supporting Information.

Figure 4 summarizes the results from the restricted version of the model that excludes segregation, presenting several key predictions. Panel A shows that the predicted life-cycle profile of earnings dispersion remains largely unchanged relative to the benchmark results in Figure 3. However, the proportion of the variance attributable to between-firm differences declines, with a life-cycle average of 54%, compared to 60% in the benchmark model. The omission of segregation substantially alters the variance decomposition. As shown in Panel B, there is a pronounced decrease in the share of overall variance accounted for by the worker-specific component, alongside a marked increase in the importance of the sorting component. On average, individual effects account for only 35% of total variance, in contrast to 60% in the benchmark model, while the contribution of sorting rises to 33%, more than double the 15% observed in the benchmark.

Substantial differences between models with and without segregation are also apparent in the decomposition of the between-firm variance. In the absence of segregation, between-firm variance is, by construction, attributed solely to firm-related components and is overwhelmingly dominated by the sorting share, as illustrated in Panel C. Panel D further reveals that the sorting correlation exceeds unity at younger ages, with a life-cycle average correlation of 1. This pattern indicates that omitting segregation leads to a significant upward bias in the estimated sorting component. The source of this bias lies in the omission of the segregation term of Equation (8), which captures the contribution of worker heterogeneity within co-worker covariances. When segregation is excluded from the model, the sorting covariance becomes the sole channel through which worker heterogeneity influences co-worker moments. As a result, the sorting component absorbs the entire effect of worker heterogeneity, substantially inflating its estimated contribution.

5.6 | Comparison With a Standard Earnings Dynamics Model

Our model nests a standard individual earnings dynamics model, featuring RW permanent shocks, autoregressive AR(1) transitory shocks, and period-specific loading factors for each component. When worker and firm effects are correlated due to sorting, relying solely on the standard model risks overstating the contribution of worker-specific factors to earnings inequality, as it does not account for firm heterogeneity.

To evaluate this possibility, we estimate the standard earnings dynamics model using only the individual-level covariance structure.

TABLE 5 | Parameter estimates—standard earnings dynamics model without firm effects.

	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 warnings (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

Note: Equally Weighted Minimum Distance 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; $\chi^2(10{,}485) = 87381.3$.

Estimates for the permanent wage component from the standard model, as reported in Panel A of Table 5, indicate that during the initial part of the life cycle, when firm heterogeneity plays an important role in explaining earnings dispersion, the RW parameters are substantially larger than those obtained from the baseline model that accounts for firm effects. Additionally, the estimated serial correlation of mean-reverting shocks in the standard model is 0.65 (see Panel B of Table 5), a value consistent with findings from other studies on individual earnings dynamics and notably higher than the baseline of 0.43.[28] This pattern underscores the potential for the standard model to overstate the persistence and magnitude of individual-specific shocks when firm-level heterogeneity is omitted.

Figure 5 summarizes the findings from the standard individual earnings dynamics model that omits firm effects, showing the predicted variance components across the life cycle. Although the overall variance predictions closely mirror those of the baseline model depicted in Figure 3, the allocation of earnings dispersion between the individual permanent and transitory components diverges substantially. In the baseline, the proportion of permanent inequality rises from 30% at the beginning of the working life to 75% by the end, while the contribution of individual transitory shocks declines from 25% to less than 5% over the same period. In contrast, the standard specification underlying Figure 5 predicts that, at age 25, approximately 60% of inequality is attributable to individual-specific permanent factors and 40% to transitory factors, with these shares shifting to 80% and 20%, respectively, by age 55. These findings highlight that the standard specification, which excludes firm effects, systematically overstates the relative importance of both the permanent and transitory individual components, especially in the early career stages when firm effects and worker-firm sorting are most influential.

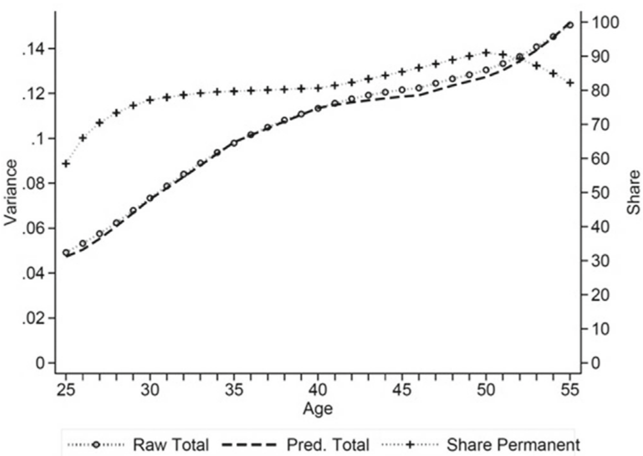

FIGURE 5 | Raw and predicted variances and permanent variance share over the life cycle—standard earnings dynamics model without firm effects. *Note:* The figure reports raw empirical moments and their fitted counterparts derived from a standard earnings dynamics model without firm effects. The fitted 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 5 and Table A5 in the Supporting Information.

6 | Regional Heterogeneity

The findings in the previous section underscore the prominent role of firm heterogeneity in accounting for earnings inequality in the early stages of working life before individual heterogeneity becomes the dominant factor. The transition in the relative importance of individual and firm heterogeneity is shaped by processes such as human capital accumulation and

TABLE 6 | 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}	0.0092	0.00011	0.0120	0.00027	0.0042	0.00018
σ^2_{u26-30}	0.0022	0.00002	0.0033	0.00004	0.0008	0.00003
σ^2_{u31-35}	0.0020	0.00001	0.0025	0.00003	0.0015	0.00004
σ^2_{u36-40}	0.0012	0.00001	0.0019	0.00003	0.0011	0.00003
σ^2_{u41-45}	0.0009	0.00001	0.0012	0.00003	0.0010	0.00003
σ^2_{u46-50}	0.0010	0.00001	0.0008	0.00003	0.0008	0.00003
σ^2_{u51-55}	0.0005	0.00002	0.0010	0.00004	0.0011	0.00006
			(B) Firm			
$\sigma^2_{\phi q1}$	0.0110	0.00012	0.0159	0.00032	0.0294	0.00039
$\sigma^2_{\phi q2}$	0.0092	0.00014	0.0167	0.00039	0.0291	0.00056
$\sigma^2_{\phi q3}$	0.0121	0.00019	0.0218	0.00052	0.0239	0.00075
$\sigma^2_{\phi q4}$	0.0115	0.00021	0.0186	0.00052	0.0290	0.00100
$\sigma_{\phi q1q2}$	0.0091	0.00012	0.0150	0.00035	0.0269	0.00045
$\sigma_{\phi q1q3}$	0.0087	0.00012	0.0151	0.00036	0.0246	0.00046
$\sigma_{\phi q1q4}$	0.0073	0.00014	0.0163	0.00040	0.0225	0.00050
$\sigma_{\phi q2q3}$	0.0098	0.00015	0.0180	0.00043	0.0264	0.00060
$\sigma_{\phi q2q4}$	0.0067	0.00014	0.0169	0.00043	0.0228	0.00063
$\sigma_{\phi q3q4}$	0.0095	0.00017	0.0208	0.00051	0.0235	0.00074
			(C) Correlated effects			
			(C.1) Worker-firm sorting			
$\sigma_{\phi\lambda}$	0.0006	0.00002	0.0011	0.00004	0.0012	0.00002
$\sigma_{\phi u26-30}$	0.0006	0.00001	0.0001	0.00003	0.0013	0.00004
$\sigma_{\phi u31-35}$	0.0002	0.00001	0.0003	0.00002	0.0001	0.00002
$\sigma_{\phi u36-40}$	0.0000	0.00001	0.0001	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	0.0003	0.00003
			(C.2) Co-worker segregation			
μ_{25-30}	0.4174	0.00381	0.6062	0.00529	0.6410	0.01274
μ_{31-35}	0.4164	0.00326	0.5817	0.00430	0.5592	0.00787
μ_{36-40}	0.4092	0.00313	0.5642	0.00400	0.5658	0.00613
μ_{41-45}	0.3979	0.00303	0.5606	0.00378	0.5843	0.00532
μ_{46-50}	0.3976	0.00284	0.5808	0.00356	0.6135	0.00508
μ_{51-55}	0.4056	0.00286	0.6027	0.00378	0.6349	0.00556

Note: Equally Weighted Minimum Distance 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: 6,640,943 (North), 2,929,165 (Center), 2,769,881 (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: 154 in Columns 1 and 3 and 152 in Column 2. The parameter $\sigma_{\phi\lambda}$ is estimated based on the constraint described in Equation (9). $\chi^2(21011) = 256585.05$ in Column 1; $\chi^2(21013) = 117181.43$ in Column 2; and $\chi^2(21011) = 1623609.2$ in Column 3.

worker turnover, both of which are influenced by the overall functioning of the labor market and broader economic conditions. In this respect, Italy provides a valuable setting for exploring how earnings dynamics vary across diverse economic environments while operating under a unified institutional framework.

One of the most salient features of the Italian economy is its pronounced regional disparity. Northern regions are distinguished by the presence of large, innovative manufacturing firms, a well-developed financial sector, and comparatively low unemployment rates. In contrast, the southern regions are

TABLE 7 | 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			
$\sigma^2_{\varepsilon 26}$	0.0110	0.0002	0.0124	0.0005	0.0079	0.0003
κ_{27-30}	−0.0250	0.0043	−0.0697	0.0094	−0.1037	0.0078
κ_{31-35}	0.0407	0.0032	−0.0528	0.0084	−0.0011	0.0075
κ_{36-40}	0.0191	0.0028	0.0658	0.0075	0.0149	0.0073
κ_{41-45}	−0.0700	0.0034	−0.0265	0.0040	−0.0452	0.0086
κ_{46-50}	−0.1689	0.0078			−0.0469	0.0141
κ_{51-55}	0.3467	0.0079			−0.3077	0.0818
ρ	0.4649	0.0055	0.3151	0.0111	0.6029	0.0080
$\sigma^2_{\upsilon 1939}$	0.0081	0.0007	0.0015	0.0015	0.0055	0.0023
$\sigma^2_{\upsilon 1940}$	0.0078	0.0007	0.0021	0.0014	0.0082	0.0023
$\sigma^2_{\upsilon 1941}$	0.0101	0.0008	0.0095	0.0015	0.0113	0.0023
$\sigma^2_{\upsilon 1942}$	0.0109	0.0008	0.0113	0.0015	0.0157	0.0023
$\sigma^2_{\upsilon 1943}$	0.0117	0.0008	0.0117	0.0015	0.0156	0.0022
$\sigma^2_{\upsilon 1944}$	0.0105	0.0008	0.0117	0.0015	0.0159	0.0022
$\sigma^2_{\upsilon 1945}$	0.0108	0.0008	0.0137	0.0014	0.0142	0.0021
$\sigma^2_{\upsilon 1946}$	0.0105	0.0007	0.0117	0.0012	0.0118	0.0018
$\sigma^2_{\upsilon 1947}$	0.0099	0.0007	0.0134	0.0012	0.0164	0.0018
$\sigma^2_{\upsilon 1948}$	0.0099	0.0006	0.0091	0.0011	0.0146	0.0018
$\sigma^2_{\upsilon 1949}$	0.0088	0.0007	0.0098	0.0012	0.0192	0.0018
$\sigma^2_{\upsilon 1950}$	0.0097	0.0006	0.0118	0.0012	0.0214	0.0018
$\sigma^2_{\upsilon 1951}$	0.0113	0.0007	0.0103	0.0011	0.0192	0.0017
$\sigma^2_{\upsilon 1952}$	0.0117	0.0006	0.0125	0.0011	0.0217	0.0018
$\sigma^2_{\upsilon 1953}$	0.0133	0.0006	0.0132	0.0011	0.0185	0.0017
$\sigma^2_{\upsilon 1954}$	0.0152	0.0006	0.0124	0.0010	0.0207	0.0016
$\sigma^2_{\upsilon 1955}$	0.0142	0.0006	0.0145	0.0010	0.0185	0.0015
$\sigma^2_{\upsilon 1956}$	0.0150	0.0005	0.0119	0.0009	0.0206	0.0014
$\sigma^2_{\upsilon 1957}$	0.0167	0.0005	0.0173	0.0010	0.0221	0.0014
$\sigma^2_{\upsilon 1958}$	0.0186	0.0005	0.0187	0.0009	0.0214	0.0013
$\sigma^2_{\upsilon 1959}$	0.0199	0.0005	0.0209	0.0009	0.0300	0.0013
$\sigma^2_{\upsilon 1960-1982}$	0.0202	0.0003	0.0178	0.0006	0.0198	0.0005
			(B) Firm			
$\sigma^2_{\xi q1}$	0.0032	0.0001	0.0060	0.0002	0.0111	0.0002
$\sigma^2_{\xi q2}$	0.0070	0.0002	0.0065	0.0003	0.0084	0.0002
$\sigma^2_{\xi q3}$	0.0072	0.0002	0.0056	0.0003	0.0101	0.0003
$\sigma^2_{\xi q4}$	0.0121	0.0003	0.0097	0.0005	0.0099	0.0003

Note: Equally Weighted Minimum Distance 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: 6,640,943 (North), 2,929,165 (Center), 2,769,881 (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: 154 in Columns 1 and 3 and 152 in Column 2. $\chi^2(21011) = 256585.05$ in Column 1; $\chi^2(21013) = 117181.43$ in Column 2; and $\chi^2(21011) = 1623609.2$ in Column 3. Age splines for AR(1) innovations after age 40 are reduced to 1 in Column 2.

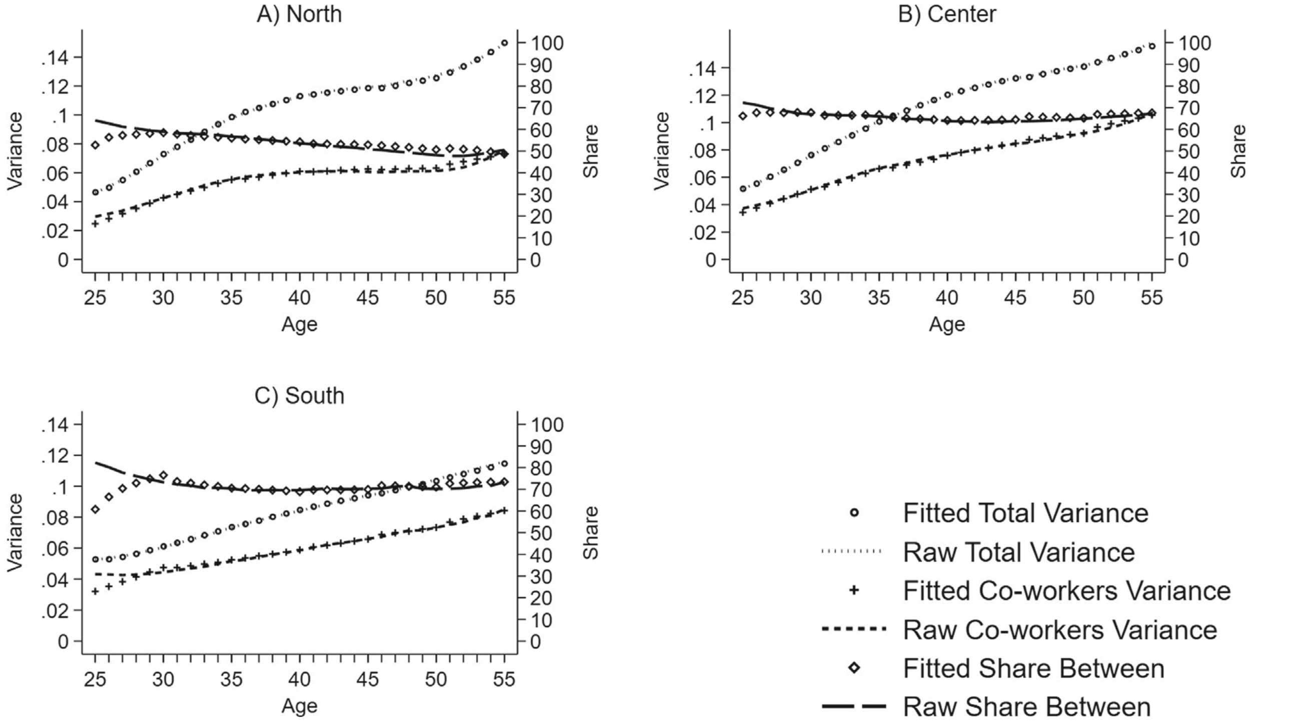

FIGURE 6 | Raw and predicted variances and between-firms variance share over the life cycle, by geographical area. *Note:* The figure reports raw empirical moments and their fitted counterparts derived from the earnings dynamics model estimated by geographical area. The fitted figures are predicted by 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 Tables 6 and 7 and Table A6 in the Supporting Information.

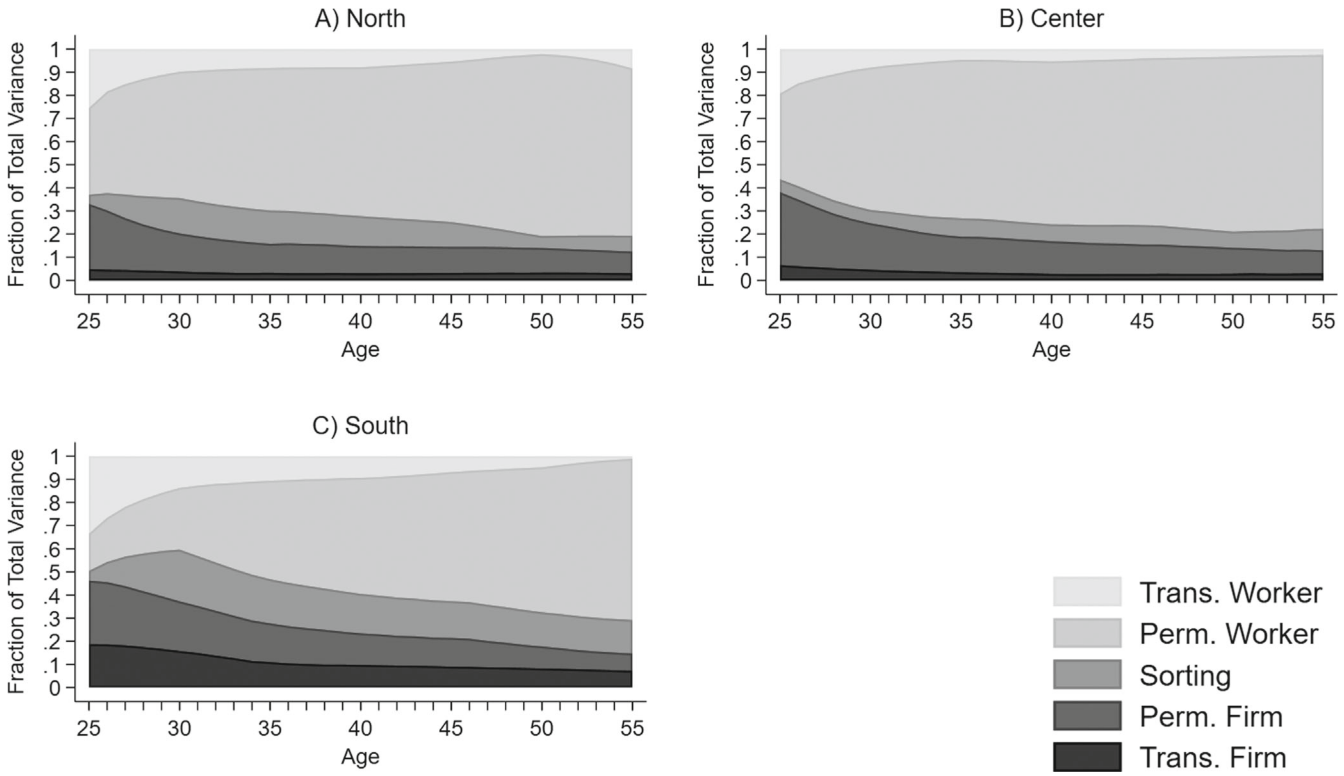

FIGURE 7 | Decomposition of total variance over the life cycle, by geographical area. *Note:* The figure reports the variance decomposition derived according to Equation (7) by geographical area. Variance components are predicted by area for any cohort-age combination that is present in the sample and then averaged across cohorts by age. Parameter estimates underlying the decomposition are reported in Tables 4 and 5 and Table A4 in the Supporting Information.

characterized by a preponderance of smaller firms engaged in more traditional production and relatively high unemployment, especially among the young. The central regions exhibit intermediate features, occupying a position between the economic profiles of the north and south. These diverse regional contexts are likely to generate distinct patterns of earnings dynamics over the life cycle, with firm heterogeneity playing a particularly significant role. This section examines these regional variations in earnings dynamics.

We divide the estimation sample into three areas—North, Center, and South—according to the province of work.[29] The North accounts for the majority of person-year observations in the sample (59%), followed by the Center (23%) and South (18%). Individual earnings profiles are assigned to the area where most of each individual's earnings observations occur, resulting in 54% of individuals classified in the North, 24% in the Center, and 22% in the South. Discrepancies between current and prevalent areas are primarily attributable to temporary migrations to the North.

The regional subsamples contain 1,685,499 firms in the North, 952,386 in the Center, and 1,056,163 in the South. The total number of firms across areas exceeds the overall firm count for the estimation sample, as multiplant firms may operate in more than one area. With the data partitioned by prevalent area, we re-estimate individual and co-worker moments, and fit the earnings dynamics models separately for each area.[30]

Table 6 presents estimates of the permanent components of earnings by area, while Table 7 provides estimates for the transitory components; period-specific loading factors are detailed in Table A8 in the Supporting Information. A comparison of the individual-specific RW process parameters across areas reveals a marked distinction for the South, especially during the early stages of workers' careers. In this area, the influence of individual earnings dynamics among young workers is substantially lower than in the North and Center, with parameter estimates ranging between one-half and a third of those observed for other areas. This evidence for the South is consistent with challenges in accumulating human capital through on-the-job experience, a situation likely exacerbated by persistently high rates of youth unemployment.

Worker segregation is more pronounced in the Center and South compared to the North. The average correlation of worker effects among co-workers is 0.4 in the North, rising to approximately 0.6 in both the Center and South. This regional variation is consistent with a higher prevalence of informal job-search networks in central and southern Italy, which, as discussed in Section 3, can generate worker segregation. A further key distinction across areas concerns firm heterogeneity, which is estimated to be roughly three times greater in the South than in the North. The heightened wage dispersion observed between firms in the South may reflect a more rigid labor market structure and reduced worker mobility or turnover. In such an environment, firm-specific wage premia are less likely to be eroded through competitive reallocation of workers across firms, thereby sustaining higher levels of between-firm wage inequality.

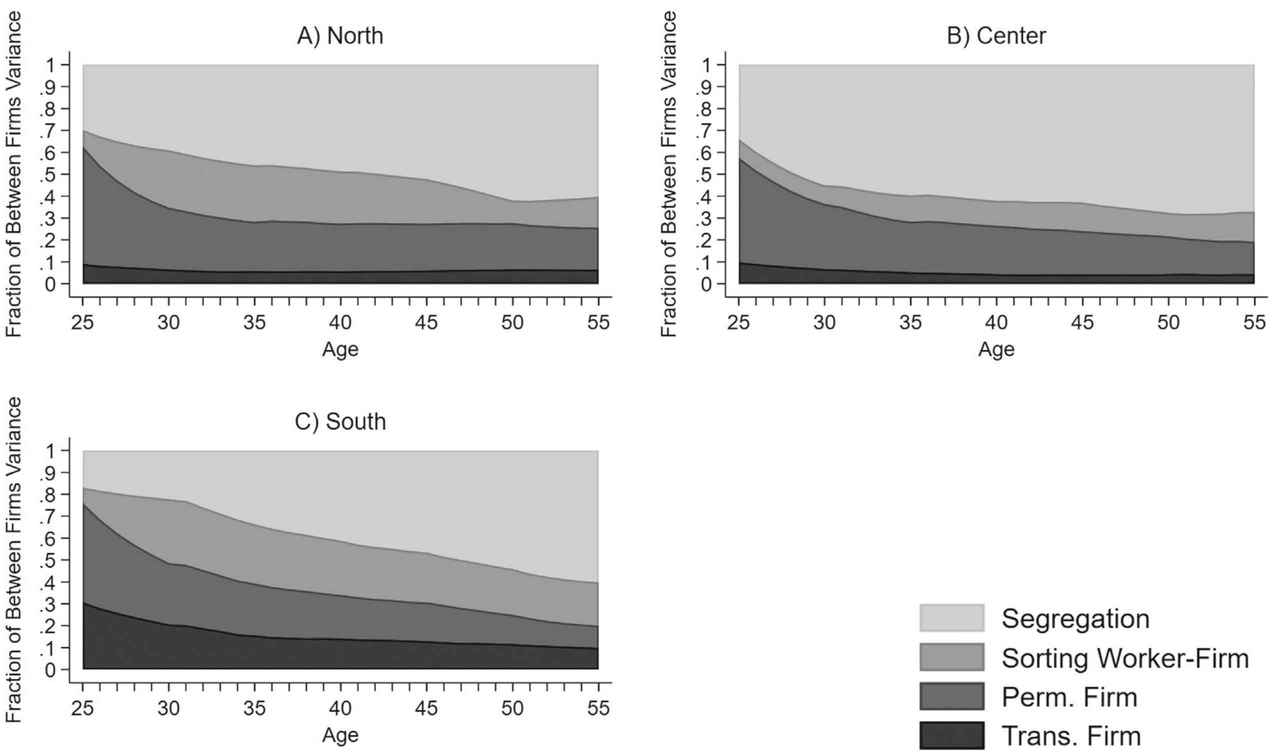

FIGURE 8 | Decomposition of between-firm variance over the life cycle, by geographical area. *Note:* The figure reports the variance decomposition derived according to Equation (8) by geographical area. Variance components are predicted by area for any cohort-age combination that is present in the sample and then averaged across cohorts by age. Parameter estimates underlying the decomposition are reported in Tables 4 and 5 and Table A4 in the Supporting Information.

Table 7 indicates that transitory shocks exhibit greater persistence in the South, providing further evidence of stronger labor market rigidity in this region. A notable distinction also emerges in the dispersion of firm-specific transitory shocks; while this dispersion increases with firm age in both the North and the Center, no such pattern is observed in the South. As discussed in Section 5, the age-related increase in the volatility of firm-specific transitory shocks aligns with the notion that older firms are more exposed to stock market fluctuations. In contrast, the findings from Table 7 suggest that southern firms could have more limited access to stock markets compared to their northern counterparts, which may account for the absence of an age-related pattern of transitory fluctuations in the South.

Figure 6 presents the area-specific implications of the estimated model for life-cycle variance profiles and the proportion of variance attributable to differences between firms, alongside the corresponding empirical moments and between-firm shares calculated from the raw data. In both the North and Center of Italy, overall earnings dispersion increases more rapidly before age 40, mirroring the national trend and reflecting higher rates of worker turnover, greater opportunities for promotion, and more rapid accumulation of human capital in the early stages of working life. In contrast, the South displays a markedly different pattern: The growth of earnings dispersion remains relatively stable throughout the life cycle, and the age profile of variance in the South closely resembles that observed among older workers in the North and Center. Another notable regional distinction emerges in the share of variance explained by between-firm differences, which is 55% in the North but rises to 70% in both the Center and South.

Individual heterogeneity plays a substantially larger role in shaping earnings trajectories in the North compared to other regions. This distinction is highlighted by the variance decompositions over the life cycle, as illustrated in Figure 7. In the North, the permanent individual component accounts for 45% of the variance at age 30, whereas in the South, this share only reaches 40% by age 40. In contrast, firm-related wage components are more relevant throughout working life in the Center and, especially, in the South than in the North.

A regional decomposition of between-firm wage variance reveals distinct patterns across Italy, as shown in Figure 8. In the South, firm-related factors, specifically permanent firm effects and worker-firm sorting, account for the majority of between-firm wage dispersion. This preponderance reflects a more frictional labor market environment, characterized by greater heterogeneity in firm wage-setting practices and employment conditions.

The contribution of worker segregation to between-firm earnings dispersion differs markedly by area. The share attributable to segregation depends on two factors: The intensity of segregation, captured by the $\mu_{(t-c)}$ parameters of Equation (6), and the degree of worker heterogeneity, which depends on the variance of both the RW initial conditions (σ^2_λ) and its innovations ($\sigma^2_{u(t-c)}$). Worker heterogeneity is more pronounced in the North and Center, while segregation is higher in the Center and South. Consequently, the

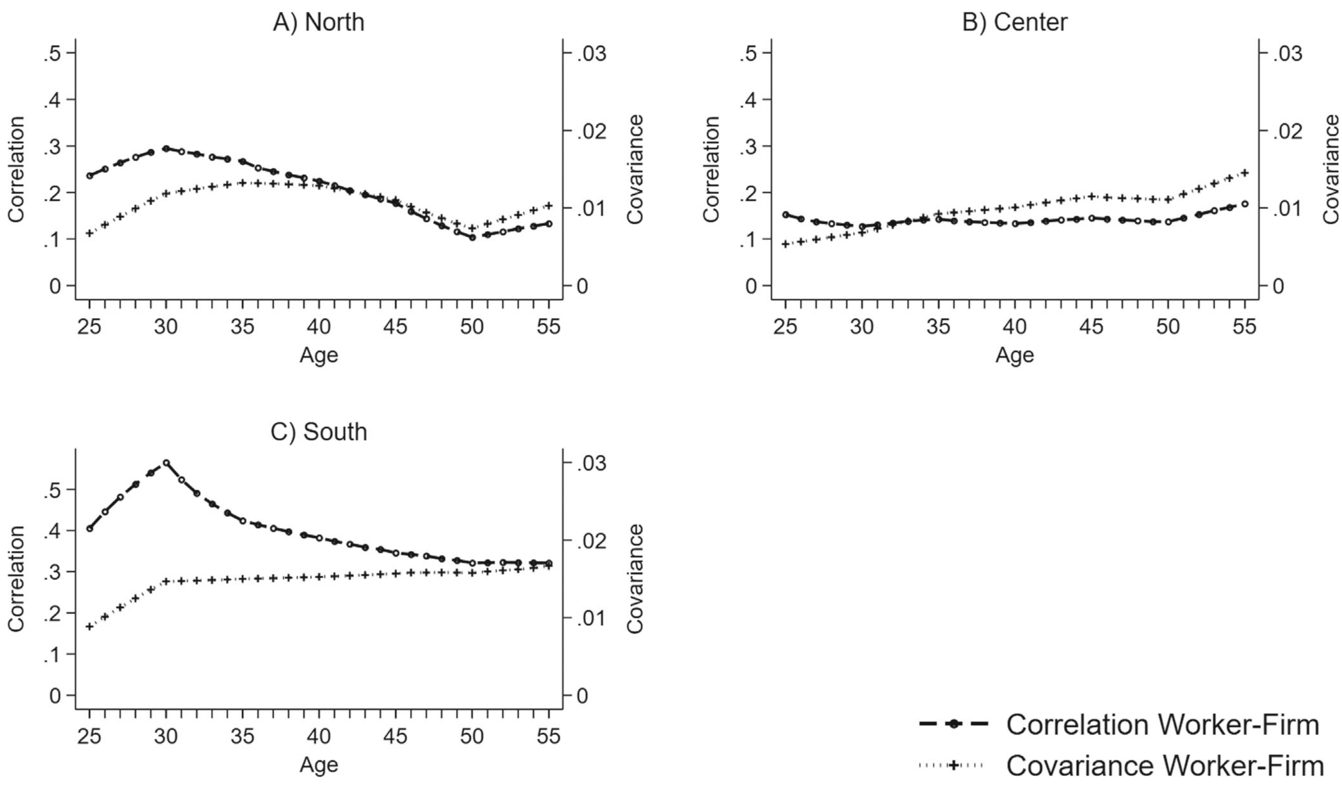

FIGURE 9 | Worker-firm sorting over the life cycle, by geographical area. *Note:* The figure reports sorting measures over the life cycle derived by area from the earnings dynamics model. The sorting covariance is obtained by applying Equation (5). Predictions are derived by area for any cohort-age-lag combination that is present in the data and then averaged across cohorts by age.

share of between-firm variance explained by segregation reaches its highest level in the Center (60%), is lowest in the South (40%), and is intermediate in the North (49%). This pattern implies that, although segregation is the greatest in the South, its impact on inequality is muted due to the more compressed distribution of worker effects in that area.

Additionally, evidence from Figure 9 indicates that worker-firm sorting is greater in the North compared to the Center and South, underscoring regional differences in the mechanisms shaping between-firm wage inequality.

7 | Conclusion

Incorporating firm effects, our model extends the standard empirical model of individual earnings dynamics, which traditionally centers on permanent and transitory shocks. In addition to capturing heterogeneity at both the worker and firm levels, our model explicitly accounts for worker-firm sorting and worker segregation between firms. 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*.

Our study contributes to the literature on firm-driven wage inequality by introducing an approach that does not require worker mobility between firms, thereby circumventing the limited-mobility bias commonly associated with two-way FE models. Prior research has identified significant challenges in standard specifications: Bonhomme et al. (2023) emphasize that omitting the dynamics of both worker and firm effects can lead to substantial misspecification in two-way FE frameworks. Lachowska et al. (2023) incorporate dynamics in firm effects but maintain constant worker effects over time. Our methodology advances the literature by allowing for dynamic processes in both worker and firm effects, providing a more comprehensive account of the sources and evolution of wage inequality.

The analysis reveals substantial variation in the relative influence of workers and firms in shaping wage inequality over the working life. Among young workers, heterogeneity attributable to both firms and individuals plays an equally important role in explaining wage differences. As careers progress, the contribution of individual heterogeneity becomes increasingly prominent, ultimately emerging as the primary determinant of wage dispersion. This pattern is driven by the more rapid accumulation of individual-specific heterogeneity at younger ages, a dynamic consistent with higher rates of human capital investment and worker mobility early in the career, both of which diminish with age.

Worker-firm sorting is found to be both substantial and dynamic, exhibiting pronounced life-cycle variation that reflects the evolution of individual heterogeneity, with the most pronounced sorting among young workers. We also reveal a substantial degree of worker segregation: With approximately 60% of overall earnings inequality attributable to wage differences between firms, the majority of this between-firm dispersion stems from worker segregation.

The evidence indicates that the quality of initial jobs can shape opportunities for skill development and earnings growth, resulting in persistent effects on wage inequality. This finding underscores the importance of early-career firm assignments in determining long-term labor market outcomes. Consequently, policy interventions that enhance the allocation of young workers to firms, such as measures to reduce information asymmetries or facilitate early job mobility, may play a critical role in mitigating wage disparities over the life course.

We estimate our model using data on the population of private sector employers and employees in Italy, as provided by the National Social Security Institute. The Italian context offers a distinctive setting for the analysis of earnings dynamics, as national wage floors established through collective agreements co-exist with employer-determined wage adjustments that are often worker-specific. While institutional factors play a significant role in shaping wage outcomes, they do not fully account for the observed variation in earnings, allowing both worker- and firm-level heterogeneity to exert substantial influence. Moreover, Italy is characterized by a substantial degree of regional variation in economic conditions, with pronounced differences in firm size, industrial structure, and labor market performance between the North, Center, and South. These regional contrasts provide a valuable opportunity to investigate how earnings dynamics evolve across different economic environments, all within the framework of a unified institutional system.

In Southern Italy, firm-specific heterogeneity is an important determinant of wage dispersion throughout the working life, while the growth of worker-related heterogeneity over the life cycle is notably slower compared to the Center and North. This reduced individual heterogeneity aligns with evidence of lower returns to human capital investments in the South, which may be adversely affected by frequent career interruptions due to persistently high youth unemployment rates. The pronounced role of firm heterogeneity in the area is indicative of persistent labor market frictions and limited worker mobility, factors that hinder efficient reallocation and contribute to sustained differences in wage-setting practices among firms.

Applying our model of individual earnings dynamics with firm effects to datasets from other countries could yield contrasting patterns in the decompositions of wage inequality over the life cycle. Such cross-country analyses would enhance our understanding of how institutional settings, labor market structures, and economic environments shape the evolution of earnings inequality and the respective roles of worker- and firm-level heterogeneity.

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Data Availability Statement

The data used in this article are drawn from Italian administrative registers held by the Social Security Institute (INPS) and are confidential. Physically, these administrative micro data are located on servers at INPS and may not be transferred to computers outside INPS due to data security considerations. The replication package contains the file Data.txt, which describes how to obtain access to the INPS data for research purposes.

Endnotes

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

[2] Casarico and Lattanzio (2024) show that in Italy, gender differences in firm effects explain about a third of the gender pay gap.

[3] 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.

[4] Evidence from structural models with two-sided heterogeneity suggests that worker-firm sorting is larger than typically found by correlating AKM fixed effects (Borovickova and Shimer 2017; Lentz et al. 2023).

[5] CRE models of variance components for worker and firm heterogeneity were introduced in Woodcock (2008).

[6] The CRE approach is also robust to limited-mobility bias; however, it treats individual effects as time-invariant.

[7] 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.

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

[9] The autocovariance function of the AR(1) process has a recursive structure (see Equation 7 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 modeling 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.

[10] As a robustness check, we estimate an augmented version of our model that includes match-specific heterogeneity, modeled as a RW in tenure. The specification of the wage process for this model is given by $w_{ijt} = \alpha_t\left(\lambda_{it} + \eta_{ijt}\right) + \delta_t\phi_{jt} + \gamma_t\psi_{ijt}$, where $\eta_{ijt} = \mathbb{I}[J(i,t) = J(i,t-1)]\eta_{ijt-1} + \vartheta_{ijt} = \sum_{k=t-\tau}^{t}\vartheta_{ijk}$, $\vartheta_{ijt} \sim \left(0, \sigma_{\vartheta}^2\right)$,$\tau$ is workplace tenure and $\mathbb{I}[J(i,t) = J(i,t-1)]$ is a dummy for stayers, such as η_{ijt} is an RW that accumulates within matches. A model with RW in age, RW in tenure, and AR(1) transitory shocks yields quantitatively negligible and statistically insignificant estimates of match parameters. When we adopt a white noise structure on the transitory component, the estimates (reported in the Figure A2 and Table A1 in the Supporting Information) indicate that match effects account, on average, for only about 3% of life-cycle wage dispersion, lending support to our baseline specification without match effects.

[11] To further dispel concerns about endogenous mobility, we performed an event study on the wage effects of mobility in the spirit of Card et al. (2013), comparing the wage changes of workers moving from high- to low-paying firms with the wage changes of workers moving in the opposite direction. Given the life-cycle focus of our analysis, the event study distinguished movers at different phases of their careers. The results of this exercise are reported in Figure A3 in the Supporting Information, showing that, for each of the three career stages considered, wage changes are symmetric between upward and downward movers, suggesting that movers are not sorted based on match effects, lending support to our specification without match effects.

[12] Currarini et al. (2009) show that homophily in network formation interacts with opportunity access to produce social and economic segregation.

[13] Our focus on segregation in persistent individual effects aligns with the literature, where segregation is typically defined as the covariance of worker fixed effects among co-workers (e.g., Lopes de Melo 2018; Song et al. 2019). We abstract from segregation in transitory shocks, which are assumed to be orthogonal not only with persistent effects for a given individual but also across individuals. In our model, any residual correlation in transitory shocks across co-workers, if present, would likely be absorbed by the variance of firm-specific transitory shocks.

[14] The variance–covariance of firm effects is constant with respect to workers age but varies with the age of the firm. This latter dependence is identified by exploiting variation in average age of the firm across empirical earnings moments (both at the individual and co-worker levels).

[15] Alternatively, we may simply fix this covariance parameter to zero. This alternative strategy is akin to that followed by Baker and Solon (2003) who, faced with the non-separability of initial conditions for a mixed RW-RG process of life-cycle earnings, assumed that the initial condition of the RW was zero, such that 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 could in principle lead to underestimate sorting not only at age 25 but throughout the life cycle. Empirically, using the constraint we describe 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.

[16] To further illustrate that worker mobility is not needed to identify the model with our moment restrictions, in Table A2 in the Supporting Information, we report estimates of the earnings dynamics model based only on stayers' data, which would be unfeasible if worker mobility were needed for deriving the identifying restrictions.

[17] A discussion of Minimum Distance estimation of earnings dynamics models with unbalanced panels is provided by Haider (2001).

[18] See, among others, Baker and Solon 2003; Moffitt and Gottschalk 2012; Blundell et al. 2015; Hoffmann 2019.

[19] The estimates of the time loading factors are reported in Table A4 in the Supporting Information.

[20] The 25th percentile of firm age across empirical moments is 16.1, the median is 18.3, and the 75th percentile is 20.5.

[21] Lachowska et al. (2023) report intertemporal correlations of firm-specific effects of 0.74 on average.

[22] Lentz et al. (2023) distinguish between nonpecuniary and pecuniary components of sorting, the latter notion being analogous to the covariance of worker and firm effects in models of wage determination. They find that pecuniary sorting wanes over the life cycle.

[23] In Table A5 in the Supporting Information, we report estimates from a model where also the individual-specific component of transitory shocks is specified as WN, showing that overall results are very similar those discussed in the text.

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

[25] 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.

[26] Figure 3C shows that the variance of firm-specific transitory shocks is relatively small compared to other components. As noted in Footnote 13, any segregation in transitory shocks—if present—would be absorbed by this component in our model. Given its limited magnitude, the contribution of such transitory segregation is likely negligible, further justifying our modeling choice to focus on permanent components when modeling segregation.

[27] Parameter estimates for period loadings of the model without segregation are reported in Table A6 in the Supporting Information.

[28] Estimates of period-specific loading factors for the standard earnings dynamics model without firm effects are reported in Table A7 in the Supporting Information.

[29] The North includes men working in the following regions: Valle d'Aosta, Liguria, Lombardia, Piemonte, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, and Emilia-Romagna. The Center includes Toscana, Umbria, Marche, Lazio, and Abruzzo. The South includes Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, and Sardegna.

[30] For the Center subsample, we simplified the age-dependent AR(1) innovation variance specification to address convergence issues, reducing spline knots beyond age 40 from three to one.

References

Abowd, J., F. Kramarz, and D. Margolis. 1999. "High Wage Workers and High Wage Firms." *Econometrica* 57, no. 2: 411–445.

Altonji, J. G., and L. M. Segal. 1996. "Small-Sample Bias in GMM Estimation of Covariance Structures." *Journal of Business and Economic Statistics* 14, no. 3: 353–366.

Altonji, J. G., A. A. Smith Jr., and I. Vidangos. 2013. "Modeling Earnings Dynamics." *Econometrica* 81, no. 4: 1395–1454.

Andrews, M., L. Gill, T. Schank, and R. Upward. 2008. "High Wage Workers and Low Wage Firms: Negative Assortative Matching or Limited Mobility Bias?" *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 171, no. 3: 673–697.

Baker, M., and G. Solon. 2003. "Earnings Dynamics and Inequality Among Canadian Men, 1976-1992: Evidence From Longitudinal Income Tax Records." *Journal of Labor Economics* 21, no. 2: 267–288.

Barth, E., A. Bryson, J. C. Davis, and R. Freeman. 2016. "It's Where You Work: Increases in the Dispersion of Earnings Across Establishments and Individuals in the United States." *Journal of Labor Economics* 34, no. S2–2: S67–S97.

Blundell, R. 2014. "Income Dynamics and Life-Cycle Inequality: Mechanisms and Controversies." *Economic Journal* 124, no. 576: 289–318.

Blundell, R., M. Graber, and M. Mogstad. 2015. "Labor Income Dynamics and the Insurance From Taxes, Transfers, and the Family." *Journal of Public Economics* 127: 58–73.

Bonhomme, S., K. Holzheu, T. Lamadon, E. Manresa, M. Mogstad, and B. Setzler. 2023. "How Much Should We Trust Estimates of Firm Effects and Worker Sorting?" *Journal of Labor Economics* 41, no. 2: 291–322.

Borovickova, K. and R. Shimer. 2017. "High Wage Workers Work for High Wage Firms", NBER Working Paper 24074.

Card, D., A. R. Cardoso, J. Heining, and P. Kline. 2018. "Firms and Labor Market Inequality: Evidence and Some Theory." *Journal of Labor Economics* 36, no. S1: 13–70.

Card, D., A. R. Cardoso, and P. Kline. 2016. "Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women." *Quarterly Journal of Economics* 131, no. 2: 633–686.

Card, D., J. Heining, and P. Kline. 2013. "Workplace Heterogeneity and the Rise of West German Wage Inequality." *Quarterly Journal of Economics* 128, no. 3: 967–1015.

Carneiro, A. C., P. Portugal, P. Raposo, and P. Rodrigues. 2023. "The Persistence of Wages." *Journal of Econometrics* 233: 596–611.

Casarico, A., and S. Lattanzio. 2024. "What Firms Do: Gender Inequality in Linked Employer-Employee Data." *Journal of Labor Economics* 42, no. 2: 325–355.

Currarini, S., M. O. Jackson, and P. Pin. 2009. "An Economic Model of Friendship: Homophily, Minorities, and Segregation." *Econometrica* 77, no. 4: 1003–1045.

Erickson, C., and A. Ichino. 1995. "Wage Differentials in Italy: Market Forces, Institutions, and Inflation." In *Differences and Changes in Wage Structures*, edited by R. B. Freeman and L. F. Katz. University of Chicago Press.

Friedrich, B., L. Laun, C. Meghir, and L. Pistaferri. 2024. "Earnings Dynamics and Firm-Level Shocks." NBER Working Paper No. 25786, revised version.

Guvenen, F. 2007. "Learning Your Earning: Are Labor Income Shocks Really Very Persistent?" *American Economic Review* 97, no. 3: 687–712.

Haider, S. J. 2001. "Earnings Instability and Earnings Inequality of Males in the United States: 1967-1991." *Journal of Labor Economics* 19, no. 4: 799–836.

Hoffmann, E. B., D. Malacrino, and L. Pistaferri. 2022. "Labor Reforms and Earnings Dynamics: The Italian Case." *Quantitative Economics* 13, no. 4: 1637–1667.

Hoffmann, F. 2019. "HIP, RIP, and the Robustness of Empirical Earnings Processes." *Quantitative Economics* 10, no. 3: 1279–1315.

Huggett, M., G. Ventura, and A. Yaron. 2011. "Sources of Lifetime Inequality." *American Economic Review* 101, no. 3: 2923–2954.

Kline, P. 2024. "Firm Wage Effects." In *Handbook of Labor Economics*, edited by C. Dustmann and T. Lemieux, vol. 5, 115–181, North Holland.

Kline, P., R. Saggio, and M. Sølvsten. 2020. "Leave-Out Estimation of Variance Components." *Econometrica* 88, no. 5: 1859–1898.

Lachowska, M., A. Mas, R. D. Saggio, and S. A. Woodbury. 2023. "Do Firm Effects Drift? Evidence From Washington Administrative Data." *Journal of Econometrics* 233, no. 2: 375–395.

Lentz, R., S. Piyapromdee, and J.-M. Robin. 2023. "The Anatomy of Sorting—Evidence From Danish Data." *Econometrica* 91, no. 6: 2409–2455.

Lopes de Melo, R. 2018. "Firm Wage Differentials and Labor Market Sorting: Reconciling Theory and Evidence." *Journal of Political Economy* 126, no. 1: 313–346.

Low, H., C. Meghir, and L. Pistaferri. 2010. "Wage Risk and Employment Risk Over the Life Cycle." *American Economic Review* 100, no. 4: 1432–1467.

Magnac, T., N. Pistolesi, and S. Roux. 2018. "Human Capital Investments and the Life Cycle of Earnings." *Journal of Political Economy* 126, no. 3: 1219–1249.

Manacorda, M. 2004. "Can the Scala Mobile Explain the Fall and Rise of Earnings Inequality in Italy? A Semiparametric Analysis, 1997-1993." *Journal of Labor Economics* 22, no. 3: 585–613.

Meghir, C., and L. Pistaferri. 2004. "Income Variance Dynamics and Heterogeneity." *Econometrica* 72, no. 1: 1–32.

Meghir, C., and L. Pistaferri. 2011. "Earnings, Consumption, and Life-Cycle Choices." In *Handbook of Labor Economics*, edited by O. Ashenfelter and D. Card, vol. 4, 773–854. North Holland.

Moffitt, R., and P. Gottschalk. 2012. "Trends in the Transitory Variance of Male Earnings: Methods and Evidence." *Journal of Human Resources* 47, no. 1: 204–236.

Page, M., and G. Solon. 2003. "Correlations Between Brothers and Neighboring Boys in Their Adult Earnings: The Importance of Being Urban." *Journal of Labor Economics* 21, no. 4: 831–856.

Song, J., D. J. Price, F. Guvenen, N. Bloom, and T. von Wachter. 2019. "Firming Up Inequality." *Quarterly Journal of Economics* 134, no. 1: 1–50.

Woodcock, S. 2008. "Wage Differentials in the Presence of Unobserved Worker, Firm, and Match Heterogeneity." *Labour Economics* 15, no. 4: 771–793.

Woodcock, S. 2023. "The Determinants of Displaced Workers' Wages: Sorting, Matching, Selection, and the Hartz Reforms." *Journal of Econometrics* 233: 568–595.

Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Figure A1:** Empirical autocovariance function by cohort and age. **Figure A2:** Predictions and variance decompositions—model with match effect. **Figure A3:** Event study of wages for job changers over the life cycle. **Table A1.1:** Parameter estimates of permanent earnings components—model with match effect. **Table A1.2:** Parameter estimates of transitory earnings components—model with match effect. **Table A1.3:** Estimates of time shifters—model with match effect. **Table A2.1:** Parameter estimates of permanent earnings components—stayers data. **Table A2.2:** Parameter estimates of transitory earnings components—stayers data. **Table A2.3:** Estimates of time shifters—stayers data. **Table A3:** Parameters of the earnings model. **Table A4:** Estimates of time shifters—main model. **Table A5.1:** Parameter estimates of permanent earnings components—model with WN person-specific errors. **Table A5.2:** Parameter estimates of transitory earnings components—model with WN person-specific errors. **Table A5.3:** Estimates of time shifters—model with WN person-specific errors. **Table A6:** Estimates of time shifters—model without segregation. **Table A7:** Estimates of time shifters—standard earnings dynamics model without firm effects. **Table A8.1:** Estimates of time shifters by geographical area—North. **Table A8.2:** Estimates of time shifters by geographical area—Center. **Table A8.3:** Estimates of time shifters by geographical area—South.