Separations on the Job Ladder

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Abstract

Using matched employer-employee data from Italy, Germany, and Austria, we document a U-shaped relationship between within-job wage changes and separations: workers experiencing both wage cuts and wage gains are more likely to leave their employer. The pattern disappears once wage changes are standardized within tenure groups, pointing to a compositional job-ladder mechanism. To interpret this fact, we develop and estimate a random-search model with worker and firm heterogeneity, learning, persistent match productivity, and on-the-job renegotiation. History-dependent learning drives heterogeneity in wage-change volatility, while renegotiation capital stabilizes wages as workers move up the ladder. Learning frictions reduce aggregate output by 1.3%.

Keywords: Separations, Wage Dynamics, Learning, Job Ladder
JEL codes: E24, E25, J24, J31, J63, J64

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1 Introduction

Young workers experience both rapid wage changes and frequent job separations. While each of these features of early careers has been studied extensively, less is known about how they are related at the individual level. This paper studies the joint dynamics of on-the-job wage changes and job separations over the life cycle, and asks what this relationship reveals about labor market mobility and the sources of wage instability early in the career.

Using matched employer-employee data for Italy, Austria, and Germany, we document a previously undocumented U-shaped relationship between on-the-job wage changes and subsequent job separations. Workers experiencing both unusually low and unusually high wage growth are more likely to separate from their employer in the following period. The left tail is consistent with standard views of declining match quality, but the right tail marks a departure from the classic Topel and Ward (1992) pattern of a monotonic negative association between wage growth and separation. The pattern is strongest at the beginning of the career, precisely when wage volatility and job mobility are highest. The finding is robust across three institutional settings: Relative to the lowest separation hazard wage-growth decile, a 5 log-point wage cut is associated with 15-25% higher odds of separation, while a 5 log-point wage gain is associated with 6–14% higher odds. Within-tenure standardization of wage changes eliminates the convexity, implying that the U-shape is primarily compositional rather than behavioral: workers at low rungs of the job ladder face both wider wage changes and higher separation rates.

This finding changes how we interpret wage instability over the life cycle. Large wage changes do not simply reflect unusually good or unusually bad shocks within otherwise mature employment relationships. Instead, they identify workers and matches that are still in the learning-and-sorting phase of the job ladder. The documented U-shape therefore links two central dimensions of early-career instability, wage volatility and separation risk, and shows that they arise jointly from where workers are in the career and firm hierarchy. This provides a new window into the sources of labor market risk over the life cycle and helps distinguish between instability arising from learning and sorting, on the one hand, and instability arising within already mature employment relationships, on the other.

To explain this pattern, we develop and estimate a random search model with on-the-job search, worker learning, persistent match productivity, and sorting on the job ladder, building on Pinheiro and Visschers (2015) and Jarosch (2023). In the model, workers early in their careers face greater uncertainty about productivity and are more likely to move across firms. As workers accumulate information and sort toward better matches, both wage-change volatility and separation risk decline. In the estimated model, two features are quantitatively central for wage dynamics: persistent match productivity makes learning history-dependent, and outside offers create renegotiation capital that stabilizes wages in the face of shocks to current match productivity. Together, these forces reproduce the U-shaped relationship between wage changes and subsequent separations and link wage variability to workers' position on the job ladder.

The paper makes three main contributions. First, it documents a robust U-shaped relationship between within-job wage changes and subsequent separations in matched employer-employee data from three European countries. Second, it shows that the right tail of this relationship is primarily compositional and tied to career stage and firm heterogeneity, rather than reflecting a behavioral response of workers to large wage gains. Third, it provides a quantitative framework in which learning and job-ladder dynamics jointly account for the observed relationship between wage volatility and separations.

More broadly, the paper shows that the job ladder shapes not only the level of wages through sorting, but also the variability of wages over the career. In the model, wage predictability rises as workers climb the ladder because learning frictions fade and renegotiation capital accumulates. Quantitatively, these mechanisms matter for both aggregate efficiency and the trade-off between wage stability and output.

The quantitative analysis delivers three results. First, a variance decomposition reveals that both wage renegotiation and learning are quantitatively important but operate differently. History-dependent learning—cross-worker differences in belief precision shaped by past job sequences—is the dominant source of heterogeneity in within-job wage-change volatility across workers at a given experience level. Negotiation capital, in turn, acts as a stabilizing force: absent the accumulated contract benchmark, the standard deviation of wage changes for job-to-job movers would rise. Workers at high-quality firms benefit from both channels simultaneously, which is why wage predictability increases as workers climb the job ladder. Second, learning frictions reduce aggregate output by 1.3% relative to a full-information benchmark, with the productivity gap concentrated at intermediate experience where mobility decisions are most consequential. Third, counterfactual policies reveal non-trivial trade-offs: apprenticeship-style certification that reduces initial uncertainty stabilizes early-career wages but *lowers* output, because better-informed workers become more selective at labor-market entry and forgo the option value of experimentation in marginal matches.

This paper relates to three strands of literature. First, the paper relates to the empirical literature on wage growth, job mobility, and separations over the life cycle. A classic benchmark is Topel and Ward (1992), who show that wage growth and job mobility are tightly linked early in workers' careers. A related literature studies whether wage growth at the current job predicts subsequent separation once wage levels are taken into account, generally finding either a negative relationship or limited predictive power.[1] Relative to this literature, we document a non-monotonic relationship: workers experiencing both unusually low and unusually high within-job wage growth are more likely to separate from their employer in the following period.

Second, the paper relates to models of learning and career dynamics. In classic mismatch models, such as Jovanovic (1979), wage changes reflect updated information about match quality. Related models with dynamic match productivity, such as Prat (2006) and Liu (2019), likewise link wage dynamics to changing assessments of the match, but do not naturally imply that within-job wage changes should predict future separation once wage levels are taken into account. A related literature studies learning about worker ability and comparative advantage across jobs or occupations. In this tradition, Gibbons and Waldman (1999) emphasize learning about worker ability over the career, and Lange (2007) provides the first estimate of the speed of employer learning, finding that initial expectation errors decline by half within three years. Groes et al. (2015) document a U-shaped pattern of occupational mobility, with workers at both extremes of the wage distribution within an occupation more likely to switch occupations. More recently, Pastorino (2015) and Pastorino (2024) show that uncertainty and learning can shape wage growth and mobility both directly and indirectly through sorting over the career. Relative to this literature, our paper focuses on a different empirical object—the relationship between within-job wage changes and subsequent employer separation—and asks whether the resulting U-shape can be explained by the interaction of learning and job-ladder dynamics.[2]

Third, the paper relates to the literature on job ladders, firm sorting, and heterogeneous career dynamics. A central insight of this literature is that workers climb ladders defined by wages, productivity, and job security, and that earnings dynamics depend on both where workers move and the types of firms they are matched with. In this spirit, Jarosch (2023) emphasizes that workers climb an earnings ladder along multiple dimensions, while Bertheau and Vejlin (2025) study progression up firm wage and productivity ladders and Borovičková and Macaluso (2025) analyze heterogeneous life-cycle wage growth and transition patterns

[1] For related empirical work, see, among others, Bingley and Westergaard Nielsen (2006), Galizzi and Lang (1998), McLaughlin (1991), Kim (1999), Kahn and Griesinger (1989), Bartel and Borjas (1981), van der Klaauw and Dias da Silva (2011), and Solnick (1988).

[2] For related contributions on occupational mobility, learning, and career dynamics, see also Neal (1999), Perticara (2004), Gielen and van Ours (2006), Papageorgiou (2013), and Pfeifer and Schneck (2012).

across workers. Relatedly, Pinheiro and Visschers (2015) highlight how firm-specific unemployment risk shapes wage differentials. Our contribution to this literature is to show that the volatility of within-job wage changes itself contains information about subsequent mobility, especially early in the career, and to provide a quantitative framework in which learning, renegotiation capital, and firm heterogeneity jointly generate this pattern.

The remainder of the paper proceeds as follows. Section 2 describes the data. Section 3 presents the empirical design and Section 4 presents the empirical evidence. Section 5 develops the theoretical model. Section 6 describes the structural estimation procedure and parameter identification. Section 7 applies the parameter estimates to understanding the sources and implications of wage variability on the job ladder. Section 8 concludes.

2 Data and Sample Construction

This section describes the administrative linked employer-employee data used in the empirical analysis and the construction of the harmonized worker-year panel. We combine three datasets from Italy, Germany, and Austria. The three data sources differ in institutional setting, sampling design, period coverage, and wage measurement, so a common empirical pattern across them is informative about the generality of the result. Appendix A.1 provides additional details.

2.1 Administrative Data Sources

We use three administrative linked employer-employee datasets: the Italian Veneto Worker History (VWH), the German Linked Employer-Employee Data from the IAB (LIAB), and the Austrian Social Security Database (AMDB). All three datasets are derived from social security records and share a common linked worker-employer structure, but they differ in coverage and design.

The Italian VWH covers employers mainly in the provinces of Treviso and Vicenza in North-East Italy, while the Austrian AMDB covers all of Austria. By contrast, the German LIAB is based on establishments surveyed in the IAB Establishment Panel and the workers employed in those establishments. Period coverage also differs: the VWH spans 1975–2001, the LIAB 1993–2010, and the AMDB 2000–2016.[3]

The LIAB contains the richest set of worker and employer observables, including education,

[3]The employer identifiers are not fully identical across datasets: the LIAB is establishment-based, the VWH is firm-based, and the AMDB uses an administrative employer unit.

occupation, and detailed employer characteristics, although full coworker coverage is available only for 1999–2009. The Austrian AMDB provides comprehensive coworker coverage but more limited worker-level observables. The Italian VWH lies between the two in terms of information content and has the longest time span. Wage reporting also differs across datasets: wages are subject to a reporting ceiling in Germany and Austria, but not in Italy.

2.2 Construction of the Harmonized Worker-Year Panel

We harmonize the three datasets using a common worker-year panel construction similar to Card et al. (2013) and Kline et al. (2020). For each worker and calendar year, we identify the highest-paying employment spell and define it as the worker's *main spell* (or "dominant job" in the terminology of Kline et al. 2020). All wages and transitions used in the analysis are defined relative to these main spells.

We then apply a common set of transformations and data-cleaning steps across countries. To make wages comparable across datasets, we express earnings in each main spell as real daily wages and work with their logarithm.[4] We then implement the data cleaning procedure following Kline et al. (2020). We restrict attention to workers aged 19–63, drop workers with daily wages below 5 real euros, and remove observations with absolute log wage changes greater than one. We also exclude workers with missing sex information, workers ever employed in the public sector, and workers holding ten or more jobs in a given year.[5] A detailed attrition table is provided in Appendix Table A.1.

The harmonized panel allows us to define the key variables consistently across countries. Labor-market experience is measured as the number of years in which a worker is observed in a main spell. Tenure is measured as the number of consecutive years at the same employer; the tenure clock resets after a non-employment spell longer than one month, even if the worker later returns to the same employer.[6] Separations are defined as transitions out of the current employer, either to non-employment or to a new employer. Wage growth is measured as $\Delta W_t \equiv W_t - W_{t-1}$, where W_t denotes log daily wages in the worker's main spell. We also compute employer size from the worker-employer data.

[4]For the VWH and AMDB, daily wages are obtained by dividing spell earnings by days worked in the spell. The LIAB directly reports daily wages.

[5]Relative to Kline et al. (2020), we use a less restrictive treatment of missing wage observations. Rather than removing workers entirely when wages are missing in a given year, we exclude only the affected worker-year observation, since wage changes are undefined for that transition. This approach preserves the surrounding employment history and avoids introducing additional sample selection through intermittent non-employment or imperfectly measured unemployment spells.

[6]We additionally construct a continuous-employment measure that resets after any non-employment spell of more than one month. This variable is used in the standardization exercise in Section 4.3.

Some country-specific observables are available only in subsets of the data. In Germany, the LIAB records employment type, education, occupation, and detailed employer characteristics, including industry and employer size, and also provides administrative tenure and experience measures. In Italy, we observe sector and worker qualification. In Austria, we observe sector but no worker-level characteristics beyond age and sex.

The harmonized worker-year panel serves as the starting point for both the reduced-form analysis and the structural estimation. Section 4 uses a restricted empirical analysis sample based on the additional sample restrictions described in Section 2.3. By contrast, Section 6.1 returns to the broader Italian worker-year panel to construct the estimation moments.

2.3 Empirical Analysis Sample Restrictions

Our analysis imposes five additional sample restrictions in the empirical analysis sample. The first three are designed to ensure that wage changes reflect changes in wage rates rather than hours worked, to maintain a focus on common contract types, and to allow us to observe workers from the beginning of their careers. The latter two remove separations and wage movements that are unlikely to reflect worker-employer match dynamics.

First, because hours worked are not observed in the Italian and Austrian data, an earnings change may reflect either a change in the wage rate or a change in hours. To reduce this concern, we restrict the analysis to men, for whom full-time employment is substantially more prevalent.[7] This concern is especially relevant early in the career, when labor-force attachment is more variable. In the LIAB, where part-time status is observed, we directly assess the importance of this issue in Section 4.2 by excluding part-time spells.

Second, we restrict attention to workers who enter the data before age 30. This allows us to measure tenure and experience from the beginning of the career and focuses the analysis on the phase of the life cycle in which mobility and wage growth are most pronounced.[8]

Third, we exclude apprentices, whose contracts follow distinct training and wage-setting rules. Their earnings dynamics are therefore not directly comparable to those of regular employment relationships.

Fourth, we exclude separations associated with employer disappearance or mass layoffs, since these events are more likely to reflect employer-level shocks than worker-employer match

[7] In 2010, 28.7% of employed women in the EU worked part-time, compared with 6.5% of employed men. The corresponding country-specific figures were 45.9% and 8.5% in Germany, 28.5% and 5.2% in Italy, and 45.2% and 8.5% in Austria (Eurostat, 2026).

[8] Reassuringly, in the LIAB, our constructed experience and tenure measures are highly correlated with the corresponding administrative measures, with correlations of 0.80 and 0.84, respectively.

dynamics. Following Schmieder et al. (2012), we define a mass layoff as an event in which an employer with more than 50 employees separates from more than 30% of its prior-year workforce.

Fifth, to avoid contamination of wages by severance payments and other non-standard components around the separation year, we measure wage growth using the lagged change $\Delta W_{t-1} \equiv W_{t-1} - W_{t-2}$ when relating wage changes to separations in period t. This timing convention follows Liu (2019) and is discussed further in Section 3. We additionally trim the extreme 4 percent of the wage-change distribution, retaining the central 96 percent of observations.

2.4 Summary Statistics for the Empirical Analysis Samples

Tables A.2 and A.3 report summary statistics for the baseline empirical analysis samples. The three country samples are broadly comparable along the dimensions most relevant for the analysis. Median worker age ranges from 31 in Italy to 33 in Germany. Median tenure is 6 years in all three countries, while median labor-market experience is 9 years. Average annual wage growth is highest in Italy (2.94%) and lowest in Germany (1.95%). Average separation rates are 7.43% in Italy, 8.05% in Germany, and 8.97% in Austria. These levels are broadly consistent with the existing literature.[9]

3 Empirical Strategy

These descriptive patterns motivate the empirical analysis that follows. We relate on-the-job wage changes to subsequent job separation. The object of interest is the probability that worker i separates from employer j in year t as a function of the wage change $\Delta W_{i,j,t-1}$ observed in the previous year. We focus on lagged wage growth throughout. Wages measured in the separation year may reflect severance payments and other nonstandard earnings com-

[9] Using the EU Labour Force Survey for 2014, Symeonaki et al. (2018) report separation rates of 11.85% for Italy and 12.5% for Austria among workers aged 15–24; the somewhat lower rates in our sample are consistent with its higher average age. For Italy, the mean wage growth of 2.94% is close to the 2% annual growth documented for 1981–1982 in Galizzi and Lang (1998). For Germany, Lluis (2005) reports an average on-the-job wage growth rate of 1.92% for men with 0–10 years of tenure in the GSOEP for 1985–1996, closely matching our estimate of 1.95% over a more recent period. Anger (2011) similarly finds average wage growth of 2–2.4% in Germany for 1984–2005 among workers aged 20–60. The average employer size in Germany is substantially larger than in Italy and Austria, reflecting the oversampling of large employers, cf. Fischer et al. (2014). Employer sizes in Italy and Austria are very similar. Because of its geographic focus on a highly industrialized region, the Italian dataset has the highest share of manufacturing observations at approximately 56%, followed by Germany at 54% and Austria at 39%. For comparison, Grinza (2021), using a similar vintage of the VWH, reports 65% of her sample in manufacturing.

ponents mechanically linked to the separation outcome. Using lagged wage growth therefore reduces this source of contamination and ensures that the wage change is measured at least one year before the potential separation. We return to this timing issue in the robustness analysis in Section 4.2.

We document the U-shaped relationship using three complementary specifications. First, we present non-parametric binned estimates that impose minimal structure. Second, we estimate a logit with wage-change-bin indicators, which expresses the pattern in odds-ratio terms relative to the lowest-risk bin. Third, we estimate a quadratic linear probability model (LPM), which summarizes the relationship with a linear term and a curvature term and allows the inclusion of controls.

Non-parametric estimates. We begin by estimating average separation rates within decile bins of the wage-change distribution, without imposing a functional form or adding covariates. Let $k = 1, \ldots, 10$ index decile bins of $\Delta W_{i,j,t-1}$. For each bin k, we compute

$$\widehat{p}_k = \frac{1}{N_k} \sum_{i,j,t} \mathbf{1}\{\Delta W_{i,j,t-1} \in k\} \, \text{Separation}_{i,j,t}, \tag{1}$$

where $N_k = \sum_{i,j,t} \mathbf{1}\{\Delta W_{i,j,t-1} \in k\}$. These estimates trace out the conditional separation probability across the wage-change distribution with minimal structure.

Logit odds ratios. Next, we estimate a logit model with indicators for wage-change bins. Let b denote the bin with the lowest average separation rate in the sample, which serves as the omitted category. The specification is

$$\Pr(\text{Separation}_{i,j,t} = 1 \mid \Delta W_{i,j,t-1}) = \Lambda\left(\alpha + \sum_{k \neq b} \mathbf{1}\{\Delta W_{i,j,t-1} \in k\} \, \beta_k\right), \tag{2}$$

where $\Lambda(\cdot)$ denotes the logistic cdf. For each bin $k \neq b$, e^{β_k} is the odds ratio of separation relative to the reference bin b. We do not include additional covariates in the baseline logit. In nonlinear probability models, adding regressors changes the scale of the latent index, so coefficients are not directly comparable across specifications (Allison, 1999). In the robustness analysis, we instead estimate analogous logits using deciles of residualized wage growth, after partialling out sector, occupation (where available), year, tenure, and experience.

Linear probability model. Finally, we estimate a quadratic linear probability model,

$$\text{Separation}_{i,j,t} = \alpha + \beta_0\, \Delta W_{i,j,t-1} + \beta_1\, (\Delta W_{i,j,t-1})^2 + \mathbf{X}'_{i,j,t-1}\boldsymbol{\beta}_x + \eta_{i,j,t}, \tag{3}$$

where $\mathbf{X}_{i,j,t-1}$ includes lagged log wages, lagged experience, lagged tenure, lagged employer size, and lagged employer-size growth. The coefficient β_1 captures the curvature of the relationship between wage growth and separation. A positive β_1 indicates a U-shaped pattern. We use the LPM because it provides a parsimonious summary of the relationship and allows coefficients to be compared across specifications with different control sets. Since equation (3) imposes a symmetric quadratic form, β_1 should be interpreted as summarizing the average curvature across positive and negative wage changes.

4 Empirical Results

We document a robust U-shaped relationship between on-the-job wage changes and subsequent separation in Italy, Germany, and Austria. Section 4.1 establishes the pattern. Section 4.2 examines its robustness. Section 4.3 uses within-group standardization to assess whether the U-shape reflects compositional differences across tenure levels or within-worker responses to wage changes. Section 4.4 summarizes the evidence.

4.1 A U-shaped Relationship Between Wage Changes and Separations

Figure 1 presents the main result using the non-parametric and logit specifications from Section 3. The left axis plots average separation rates by wage-change decile. The right axis plots the odds ratio of separation in each bin relative to the wage-change bin with the lowest separation rate.

A clear U-shaped relationship appears in all three countries. Separation rates rise in both tails of the wage-change distribution, with the lowest hazard concentrated around moderate positive wage growth. Relative to the lowest-hazard bin, a 10 log-point wage fall is associated with 20% higher odds of separation in Italy, 26% in Germany, and 38% in Austria. A 10 log-point wage gain is associated with 10% higher odds in Italy, 21% in Germany, and 10% in Austria. Appendix Table A.5 reports the logit estimates. The right tail is the main departure from Topel and Ward (1992), who document a monotone negative relationship between wage growth and separation in U.S. data.

Table 1 reports the quadratic linear probability model. Columns (1), (3), and (5) include lagged wage levels only, while columns (2), (4), and (6) report an augmented specification that additionally controls for lagged experience, lagged tenure, and employer-level size controls.[10] Across both specifications, the estimated relationship remains U-shaped in all three countries: the coefficient on ΔW_{t-1} is negative and the coefficient on $(\Delta W_{t-1})^2$ is positive throughout.

The augmented specification is useful because it absorbs systematic differences in worker career stage and employer scale that may be correlated with both wage growth and subsequent separations. The qualitative pattern is present in the parsimonious specification and remains stable once these additional controls are included. The main result is therefore not driven by differences in tenure, experience, or employer size.

Appendix Table A.6 compares the quadratic specification with a purely linear specification of the kind emphasized by Topel and Ward (1992). In the linear specification, a 20 log-point wage gain lowers predicted separation by 0.3 percentage points in Italy, 0.6 percentage points in Germany, and 1.6 percentage points in Austria. In the quadratic specification, the same wage gain raises predicted separation by 2.8 percentage points in Italy, 3.3 percentage points in Germany, and 1.3 percentage points in Austria.

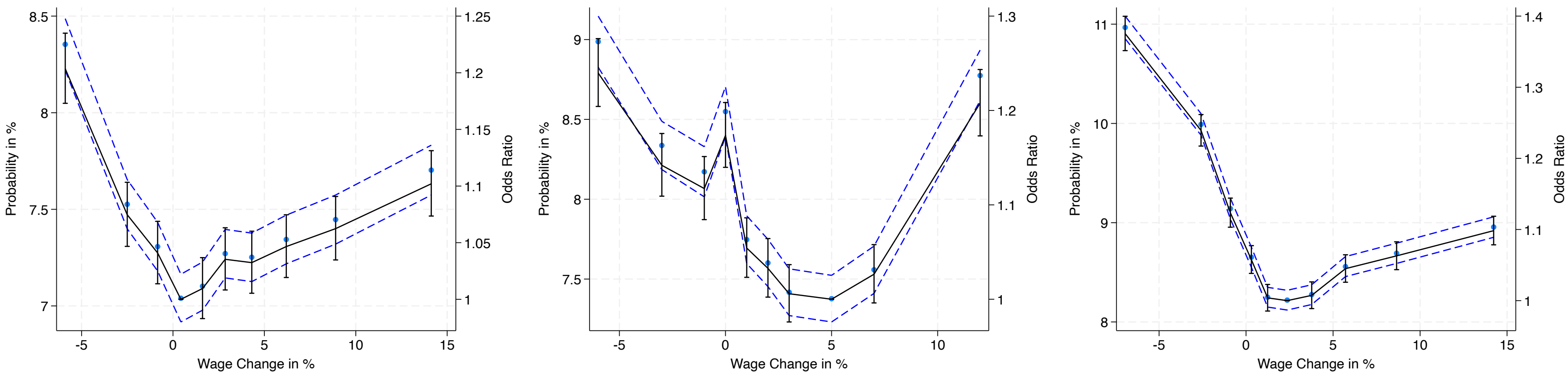
These magnitudes are economically meaningful. As a benchmark, Appendix Table A.4 shows that the decline in separation rates between ages 25 and 35 is 5.0 percentage points in Italy, 2.1 percentage points in Germany, and 5.4 percentage points in Austria. The gain-side effect implied by the quadratic specification therefore exceeds the full 10-year age gradient in Germany and amounts to more than half of it in Italy. The implied minimum of the quadratic occurs at $-\hat{\beta}_0/(2\hat{\beta}_1)$ and lies at approximately 4–5 log points of wage growth across countries. Lagged wage levels and tenure enter with the expected signs.

The LPM and logit estimates are consistent in sign and broadly similar in magnitude.[11] The LPM yields somewhat flatter tails, as expected from its constant marginal effects, but both specifications imply the same qualitative pattern.

[10] Our baseline analysis uses the full Italian VWH, in line with the related literature (Kline et al., 2020). This is the natural benchmark because it preserves comparability with existing work and maximizes sample size. At the same time, the VWH represents the universe of employment relationships only for employers located in Treviso and Vicenza, which is relevant for our construction of employer size. We therefore re-estimate the specification on the subset of employers in the fully covered provinces. As shown in Table A.12 (columns (7)–(10)), the U-shaped relationship remains clearly visible and is, if anything, somewhat stronger in the restricted sample, despite a reduction of the Italian sample to about 40% of its baseline size.

[11] Evaluating the LPM at ± 10 log-point wage changes relative to zero growth yields: Italy, +0.45 pp (gain) and +1.47 pp (cut); Germany, +0.37 pp (gain) and +2.21 pp (cut); Austria, −0.28 pp (gain) and +2.12 pp (cut). The small negative estimate for Austria on the gain side reflects that the LPM minimum lies slightly to the right of zero. The LPM minimum is a different object from the logit reference bin, which is the observed lowest-hazard bin. Relative to baseline separation rates of 7.43% in Italy, 8.05% in Germany, and 8.97% in Austria, the positive LPM effects correspond to changes of roughly 5–29%.

Figure 1: Wage Changes and Subsequent Separations



(a) Italy (b) Germany (c) Austria

Notes: The figure plots separation in year t against wage growth in year $t-1$ by country. The solid line and markers show non-parametric within-bin separation rates (left axis). The dashed line shows the odds ratio of separation relative to the lowest-hazard wage-change bin from the logit specification (right axis). Wage changes are measured in log points. Error bars are based on the within-bin linear predictor of separation. Each marker corresponds to one wage-change decile bin and represents approximately 120,000 observations in Germany, 160,000 in Italy, and 290,000 in Austria.

Table 1: Wage Changes and Subsequent Separations: Linear Probability Model

	Italy		**Germany**		**Austria**	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔW_{t-1}	-0.051***	-0.086***	-0.092***	-0.150***	-0.120***	-0.150***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)
ΔW^2_{t-1}	0.960***	0.840***	1.290***	1.080***	0.920***	0.580***
	(0.040)	(0.040)	(0.063)	(0.063)	(0.028)	(0.028)
W_{t-1}	-0.061***	-0.029***	-0.027***	0.003**	-0.056***	-0.039***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience$_{t-1}$		0.0004***		0.0002*		0.0029***
		(0.0001)		(0.0001)		(0.0001)
Tenure$_{t-1}$		-0.0056***		-0.0073***		-0.0095***
		(0.0001)		(0.0001)		(0.0001)
Obs.	1,645,579	1,645,579	1,229,924	1,229,924	2,928,498	2,928,498

Notes: The table reports coefficients from linear probability models of separation in year t on lagged wage changes and lagged log wages. The estimating equation is Equation (3). Columns (2), (4), and (6) additionally control for lagged experience, lagged tenure, lagged employer size, and lagged employer-size growth. In Germany, employer size corresponds to observed establishment size. In Italy and Austria, it is constructed as the number of workers attached to the employer identifier in a given year. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The fact that the same pattern emerges in all three datasets is notable given their differences in coverage, sampling design, and employer identifiers. The Italian results are particularly informative because the VWH records wages without a reporting ceiling, unlike the LIAB and AMDB. The presence of a similarly pronounced U-shape in Italy therefore indicates that wage censoring is unlikely to be the main source of the pattern. More broadly, the cross-country replication makes it unlikely that the results are an artefact of any one data construction.

4.2 Robustness and Sensitivity

We assess the robustness of the U-shaped relationship in five ways. First, we verify in the German data that part-time work is not driving the result. Second, we residualize wage growth with respect to observable characteristics. Third, we distinguish different types of separations. Fourth, we control for workers' relative wage position within occupation. Fifth, we examine whether the pattern is consistent with a simple search-intensity interpretation. We then report two additional sensitivity checks concerning the timing convention and the East–West split in Germany.

Part-time work. Excluding part-time spells in the German data leaves the results unchanged and makes the U-shape slightly more pronounced. Appendix Table A.12 (columns (1) and (2)) reports the re-estimated linear probability model, in which the coefficient on squared wage growth rises from 1.29 in the baseline to 1.35. These results indicate that part-time is not an important driver of the German estimates.

Residualized wage changes. Residualizing wage growth with respect to observable characteristics leaves the U-shape intact. Specifically, we regress wage growth on year fixed effects, lagged tenure, lagged experience, lagged age, and industry dummies. For Germany, we additionally control for three-digit occupation. Whereas including controls in the LPM removes additive correlation between observables and the separation probability, residualizing wage growth removes the component of wage growth that is linearly predictable from observables before re-estimating the wage-growth–separation relationship. Appendix Figure A.1 and Appendix Table A.5 (columns (3), (6) and (9)) show that the U-shape remains and becomes slightly more pronounced after residualization.

Types of transitions. The U-shape appears separately for employment-to-employment and employment-to-unemployment transitions (Table A.7), as well as for an approximation of layoffs and quits in the German data (Table A.8). One concern is that the aggregate U-shape reflects the overlay of two distinct monotone relationships: falling match productivity could simultaneously generate wage cuts and layoffs, while rising productivity could lead to voluntary quits.

To examine this possibility, we first decompose separations into employment-to-employment (E2E) transitions, defined as job changes followed by a nonemployment spell of less than one month, and employment-to-unemployment (E2U) transitions, which involve longer interruptions. Although this threshold does not perfectly separate quits from layoffs, it provides a consistent definition across all three datasets and distinguishes transitions with different implications for job-ladder position. Appendix Table A.7 estimates the LPM separately for each transition type and shows that the U-shape remains statistically significant for both E2E and E2U separations. The presence of the U-shape on both margins makes the mechanical-overlay interpretation less compelling.

We next ask whether the pattern remains when separations are restricted to likely layoffs. In Germany, unemployment benefits are suspended for the first 12 weeks following a voluntary quit but are paid immediately after an involuntary separation.[12] Appendix Table A.8

[12]Eligibility requires contributing to unemployment insurance for at least 12 of the 30 months preceding

therefore decomposes separations into those followed by benefit receipt within one month and within three months of the separation date. The U-shaped pattern remains under both layoff definitions, which suggests that it is not driven solely by voluntary quits.

Relative occupational wage position. Controlling for workers' relative wage position within occupation leaves the quadratic wage-growth coefficient essentially unchanged (Appendix Table A.9). This matters because Groes et al. (2015) and Perticara (2004) document a U-shaped relationship between relative occupational wage position and occupational switching. Our result could therefore reflect occupational sorting rather than wage changes per se. To address this possibility, we control for relative occupational wage position, defined as $W_{t-1} - \mu_o(W_{t-1})$, where μ_o is the mean log wage in occupation o. For Germany we use three-digit occupations; for Italy, sector-by-qualification groups; for Austria, where occupation is unobserved, sector. Appendix Table A.10 confirms that the occupational-wage-position U-shape is present in Germany and Italy. Appendix Table A.9 shows that controlling for it does not affect the wage-change U-shape.

Search-intensity channel. Among movers, the probability of a wage gain upon transition declines in both tails of the prior wage-change distribution (Appendix Table A.11). This is not what one would expect if endogenous search intensity were the main source of the U-shape. In models with endogenous on-the-job search, as in Topa et al. (2016), workers at low rungs of the job ladder may face both greater wage variability, because match quality and worker ability are still being learned, and higher offer arrival rates, because active search generates outside offers. If this mechanism were driving the right tail, workers experiencing large wage changes should be disproportionately likely to move to higher-paying jobs. Instead, the share of upward-paying transitions is lowest in the tails. This evidence is difficult to reconcile with the simplest endogenous-search interpretation, although it does not rule out richer models in which search effort rises without systematically improving match quality.

Sensitivity. Two additional results speak to the stability of the finding. First, replacing lagged wage growth with contemporaneous wage growth, $\Delta W_t = W_t - W_{t-1}$, produces a more pronounced U-shape in both tails (Appendix Table A.5 columns (2), (5) and (8)). We do not treat this specification as preferred, since contemporaneous wage growth is potentially more exposed to anticipatory wage adjustments. Second, the U-shape holds separately in East and West Germany, with somewhat larger magnitudes in the East (Appendix Table A.12,

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the claim. By construction, all workers in our sample satisfy this condition, so benefit receipt within the first 12 weeks is informative about involuntary separations.

columns (3)–(6)).[13] The West German estimates are quantitatively similar to those for Italy and Austria.

4.3 The Compositional Channel

The evidence so far leaves two broad interpretations of the U-shaped relationship. Under a behavioral interpretation, large wage changes and especially large wage gains raise workers' separation propensity. Under a compositional interpretation, both tails of the wage-change distribution contain disproportionate numbers of low-tenure workers, who face both higher baseline mobility and more volatile wage growth. The robustness exercises in Section 4.2 show that the pattern is not driven by part-time work, observable characteristics, occupational wage position, or a simple endogenous-search mechanism. We now assess directly whether the U-shape primarily reflects compositional differences across experience and tenure levels.

If the pattern is compositional, standardizing wage changes within tenure groups should eliminate the convexity in separation probabilities. Workers early in their careers face both greater wage volatility and higher baseline separation rates, so pooling workers across tenure levels can generate a U-shape in raw wage changes even if separation is not itself U-shaped within tenure groups. We test this implication by standardizing wage changes within progressively narrower groups. If the pattern reflects compositional differences across workers facing different wage volatility, it should disappear once workers are compared within groups with similar volatility. If instead it reflects within-group behavioral responses to wage changes, it should persist.

We replace ΔW_{t-1} with the standardized wage change $\Delta\tilde{W}_{t-1}$, obtained by subtracting the relevant group mean and dividing by the relevant group standard deviation, and estimate

$$\text{Separation}_{i,j,t} = \alpha + \beta_1 \left(\Delta\tilde{W}_{i,j,t-1}\right)^2 + \varepsilon_{i,j,t}, \tag{4}$$

where standardization is carried out over the full sample (column 1) and then within bins of age, experience, continuous employment, and tenure (columns 2–5). By construction, within-group standardization removes the group mean, so the linear term in $\Delta\tilde{W}_{t-1}$ is omitted from Equation (4). For Germany, we report results using both administratively measured experience and tenure and their sample-constructed counterparts.

Table 2 reports the results. When wage changes are standardized globally, the coefficient

[13] The IAB Establishment Panel includes East Germany only from 1996 onward; the 1993–1995 observations cover West Germany only (Fischer et al., 2014). The East–West comparison therefore pertains to 1996–2010.

Table 2: Standardized Wage Changes and Subsequent Separations: Linear Probability Model

	Overall (1)	**Age** (2)	**Experience** (3)	**Exp–Ten** (4)	**Tenure** (5)
Panel A: Italy					
$\Delta\hat{W}^2_{t-1}$	0.0017***	0.0014***	0.0014***	0.0012***	0.00023
	(0.00013)	(0.00016)	(0.00025)	(0.00023)	(0.00013)
Obs.	1,645,579	1,645,579	1,645,579	1,645,579	1,645,579
Panel B: Germany					
Panel B.1: Sample constructed variables					
$\Delta\hat{W}^2_{t-1}$	0.0031***	0.0023***	0.0025***	0.0021***	0.00058**
	(0.00017)	(0.00025)	(0.00039)	(0.00047)	(0.00016)
Panel B.2: IAB variables					
$\Delta\hat{W}^2_{t-1}$	0.0031***	0.0023***	0.0019***	0.0014***	0.00025
	(0.00017)	(0.00025)	(0.00034)	(0.00034)	(0.00047)
Obs.	1,229,924	1,229,924	1,229,924	1,229,924	1,229,924
Panel C: Austria					
$\Delta\hat{W}^2_{t-1}$	0.0026***	0.0016***	0.0022***	0.0017***	0.0015
	(0.00010)	(0.00018)	(0.00018)	(0.00037)	(0.0010)
Obs.	2,928,498	2,928,498	2,928,498	2,928,498	2,928,498

Notes: The table reports coefficients from regressions of separation in year t on squared standardized wage changes in year $t-1$ (Equation (4)). Wage changes are standardized over the full sample (column 1) and within years of age, experience, continuous employment (Exp–Ten), and tenure (columns 2–5). For Germany, panel B.2 reports results using administrative experience and tenure measures. Standard errors are clustered at the unit of standardization and reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

on $(\Delta\tilde{W}_{t-1})^2$ is positive and statistically significant in all three countries. In Germany, the estimate of 0.0031 implies that a one-standard-deviation wage change raises the separation probability by about 0.32 percentage points, and a two-standard-deviation change raises it by roughly 1.3 percentage points. Given a baseline separation rate of 8.05%, these correspond to relative increases of approximately 4% and 16%. Italy and Austria show comparable, though somewhat smaller, magnitudes.

As the standardization becomes finer, first within age, then experience, then continuous employment, the coefficient declines steadily. Once wage changes are standardized within tenure bins, it becomes statistically indistinguishable from zero. For Germany, Table 2, panel B.2, shows that the coefficient based on administratively measured tenure is economically negligible and statistically insignificant. By contrast, the sample-constructed tenure measure in panel B.1 yields a marginally significant coefficient, which is consistent with measurement error in the constructed variable relative to the administrative measure. For Italy and Austria, the coefficient likewise becomes statistically indistinguishable from zero once standardization is carried out within tenure bins.

Taken together, the standardization evidence points to a predominantly compositional explanation of the U-shaped relationship, with most of the observed convexity arising from differences across tenure groups. In particular, the elevated right tail appears to reflect the concentration of low-tenure workers in that part of the wage-change distribution, rather than a direct effect of large wage gains on subsequent separation.

4.4 Summary

The empirical results establish three facts that guide the theory. First, within-job wage changes and subsequent separations are linked by a robust U-shaped relationship. Second, the right tail of this relationship is not explained by part-time work, observable characteristics, occupational wage position, or a simple endogenous-search mechanism. Third, the convexity largely disappears once wage changes are standardized within tenure groups, indicating that the pattern is primarily compositional. These findings suggest that the model must generate a joint decline in wage-change volatility and separation risk as workers move up the job ladder. The next section develops a framework in which learning, sorting, persistent match productivity, and renegotiation jointly produce this pattern.

5 Theoretical Framework

We develop a random search model with on-the-job search and heterogeneity across firms and workers to explain the U-shaped relationship between wage changes and separation rates documented in Section 4. The key mechanism is symmetric learning about individual productivity. Early in a career, uncertainty is high, producing large wage revisions and frequent separations. With experience, beliefs tighten, wage adjustments shrink, and endogenous mobility falls. Job-ladder climbing further dampens separations. We first present a baseline model that reproduces the pattern (Section 5.1), then extend it to match additional empirical moments and allow for more realistic features (Section 5.2).

5.1 Model Environment

Time is discrete. A continuum of risk-neutral firms and workers discount the future at $\tilde{\beta} \in (0,1)$.[14] Workers, indexed by i, have fixed unobserved productivity $a_i \sim V(a)$; firms, indexed by j, have productivity $\mu_j \sim F(\mu)$. Log output of worker i at firm j and time t is

$$y_{i,j,t} = \mu_j + a_i + m_{i,j,t},$$

where $m_{i,j,t} = \eta_{i,j,t}$ with $\eta_{i,j,t}$ i.i.d. $N(0, \sigma_\eta^2)$. Workers and firms update beliefs about a_i after observing output. At labor market entry, beliefs are normal with mean $A_0 = E[a_i]$ and variance σ_{A0}^2. Posterior beliefs with mean $A_{i,t}$ and variance $\sigma_{a,i,t}^2$ evolve by Bayes' rule:

$$\sigma_{a,i,t}^2 \;= \tfrac{\sigma_{a,i,t-1}^2}{1+s_{i,t-1}}, \qquad A_{i,t} = A_{i,t-1} + \tfrac{s_{i,t-1}}{1+s_{i,t-1}} \xi_{i,j,t}$$

where $s_{i,t-1} = \sigma_{a,i,t-1}^2 / \sigma_\eta^2$ is the signal-to-noise ratio, and $\xi_{i,j,t} = y_{i,j,t} - (A_{i,t-1} + \mu_j)$ is the surprise in observed output. As usual in Bayesian updating, belief variance declines deterministically with experience (see Appendix B.1 for the formal argument).

Unemployed workers receive benefits z and search for jobs at rate λ; employed workers receive outside offers at rate $\kappa\lambda$, both drawn from distribution $F(\mu)$. Matches dissolve exogenously at rate δ, and workers exit the labor force exogenously at rate Ψ. In the following, we denote the firm's state as $J = \mu_j$ and the worker's state at time t as $I := I_t = \{A_{i,t-1}, x_{i,t-1}\}$, with x denoting labor market experience.

Within period t, timing is as follows: (i) output is realized and beliefs update; (ii) conditional on no exogenous separation, an outside offer may arrive; (iii) the worker chooses among unemployment, staying, and switching. Wages for period t are set at the start of t based on the pre-update state.

To streamline exposition, we impose a spot-wage normalization under transferable utility: each period the worker is paid expected output, so the firm's expected flow profit is zero. We relax this assumption in Section 5.2, where we allow the surplus to be split between worker and firm and to be distributed intertemporally through renegotiation. As a result, wages $w(J, I)$ are

$$w(J, I) \;=\; \mathrm{E}[y_{i,j,t} \mid J, I] \;=\; \mu_j + A_{i,t-1}.$$

[14] For expositional convenience, the model uses the term *firm*. In the empirical sections, we use *employer* because the administrative identifier is not fully identical across datasets. Nothing in the model depends on that distinction.

In the following, we suppress the subscripts i, j and t when context permits.

Match surplus $S(J,I)$ consists of the net output gain over unemployment, an option value from learning, a continuation value from ongoing matches, and the option value of on-the-job search. Formally:

$$\begin{aligned} S(J,I) = w(J,I) - z + \beta \int (U(I') - U(I))\, dG^{I,J}(I') + \beta(1-\delta) \int S^+(J,I') dG^{I,J}(I') \\ + \beta(1-\delta)\kappa\lambda \int \int \left(S^+(J',I') - S^+(J,I')\right)^+ \, dF(J')\, dG^{I,J}(I') \\ - \beta\lambda \int S^+(J',I) dF(J') \end{aligned} \tag{5}$$

where $S^+(J,I) = \max\{S(J,I),0\}$, $\beta = \tilde{\beta}(1-\Psi)$ and $G^{I,J}$ is the transition kernel for the updated belief state (I') induced by observing output while employed at firm J with current states I. In summary, the model features four types of job separations: exogenous separations to unemployment, endogenous separations to unemployment, job-to-job mobility from viable matches, and job-to-job mobility that occurs because the incumbent match becomes non-viable after learning.

Unemployed workers enter employment if surplus is positive. The unemployment value function is hence:

$$U(I) = z + \beta \left(U(I) + \lambda \int S^+(J,I) dF(J) \right) \tag{6}$$

Given the updating process, $F(J)$, and G, the model can be solved numerically after which transitions and wage dynamics can be simulated.[15]

The model generates a U-shaped relationship between wage changes and separations because both wage-change volatility and separation risk decline with tenure. Let $X_t \equiv \Delta w_t$ denote the wage change for stayers at tenure t, and let $Y_t \equiv \mathbf{1}\{\text{separate between } t \text{ and } t{+}1\}$. Conditional on tenure, wage changes are mean zero and independent of separation risk. Across tenures, however, both $\mathrm{Var}(X_t \mid t)$ and $\Pr(Y_t = 1 \mid t)$ fall with tenure. Pooling observations across tenures therefore induces a positive covariance between X_t^2 and Y_t, so an OLS regression of Y on X^2 yields a positive coefficient. Appendix B.2 isolates a pure composition channel in an auxiliary setting in which, conditional on tenure, wage revisions are orthogonal to separation shocks. Under this restriction, pooling across tenure mechanically generates a positive coefficient on X_t^2 even in the absence of a within-tenure effect.

[15]Appendix B.5 shows that the surplus operator T is a contraction under sufficient conditions, guaranteeing a unique fixed point.

5.2 Quantitative Extensions

5.2.1 Overview

The baseline model isolates the composition mechanism linking wage-change volatility and separations, but it cannot match two salient features of the data: wage-change dispersion declines only gradually with experience and tenure, and within-job wage changes display negative serial dependence, whereas the baseline implies none by construction. We therefore extend the model in two dimensions: (i) match-specific productivity that evolves persistently and is learned over time, and (ii) surplus sharing with renegotiation in response to outside offers.

Beyond improving fit, these extensions have strong economic implications. First, they provide a disciplined account of why wage variability falls over the career. With a persistent match component, learning gradually shifts wage changes from large belief revisions early in the match toward smaller innovations later on. With renegotiation, the worker's wage becomes increasingly anchored to the evolving outside option on the job ladder; better outside offers (and the associated renegotiation benchmark) limit the pass-through of fluctuations in match productivity into wages. In this sense, the accumulation of tenure and a stronger threat point through job-ladder advancement jointly generate endogenous wage smoothing even when workers and firms continue to learn about ability. Second, the same informational frictions shape the allocation of workers across firms and matches. Because mobility and job acceptance decisions are made under imperfect information about match quality and worker productivity, learning affects the timing and direction of reallocation, and therefore the distribution of match surpluses among employed workers. As a result, even with additively separable output, learning can affect aggregate productivity through selection and reallocation. Section 7 explores these implications quantitatively.

5.2.2 Dynamic Match Productivity

We let match-specific productivity $m_{i,j,t}$ follow an AR(1) process: $m_{i,j,t} = \rho m_{i,j,t-1} + \eta_{i,j,t}$. At job start, agents hold the prior $m \sim N(0, \sigma_{m0}^2)$ and learn over time about the true match productivity. We assume that $\sigma_{m0}^2 = \sigma_\eta^2/(1-\rho^2)$, so the prior equals the unconditional variance of the AR(1) process. Let N_t denote beliefs about match productivity and $M = \{N_{t-1}, \tau\}$ the match state, with τ denoting tenure. Note that $\rho = 0$ recovers the baseline setting.[16]

[16] To see this, observe that when $\rho = 0$ the match component $m_t = \eta_t$ is i.i.d. In the Kalman filter of Appendix B.3, the prediction step then yields $\hat{m}_{t|t-1} = 0$, $P_{m,t|t-1} = \sigma_\eta^2$, and $C_{t|t-1} = 0$ at every period, so the match state returns to its prior before each update. The innovation variance reduces to $\Omega_t = \sigma_\eta^2 + P_{a,t-1}$,

Autocorrelation in match-specific productivity shapes what can be learned from output realizations. If match productivity follows a random walk ($\rho = 1$), successive observations reveal only innovations $\Delta y_t = \eta_t$ and the level $a_i + m_{i,j,t}$; they do not pin down the decomposition between time-invariant ability a_i and the match level. Consequently, posterior uncertainty about worker ability (and about the match level) does not shrink with tenure beyond what is learned from the initial observation. When $0 < \rho < 1$, mean reversion makes the match component partially predictable, so the output history becomes informative about both a_i and the current match state. Under the spot-wage used in the baseline, the period-t wage equals predicted expected output, so wage changes combine revisions in beliefs about $(a_i, m_{i,j,t})$ with new match innovations. As tenure grows, belief revisions become small and wage-change volatility declines toward the long-run variance contributed by match innovations. Moreover, mean reversion implies that positive (negative) match shocks tend to be followed by lower (higher) subsequent realizations, generating negative serial correlation in wage changes. This extension also affects separations: persistent negative match shocks are more likely to push the continuation surplus below zero, and joint updating about ability and match quality can induce inefficient mobility relative to a full-information benchmark.

5.2.3 Wage Renegotiation

We model wage renegotiation using the sequential-auction protocol of Cahuc et al. (2006) where workers have bargaining weight α. Our recursive implementation follows Jarosch (2023), who provides a dynamic formulation with a contract-state variable. We denote the current contract as R. As in Jarosch (2023), the joint surplus is invariant to the current negotiation benchmark R under transferable utility. In Appendix B.4, we derive the surplus $S(J, I, M)$ and wage equations $w(J, I, M, R)$. Note that for $\alpha = 1$, we recover the surplus equation in the baseline model.[17]

The implications of surplus sharing are transparent in two polar cases. When $\alpha = 1$, the worker captures the entire match surplus. Under the spot-wage setting used in the baseline, this implies that the worker's continuation value equals joint surplus and wage changes track revisions in expected output. When $\alpha = 0$, wages implement the outside-option constraint:

and the ability gain becomes $K_{a,t} = P_{a,t-1}/(\sigma_\eta^2 + P_{a,t-1})$, which coincides with the baseline gain K_{t-1} in (8). The spot wage $w_t = \mu_j + A_{t-1} + \hat{m}_{t|t-1} = \mu_j + A_{t-1}$ likewise reduces to the baseline expression.

[17] In the baseline we impose a spot-transfer normalization, $w_t = \mathrm{E}[y_t \mid J, I]$, which sets the firm's continuation value to zero period by period. In the renegotiation model, the bargaining protocol pins down the worker's and firm's present values via $V - U = R + \alpha(S - R)$, hence for $\alpha = 1$ we obtain $V - U = S$ and the firm's value is zero only in present value ($P = 0$). Because total surplus is invariant to intertemporal transfers, there remains scope to shift payoffs between the current wage and promised continuation without changing S when the worker captures the full surplus. As a result, $\alpha = 1$ nests the baseline surplus recursion, but equality of flow wages additionally requires adopting the same spot-wage normalization.

the worker receives the current outside option, and wage adjustments occur only when an outside offer (or a participation constraint) updates that outside option. For intermediate $\alpha \in (0, 1)$, wages combine the outside option component with partial surplus sharing, so outside offers provide insurance against match-specific shocks by limiting the extent to which wages co-move with within-match productivity. Lower α makes wages more tightly anchored to the outside option and therefore less sensitive to match shocks, whereas higher α passes through a larger share of match-level fluctuations. Accordingly, renegotiation primarily affects the distribution and serial correlation of wage changes through the frequency and size of wage resets.

The model delivers qualitative predictions for the joint dynamics of wage changes and separations, but the quantitative importance of its mechanisms is an empirical question. We therefore turn next to the structural estimation.

6 Estimation

In the following, we define the parameters of the model and provide an identification argument for the estimation by simulated method of moments (Section 6.1). We then show estimation results (Section 6.2).

6.1 Parameterization and Identification Argument

Data, sample, and timing. We estimate the model on the Italian administrative data described in Section 2. The estimation uses the whole harmonized worker-year panel, a larger sample than the empirical analysis sample in Sections 3–4. One model period corresponds to one year. Unless stated otherwise, the estimation moments are computed for workers with at most ten years of labor-market experience.

Parameter Set and Normalization. The model is parametrized by the parameter vector Θ

$$\Theta = \big\{\sigma_\mu, \sigma_\eta, \bar{a}, \sigma_a, \sigma_{A0}, \rho, \lambda, \kappa, \delta, z, \alpha, \beta\big\}.$$

All parameters except β are internally estimated. Firm productivity is drawn from $F(\mu) = \mathcal{N}(0, \sigma_\mu^2)$, where we normalize $\mathrm{E}[\mu] = 0$ because only relative productivity levels are identified. Worker ability a_i is drawn from $V(a) = \mathcal{N}(\bar{a}, \sigma_a^2)$ and initial beliefs satisfy $A_{i,0} \sim \mathcal{N}(A_0, \sigma_{A0}^2)$ with $A_0 = \bar{a}$. Match productivity m_{ijt} follows $m_{ijt} = \rho m_{ij,t-1} + \eta_{ijt}$ with $\eta_{ijt} \sim \mathcal{N}(0, \sigma_\eta^2)$. Search frictions are governed by the offer arrival rate for the unemployed λ and the relative arrival rate on the job κ, so employed workers receive offers at rate $\kappa\lambda$. Matches end exogenously with probability δ, unemployed workers receive benefit z, and wages are determined by the worker bargaining weight α. We incorporate finite working lives by assuming that, at the end of each year, workers permanently exit the labor market with probability Ψ. Using an average remaining working-life length of 32.8 years for Italy, we set $\Psi = 1/32.8$ (Eurostat, 2025). We then calibrate the effective annual discount factor to $\beta \equiv \tilde{\beta}(1-\Psi) = \frac{1-\Psi}{1+r}$, so that with $r = 8\%$ we obtain $\beta \approx 0.90$.

Moments and Identification Argument. We estimate Θ by simulated method of moments, matching a vector of labor-market, wage-level, and wage-dynamics moments. In the data and the simulations, let $E_{it} \in \{0, 1\}$ denote employment and $\Delta w_{it} \equiv w_{it} - w_{i,t-1}$. Experience x_{it} is measured in years since labor-market entry; we use bins $x \leq 3$, $3 < x \leq 6$, and $x > 6$. Table 3 collects the twelve targeted moments: unemployment and transition hazards $(u, \mathrm{EU}, \mathrm{EU{+}EE})$, wage levels $\big(\mathrm{E}[w_t],\ \mathrm{E}[w_t \mid \mathrm{UE}]\big)$, cross-sectional wage dispersion by experience $\big(\mathrm{SD}(w_t \mid x{>}6),\ \mathrm{SD}(w_t \mid x{\leq}3)\big)$, wage-change dispersion for stayers and movers $\big(\mathrm{SD}(\Delta w_t \mid \text{stayer}),\ \mathrm{SD}(\Delta w_t \mid \text{stayer}, 3{<}x{\leq}6),\ \mathrm{SD}(\Delta w_t \mid \text{mover}, x{\leq}3)\big)$, and the serial dependence and nonlinearity moments $\big(\mathrm{Corr}(\Delta w_t, \Delta w_{t+1} \mid \text{stayer}), \hat{\beta}_2\big)$, where $\hat{\beta}_2$ is the coefficient on $(\Delta w_t)^2$ in the separation regression from Section 4.[18] Note that our administrative earnings records do not allow to distinguish unemployment from non-participation. Accordingly, throughout the estimation we interpret "unemployment" as non-employment, i.e. the absence of an observed job/earnings record in year t. The hazard EU therefore measures transitions from employment to non-employment, and the stock u is the fraction non-employed. We construct the simulated counterparts using the same observability rule in the model (an observation is employed if and only if a wage is recorded). Details of the estimation procedure are collected in Appendix C.2.

Although the method jointly identifies all parameters, we now sketch partial identification arguments in three steps: (i) labor-market flow rates $(\lambda, \kappa, \delta)$ from stocks and hazards; (ii) type and learning parameters $(\sigma_\mu, \sigma_\eta, \bar{a}, \sigma_a, \sigma_{A0}, \rho)$ from wage dispersion, wage-change dynamics, and the U-shape moment; (iii) the bargaining weight α and outside option z from entry wages and acceptance behavior. We will now provide more detail on these in turn.

(i) Labor Market Flow Parameters $(\lambda, \kappa, \delta)$. Let u denote the unemployment rate and define

[18] We adapt the sample construction to the estimation setting, thereby excluding sample restrictions based on firm-wide displacements. We show robustness of our sample to the more restrictive sample from Section 4 in Appendix Table A.13. The coefficients are virtually unchanged across settings.

population hazards

$$h_{\text{EU}} \equiv \Pr(\text{E}\!\rightarrow\!\text{U}), \qquad h_{\text{EE}} \equiv \Pr(\text{E}\!\rightarrow\!\text{E}).$$

The stock–flow balance equation for unemployment yields

$$\lambda = \frac{\left[\delta + (1-\delta)s^E(\Theta)\right]}{p^U(\Theta)} \frac{1-u}{u},$$

where $p^U(\Theta)$ is the model-implied acceptance probability for unemployed workers and $s^E(\Theta)$ is the endogenous separation probability conditional on no exogenous separation. The employed job-to-job hazard and the employment–to–unemployment hazard are

$$h_{\text{EE}} \;=\; (1-\delta)\kappa\lambda\, p^E(\Theta) \qquad h_{\text{EU}} \;=\; \delta \;+\; (1-\delta)s^E(\Theta).$$

with $p^E(\Theta)$ the acceptance probability for employed workers. Given p^U, p^E, and s^E from the model, these three mappings discipline $\lambda, \kappa\lambda, \delta$.

(ii) Learning and heterogeneity $(\sigma_\eta^2, \sigma_{A0}^2, \sigma_\mu^2, \sigma_a^2, \bar{a}, \rho)$. To build intuition, consider the transparent baseline ($\alpha = 1$, $\rho = 0$). Appendix B.1 derives a closed form for the stayer wage-change variance at experience t:

$$V_t \equiv \text{Var}(\Delta w_t \mid \text{stayer}, t) = \frac{\sigma_\eta^2\, s_0^2}{(1+s_0(t-1))(1+s_0 t)}, \qquad s_0 \equiv \sigma_{A0}^2/\sigma_\eta^2.$$

The decline of V_t across experience bins is informative about s_0 (learning speed), while the level pins down σ_η and hence σ_{A0}.[19] Mover wage changes additionally reflect firm upgrading; the mover–stayer gap in $\text{SD}(\Delta w \mid \cdot)$ therefore disciplines σ_μ after accounting for the model-implied acceptance rule. Wage dispersion at high experience reflects permanent components and hence informs (σ_a, σ_μ), while $\text{E}[w]$ pins down $\bar{a}$ under the normalization $\text{E}[\mu] = 0$. When $\rho > 0$ and $\alpha \in (0,1)$, these moments continue to discipline the same primitives, but the mapping is no longer available in closed form because wage changes combine belief revisions with persistent match innovations and partial pass-through under renegotiation. In particular, α enters the wage-dynamics moments by governing the degree of pass-through: lower α attenuates the sensitivity of wages to within-match shocks through the accumulated

[19]The moment V_t is computed as the cross-sectional dispersion of Δw among stayers at experience t. In the baseline model, posterior variance is deterministic in t and $\text{E}[\Delta w_t \mid \mathcal{I}_{t-1}] = 0$, so by the law of total variance

$$\text{Var}(\Delta w_t \mid \text{stay}, t) = \text{E}[\text{Var}(\Delta w_t \mid \mathcal{I}_{t-1}, \text{stay}, t)] + \text{Var}(\text{E}[\Delta w_t \mid \mathcal{I}_{t-1}, \text{stay}, t]) = V_t.$$

In the extended model with persistent match components and renegotiation, cross-sectional dispersion additionally reflects heterogeneity in match and contract states within an experience bin.

outside option, so the wage-change dispersion and autocorrelation moments jointly discipline α alongside $(\rho, \sigma_\eta, \sigma_{A0})$.

The U-shape moment $\hat{\beta}_2$ provides additional identifying power. Appendix B.2 shows that, in the baseline, $\beta_2 = \text{Cov}_\pi(V_t, p_t)/\text{Var}(X^2)$, where $p_t = \Pr(\text{separate} \mid t)$. Since p_t declines with tenure in both data and model, matching a strictly positive $\hat{\beta}_2$ requires that V_t also decline. Higher persistence ρ flattens the tenure profile of V_t; in the limit $\rho = 1$, Lemma B.3 shows V_t is constant and $\beta_2 = 0$. Thus $\hat{\beta}_2$ places an upper bound on ρ once the hazard profile is matched. Because different combinations of $(\rho, \sigma_\eta, \alpha)$ can generate similar V_t profiles, we additionally target $\Gamma_1 \equiv \text{Corr}(\Delta w_t, \Delta w_{t+1} \mid \text{stayer})$, which Lemma B.4 shows is directly informative about ρ and which also helps separate ρ from α, since both affect the serial dependence of wage changes through the pass-through of persistent match shocks.

(iii) Bargaining and outside option (α, z). The unemployment benefit z affects the reservation rule and therefore the acceptance probability from unemployment $p^U(\Theta)$, which in turn shifts the unemployment stock u and the job-finding rate $\lambda p^U(\Theta)$ for a given λ. Conditional on matching the flow moments in part (i), variation in z is therefore disciplined by the level of unemployment and unemployment-to-employment transitions.

The bargaining parameter α governs the pass-through of match surplus into wages, affecting both wage levels and wage dynamics as noted above. Entry wages after unemployment are particularly informative because the outside option is pinned down by unemployment, so $\text{E}[w \mid \text{UE}]$ isolates how much of the initial surplus is transferred to the worker at hiring. Intuitively, z operates on the extensive margin by determining which matches form, while α operates on the intensive margin by governing how surplus is split conditional on acceptance. Accordingly, $\text{E}[w \mid \text{UE}]$ together with the wage-level moment $\text{E}[w]$ and the flow moments jointly discipline (α, z).

6.2 Estimation Results

Overview. We use 12 moments to pin down 11 parameters, hence over-identifying the model. We weight moments such that the squared regression term $\hat{\beta}_2$ is fit exactly. Table 3 shows the model fit to the data and Table 4 contains the estimates jointly with the standard errors (cf. Appendix C.2 for details). The estimated model matches the main wage-dynamics moments well. The fit is particularly strong for the non-employment rate, the overall separation rate, average wages, low-experience wage dispersion, and, most importantly, the U-shape coefficient $\hat{\beta}_2$, which is matched essentially exactly by construction. While the model overstates the *level* of wage-change dispersion for stayers, it reproduces the *decline* across experience bins well: the model generates a drop of 2.1 percentage points (from 13.9 to 11.8), close to the 2.6 point decline in the data (from 12.1 to 9.5). This is reassuring, as the decline in wage-change volatility over the career is the signature of the learning mechanism. At the same time, some discrepancies remain. The model overpredicts employment-to-nonemployment transitions (5.44 versus 2.26) while broadly matching the overall separation rate, a margin likely attenuated in the data by institutional features such as firing costs and notice periods. Relatedly, the model generates too much negative serial dependence in wage changes (-3.83 versus -1.81), a direct consequence of the high persistence $\rho = 0.94$ combined with partial surplus sharing ($\alpha < 1$), which produces mean-reverting wage dynamics as shown in Lemma B.4. Taken together, the estimates indicate that the model captures the central mechanism linking learning to wage dynamics, while remaining less successful in matching the exact split between job-to-job and job-to-non-employment transitions. We now discuss the economics of the estimated parameter vector and relate our findings to the existing literature.

Search Frictions and the Job Ladder. The estimated offer arrival rate from unemployment is $\lambda = 0.754$ per year, implying that an unemployed worker receives roughly three offers every four years. The employed arrival rate is $\kappa\lambda \approx 0.44$, so employed workers search at about 59% of the unemployed rate. This ratio is comparable to Cahuc et al. (2006), who find on French data that employed search intensity is roughly one-third to one-half the unemployed rate depending on the skill group. It is also comparable to Lise et al. (2016), who estimate that employed search intensity (s_1) is about one-third the unemployed rate (s_0) for the low-educated and about one-half for college-educated workers on U.S. NLSY data. Our annual estimates are consistent with a relatively active on-the-job search environment, reflecting the early-career Italian sample where mobility is high and workers frequently change firms to exploit productivity gains. The exogenous layoff rate $\delta = 0.05$ is tightly estimated and lies in the standard range for European labor markets. For comparison, Jarosch (2023) estimates a mean monthly separation rate of 0.76% on German data (approximately 8.7% annually), while Jolivet et al. (2006) document similar magnitudes across several European countries.

Bargaining Power. The estimated worker bargaining weight $\alpha = 0.76$ (SE$= 0.021$) is sizable and implies that workers capture a large but incomplete share of the match surplus. This stands in contrast to the seminal findings of Cahuc et al. (2006), who detect small bargaining power for intermediate- and low-skilled French workers. Jarosch (2023) finds an even higher value of $\alpha = 0.928$ on German data.[20] Our intermediate estimate of $\alpha = 0.76$ reflects a different set of forces. In our framework, $\alpha < 1$ is needed to generate endogenous *wage smoothing*: with renegotiation capital, the pass-through of match-level productivity shocks into wages is dampened by the accumulated outside option. The decline in the standard deviation of wage changes over the career - from $\mathrm{SD}(\Delta w \mid \text{stayer}, x \leq 3) = 12.1$ to $\mathrm{SD}(\Delta w \mid \text{stayer}, 3 < x \leq 6) = 9.5$ in the data - disciplines α jointly with the learning speed and the persistence of match productivity. Too high an α would imply excessive pass-through of both belief revisions and match shocks into the surplus share, overstating wage-change volatility at all experience levels. At the same time, too low an α would decouple wages from the learning process, eliminating the U-shaped relationship between wage changes and separations that is at the core of our empirical findings. The negative serial correlation in wage changes $\Gamma_1 = \mathrm{Corr}(\Delta w_t, \Delta w_{t+1} \mid \text{stayer})$ provides additional discipline: it distinguishes α from ρ, since persistent match shocks combined with partial surplus sharing generate mean-reverting wage dynamics through the renegotiation mechanism.

Outside Option. The unemployment benefit $z = 4.269$ implies an effective replacement rate of $\exp(z)/\exp(\bar{a}) \approx 56\%$ relative to the mean worker's expected output. This is plausible for the Italian institutional context and broadly in line with the European estimates in the literature. For comparison, Jarosch (2023) targets a replacement rate of 75% for Germany, reflecting the more generous German social security system.

The Speed of Learning. The signal-to-noise ratio governing learning about worker ability is $s_0 \equiv \sigma^2_{A0}/\sigma^2_\eta = (0.061/0.032)^2 \approx 3.6$. In the transparent baseline ($\alpha = 1$, $\rho = 0$), posterior variance falls as $\sigma^2_{a,t} = \sigma^2_{A0}/(1 + s_0 t)$, so the half-life of learning would be approximately $1/s_0 \approx 0.28$ years—information would resolve within two to three years, consistent with the employer learning literature (Lange, 2007). However, the estimated persistence of match productivity $\rho = 0.94$ dramatically slows effective learning. As Appendix B.1 shows, when $\rho \to 1$, successive output observations cannot separately identify worker ability from the match level, and learning about ability effectively ceases (Lemma B.3). At $\rho = 0.94$, mean reversion is slow: the half-life of a match shock is $\log(0.5)/\log(0.94) \approx 11$ years. This means the Kalman filter of Appendix B.3 faces a severe attribution problem: output surprises could reflect either favorable ability news or a persistent match draw and this ambiguity resolves only gradually as the match component mean-reverts.

[20] In Jarosch (2023), the high α arises because $\lambda_1 > \lambda_0$: if workers searched less efficiently on the job, low α would imply extremely low hiring wages for workers exiting unemployment, inconsistent with the compressed wage structure in the German data.

Table 3: Estimation moments: empirical counterparts and model fit

Moment	**Empirical counterpart**	**Data**	**Model**
u	$\Pr(E_{it} = 0)$	7.7	7.82
EU	$\Pr(E_{it} = 1, E_{i,t+1} = 0 \mid E_{it} = 1)$	2.26	5.44
EU+EE	$\Pr(E_{it} = 1, \text{Sep}_{i,t+1} = 1 \mid E_{it} = 1)$	16.02	17.50
$\text{E}[w_t]$	Mean wage	4.74	5.04
$\text{E}[w_t \mid \text{UE}]$	Mean wage UE	4.68	4.85
$\text{SD}(w_t \mid \text{high x})$	Cross-sectional SD wages, $x > 6$	27.53	23.64
$\text{SD}(w_t \mid \text{low x})$	Cross-sectional SD wages, $x \leq 3$	22.63	23.27
$\text{SD}(\Delta w_t \mid \text{stayer, young})$	SD wage changes stayers, $x \leq 3$	12.11	13.91
$\text{SD}(\Delta w_t \mid \text{stayer, mid x})$	SD wage changes stayers, $3 < x \leq 6$	9.51	11.84
$\text{SD}(\Delta w_t \mid \text{mover, low x})$	SD wage changes movers, $x \leq 3$	18.28	15.16
$\text{Corr}(\Delta w_t, \Delta w_{t+1} \mid \text{stayer})$	Correlation wage changes stayers	-1.81	-3.83
$\hat{\beta}_2$	U-shape Moment: coefficient $(\Delta w_t)^2$	99.83	99.79

Notes: The table shows the empirical data moments and the simulated moments at the best parameter estimate. "Experience" x is measured in years. E_{it} denotes employment status. The wage and wage-change dispersion moments are reported as standard deviations (SD). All moments are scaled by 100, except for average wages ($\text{E}[w_t]$,$\text{E}[w_t \mid \text{UE}]$) and the autocorrelation of wage changes $\text{Corr}(\Delta w_t, \Delta w_{t+1} \mid \text{stayer})$, with the latter scaled by factor 10.

The economic implication is an environment where learning is intrinsically fast but observationally slow. If match productivity were i.i.d. ($\rho = 0$), information would accumulate rapidly. But because match conditions are nearly permanent, workers and firms must wait for the slow mean reversion in match quality to gradually reveal the worker's true type. This is precisely the mechanism that generates the observed decline in wage-change volatility over the career: the stayer wage-change variance V_t falls as beliefs tighten, but it does so gradually because the persistent match component dominates early career wage dynamics. The U-shape coefficient $\hat{\beta}_2$ disciplines this interplay: matching a strictly positive $\hat{\beta}_2$ requires that V_t decline with tenure, which in turn places an upper bound on ρ (since $\rho = 1$ implies V_t constant and $\beta_2 = 0$). The data thus reject both extremes: pure i.i.d. match draws ($\rho = 0$, learning too fast) and a random walk ($\rho = 1$, no learning), and instead point to an intermediate regime where match persistence and Bayesian updating interact to produce the rich wage dynamics observed in the early career.

Local Sensitivity. To illustrate how the data discipline the estimated parameters, we report the model fit when individual parameters are perturbed away from their estimated values

Table 4: Estimation results for model parameters

	Parameter and Description	**Estimate**	**SE**
Productivity and Types			
σ_μ	St.Dev. firm productivity $F(\mu)$ (log)	-1.146	0.025
σ_η	St.Dev. Match-Productivity Shock (log)	-3.442	0.084
$\bar{a}$	Mean Distribution True Worker Ability $V(a)$	4.841	0.008
σ_a	St.Dev. Distribution True Worker Ability $V(a)$	0.094	0.006
σ_{A0}	St.Dev. Initial Beliefs Worker Ability	0.061	0.001
ρ	Autocorrelation Match Productivity	0.94	0.035
Labor Market			
λ	Offer Arrival Rate Unempl.	0.754	0.020
κ	Offer Arrival Rate Empl. Scaler	0.588	0.011
δ	Spontaneous Layoff Rate	0.050	0.000
z	Unemployment Benefit	4.269	0.036
α	Worker Bargaining Power	0.763	0.021

Notes: The table shows parameter estimates and standard errors of the estimates (SE). See Appendix C.2 for details.

while holding all other parameters fixed.[21] The fit is most sensitive to the bargaining weight α. Reducing α from 0.76 to 0.1 increases the standard deviation of wage changes for young stayers from 13.9 to 39.7 (data: 12.1) and raises cross-sectional wage dispersion at low experience from 23.3 to 51.6 (data: 22.6). With low α, wages are largely pinned down by the outside option R rather than current match surplus, so each renegotiation event causes a discrete jump in wages. These lumpy renegotiation-driven wage changes dominate the smooth belief revisions that characterize wage dynamics when α is high. Most strikingly, $\hat{\beta}_2$ turns strongly negative (-18.7 versus 99.8 in the data), as the dominant source of wage-change variability shifts from learning-induced belief revisions to renegotiation events whose timing is not aligned with the tenure profile of separations.

Reducing the persistence of match productivity from $\rho = 0.94$ to $\rho = 0.1$ has its most visible effect on the experience profile of wage-change volatility: the standard deviation of stayer wage changes falls from 13.5 at low experience to 9.0 at intermediate experience, a decline of 4.5 percentage points that is nearly twice the 2.6 point decline in the data (12.1 to 9.5), confirming that with near-i.i.d. match shocks learning resolves too quickly and the experience profile of V_t is too steep.

Increasing the initial uncertainty about worker ability to $\sigma_{A0} = 0.1$ (from the estimated 0.061) raises the signal-to-noise ratio to $s_0 \approx 9.8$, so learning resolves much faster. Wage-

[21] These exercises are not re-estimations; they change one parameter at a time around the estimated solution and evaluate the resulting moments.

change dispersion for young stayers rises to 17.1 (data: 12.1), reflecting outsized early-career belief revisions. At the same time, $\hat{\beta}_2$ falls to 77.8 because the tenure profiles of wage-change volatility and separation risk become misaligned: V_t drops within the first one to two years while p_t continues to decline gradually as workers climb the job ladder, weakening their covariance. These exercises confirm that the bargaining weight, match persistence, and prior precision are tightly disciplined by distinct features of the data.

Table 5: Local sensitivity of key moments to parameter perturbations

Parameter	**Key moment affected**	**Data**	**Baseline**	**Perturbed**
$\alpha = 0.1$	$\text{SD}(\Delta w_t \mid \text{stayer}, x \leq 3)$	12.11	13.91	39.68
	$\hat{\beta}_2$	99.83	99.79	-18.74
$\rho = 0.1$	$\text{SD}(\Delta w_t \mid \text{stayer}, x \leq 3) -$ $\text{SD}(\Delta w_t \mid \text{stayer}, 3 < x \leq 6)$	2.60	2.07	4.51
$\sigma_{A0} = 0.1$	$\text{SD}(\Delta w_t \mid \text{stayer}, x \leq 3)$	12.11	13.91	17.06
	$\hat{\beta}_2$	99.83	99.79	77.78

Notes: Each experiment changes one parameter from its estimated value while holding all others fixed. The full set of moments is reported in Appendix Table A.14.

7 Applications

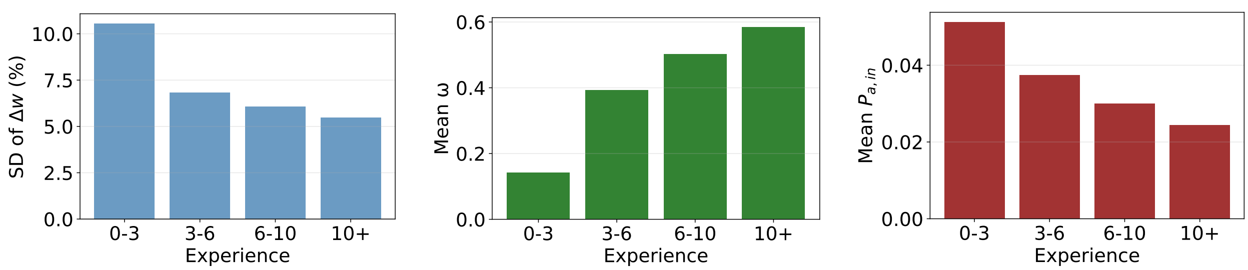
This section uses the parameter estimates to quantify how learning and the job ladder jointly shape wage dynamics and aggregate efficiency. Section 7.1 decomposes wage-change volatility into (i) renegotiation-capital and (ii) history-dependent learning under persistent match productivity. Section 7.2 quantifies output losses from imperfect information. Section 7.3 studies two counterfactual scenarios to understand the effect of policy levers that shape output and wage variability.

7.1 Job-ladder channels for wage-change volatility

Determinants of wage variability. In the estimated model, the volatility of wage changes for job stayers reflects two distinct state variables that are shaped by the job ladder. First, wages depend on the worker's contract benchmark in the sequential-auction protocol, so that the accumulation of outside-option history (denoted negotiation capital) attenuates the sensitivity of wages to within-match shocks and belief revisions. Second, with persistent match productivity ($\rho > 0$), the informativeness of output about worker ability depends on the worker's past job sequence. Conditional on current experience, workers therefore differ in their information state at the start of the current job, which affects subsequent learning-driven wage updates. We summarize these channels by the benchmark ratio ω_t and the job-start uncertainty $P_{a,\text{in}}$.

Negotiation capital. Let R_t denote the worker's current contract benchmark (the enforceable outside-option value) and let $S_t \equiv S(J_t, I_t, M_t)$ denote the joint continuation surplus of the incumbent match at the beginning of period t. For viable matches with $S_t > 0$, define the normalized benchmark $\omega_t \equiv \min\left\{\frac{R_t}{S_t}, 1\right\} \in [0,1]$. Under the bargaining rule $V_t - U_t = R_t + \alpha(S_t - R_t)$, the worker's effective surplus share in value terms is $\hat{\alpha}_t \equiv \frac{V_t - U_t}{S_t} = \alpha + (1-\alpha)\omega_t$, so higher ω_t shifts payoffs toward the benchmark component and reduces exposure to shocks that move S_t. By construction, displaced workers and entrants from unemployment start a new job with $R_t = 0$ and hence $\omega_t = 0$ (so $\hat{\alpha}_t = \alpha$).

Figure 2: Experience profiles



(a) SD Wage change (b) Negotiation capital (ω) (c) Prior uncertainty ($P_{a,\text{in}}$)

Notes: The figure is based on a simulated stationary panel with N = 1,000,000 workers and T = 20 yearly periods. Panel (a) reports the cross-sectional standard deviation of stayer wage changes, $\text{SD}(\Delta w_{t+1} \mid \text{stay}, x_t)$, in percent (wage changes are in log units and are multiplied by 100). Panel (b) reports mean negotiation capital $\omega_t = \min\{R_t/S_t, 1\}$ among the same stayer observations (defined only for viable matches with $S_t > 0$). Panel (c) reports mean job-start uncertainty $P_{a,\text{in}}$, defined as the Kalman prior variance of ability at the start of the worker's current job (Appendix B.3). All state variables $(R_t, S_t, P_{a,\text{in}})$ are measured at the beginning of period t, before the output realization and belief updating.

Labor-market history and current uncertainty. With autocorrelated match productivity, the precision of beliefs about ability at the start of a job depends on the worker's past job sequence, because each job switch resets the match prior and the match–ability covariance (Appendix B.3). Let $P_{a,t|t-1}$ denote the Kalman-filter prior variance of a_i at the beginning of period t, and define the job-start uncertainty $P_{a,\text{in}} \equiv P_{a,t|t-1}\Big|_{\text{job start}}$ as defined in Equations (14). Workers with the same experience x_t can therefore differ in $P_{a,\text{in}}$ depending on their labor-market history. Figure 2 reports experience profiles for (a) the standard deviation of stayer wage changes, (b) mean negotiation capital ω_t, and (c) mean job-start uncertainty

$P_{a,\text{in}}$.[22] Consistent with the job-ladder mechanism, average ω_t rises with experience, while $P_{a,\text{in}}$ declines; simultaneously, the dispersion of wage changes falls sharply over the first decade of the career.

Decomposing wage variability. The existing job-ladder literature has emphasized the accumulation of outside options as the primary channel through which the career trajectory shapes within-job wage dynamics (Postel-Vinay and Robin, 2002; Cahuc et al., 2006; Bagger et al., 2014). The decomposition below reveals that, in our estimated economy, history-dependent learning plays a quantitatively larger role. To quantify how negotiation capital ω_t and history-dependent learning summarized by $P_{a,\text{in}}$ account for cross-worker differences in wage-change volatility, we implement an R^2-based variance decomposition within experience bins in the simulated stayer sample.[23]

Fix an experience bin and let $y_i \equiv (\Delta w_i)^2$, $\omega_i \equiv \omega_t$, and $P_i \equiv P_{a,\text{in}}$ denote the corresponding stayer observations. We compute the total sum of squares $SS_{\text{tot}} = \sum_i (y_i - \bar{y})^2$ and the R^2 from three linear projections:

$$R^2_\omega \;:\; y_i = c_0 + c_1\omega_i + \varepsilon_i, \qquad R^2_P \;:\; y_i = d_0 + d_1 P_i + u_i, \qquad R^2_{\text{full}} \;:\; y_i = b_0 + b_1\omega_i + b_2 P_i + e_i.$$

Because ω_i and P_i are correlated, we decompose the explained variation R^2_{full} into a component uniquely attributable to ω, a component uniquely attributable to P, and a shared component:

$$R^2_{\omega\backslash P} \equiv R^2_{\text{full}} - R^2_P, \qquad R^2_{P\backslash\omega} \equiv R^2_{\text{full}} - R^2_\omega, \qquad R^2_{\text{shared}} \equiv R^2_\omega + R^2_P - R^2_{\text{full}},$$

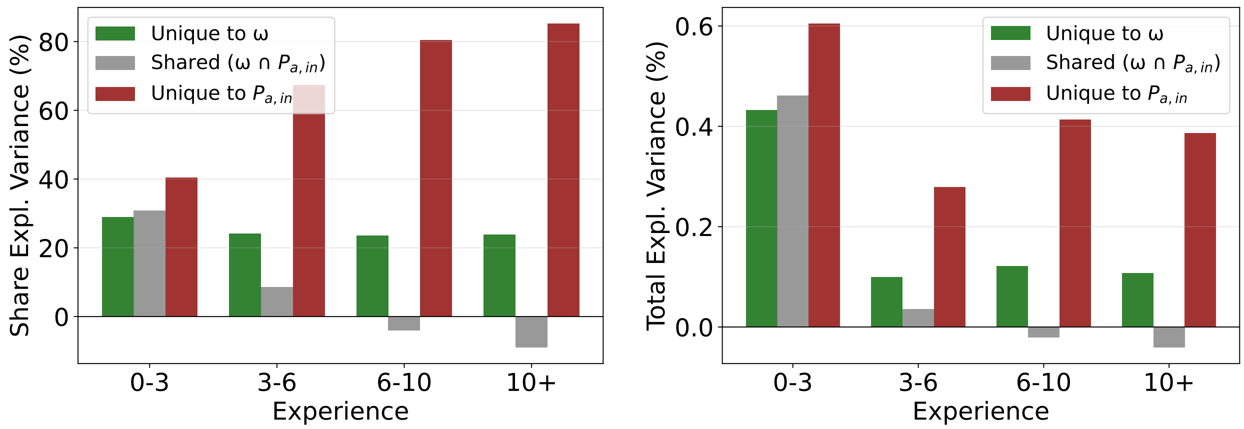
so that $R^2_{\text{full}} = R^2_{\omega\backslash P} + R^2_{P\backslash\omega} + R^2_{\text{shared}}$. We report both (i) the shares of explained variance $R^2_{\omega\backslash P}/R^2_{\text{full}}$, $R^2_{P\backslash\omega}/R^2_{\text{full}}$, and $R^2_{\text{shared}}/R^2_{\text{full}}$, and (ii) the corresponding percentage points of total variance explained (i.e., $100 \times R^2_{\omega\backslash P}$, etc.).

Figure 3 summarizes the decomposition by experience. Panel A reports the composition of explained variance, while Panel B reports the fraction of total variance in $(\Delta w)^2$ explained by ω_t and $P_{a,\text{in}}$ in percentage points. Two results stand out. First, both channels matter early in the career, but job-start uncertainty $P_{a,\text{in}}$ already accounts for the larger share of ex-

[22] We simulate data for 20 years. We measure $(R_t, S_t, P_{a,t|t-1})$ at the beginning of period t, before the output realization and belief update that generate Δw_{t+1}. We restrict attention to stayer observations when quantifying within-job wage-change volatility, because job-to-job moves reset both the match prior and the contract benchmark and therefore mechanically add additional sources of wage variation.

[23] In the implementation, the outcome is $y_{i,t} \equiv (\Delta w_{i,t+1})^2$ and the decomposition is performed separately within experience bins. This isolates cross-worker variation in the second moment of wage changes at a given experience level.

Figure 3: Decomposition of wage change variability



(a) % Explained variance (b) % Total variance

Notes: The figure reports an R^2-based variance decomposition computed within experience bins using the simulated stayer sample. The outcome is $y_{it} = (\Delta w_{i,t+1})^2$ and the covariates are negotiation capital ω_t and job-start uncertainty $P_{a,\text{in}}$, both measured at the start of period t. Within each experience bin, we compute R^2 from linear projections of y_{it} on ω_t alone, on $P_{a,\text{in}}$ alone, and on both jointly; we then report the implied unique and shared components. Panel (a) expresses each component as a share of the total explained variation (R^2_{full}). Panel (b) expresses each component as percentage points of total variation in y_{it} (i.e., $100 \times R^2$).

plained variation in the youngest experience bin. Second, from 3–6 years onward, the unique contribution of $P_{a,\text{in}}$ clearly dominates the decomposition, while the unique contribution of negotiation capital remains positive but smaller. Moreover, the shared component becomes small and then negative at higher experience levels. This pattern indicates that workers with more negotiation capital tend to be in states where part of the additional wage variability associated with history-dependent learning is offset. Overall, the decomposition shows that cross-worker differences in job-start uncertainty are the main source of heterogeneity in stayer wage-change volatility, while negotiation capital remains an important stabilizing force. This result offers a new perspective on the sources of declining wage instability over the career. A large literature on earnings dynamics documents that the variance of wage changes falls with experience (Meghir and Pistaferri, 2004; Guvenen, 2009; Altonji et al., 2013) and has attributed this pattern to the resolution of permanent-transitory uncertainty or to declining job mobility. Our decomposition provides a structural interpretation: the decline is driven primarily by the tightening of beliefs about worker ability through repeated job experiences, with the stabilizing effect of accumulated negotiation capital playing a significant but secondary role.

Job-to-job moves: upgrading versus negotiation capital. We now analyze these factors in more detail. Job-to-job movers display substantially higher wage-change volatility than stayers at all experience levels, as shown in Figure 4. The mover premium is largest early in the career and narrows only gradually with experience. In the model, a move affects subsequent wage dynamics through two offsetting mechanisms. First, moving to a new employer resets the match state and initiates learning about a new match component, which raises the variance of subsequent wage changes. Second, movers typically arrive with a higher contract benchmark and hence higher negotiation capital because outside offers update the benchmark in the sequential-auction protocol. This benchmark effect is especially visible at low experience and dampens the pass-through of within-match shocks into wages. By high experience, both movers and stayers have accumulated substantial benchmark capital, so differences in ω become much smaller even though movers remain more volatile.

We quantify the stabilizing role of negotiation capital using an accounting decomposition based on linear projections within the mover sample. Specifically, we estimate how $(\Delta w)^2$ co-moves with negotiation capital ω (and upgrading $\Delta\mu$), and construct partial counterfactuals that set $\omega = 0$ (or $\Delta\mu = 0$) while holding the remaining covariates fixed. This counterfactual isolates the role of negotiation capital for post-move wage dynamics. In the simulated economy, the standard deviation of wage changes for movers rises from 15.61% under the baseline benchmark to 17.05%. Thus, negotiation capital materially attenuates the wage volatility associated with job-to-job reallocation.

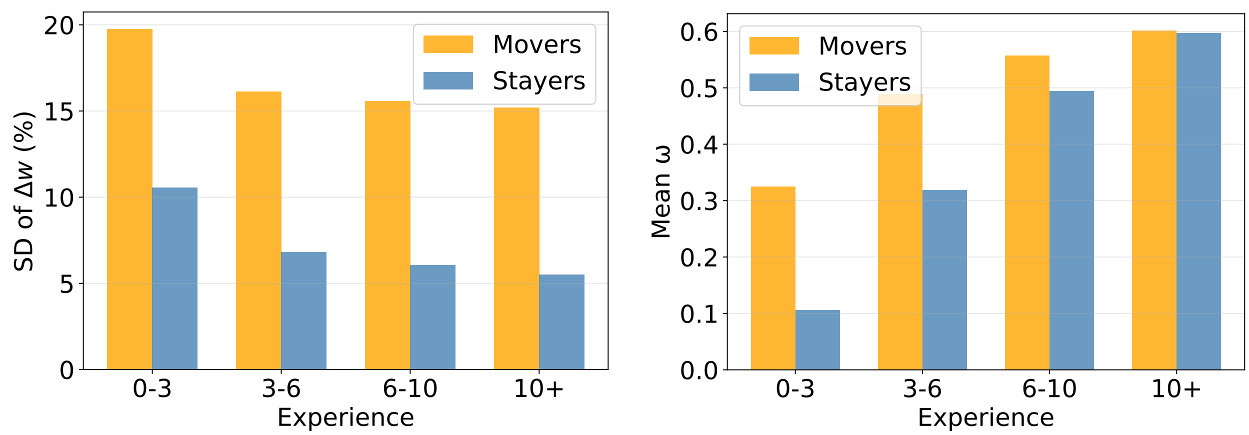
7.2 Effects on output

Learning affects not only wage dynamics but also allocative efficiency and aggregate output. To quantify the output cost of imperfect information, we compare the estimated economy with learning (L) to a full-information benchmark (FI) in which agents observe the realized match component at the post-output decision node.[24] Let $\tilde{y}_{it} \equiv \mu_{j(i,t)} + a_i + m_{it}$ denote realized log output. We measure aggregate output in employment as

$$Y \equiv \mathrm{E}[\tilde{y}_{it}\mathbf{1}\{E_{it} = 1\}] = e \cdot \bar{y}, \qquad e \equiv \Pr(E = 1), \quad \bar{y} \equiv \mathrm{E}[\tilde{y} \mid E = 1],$$

[24]The FI economy is constructed by solving the model with $\sigma_{a,0} \approx 0$, so workers have perfect knowledge of their ability upon labor market entry, and by allowing workers to observe the true match productivity m when making mobility decisions. This approach ensures internal consistency: the equilibrium objects (surplus functions, reservation thresholds) are computed under the same information structure used in the simulation. We use identical random draws for both economies, job offers, separation shocks, and match productivity innovations, so that any differences in outcomes arise solely decisions, not from sampling variation.

Figure 4: Wage-change volatility and negotiation capital: movers versus stayers



(a) SD of wage changes (b) Negotiation capital (ω)

Notes: The figure is based on the simulated worker panel. Panel (a) reports SD(Δw_{t+1}) in percent for stayers and job-to-job movers by experience group, where a mover is an employed worker who switches employers between t and t+1. Panel (b) reports mean negotiation capital ω_{t+1} at the beginning of period $t+1$, that is after a potential move, for the same groups.

The full information economy has a higher employment rate (higher by 1.6 percentage points). It also features a higher average log output by 0.061 percentage points (representing 1.3% of output).

Inefficient mobility conditional on offers. We measure misallocation at the decision node by comparing the mobility decision under learning to the FI-optimal mobility decision for workers who receive an outside offer. Let Offer_{it} indicate an on-the-job offer arrival at time t. For each experience bin, we compute the incidence of two error events among offer recipients:

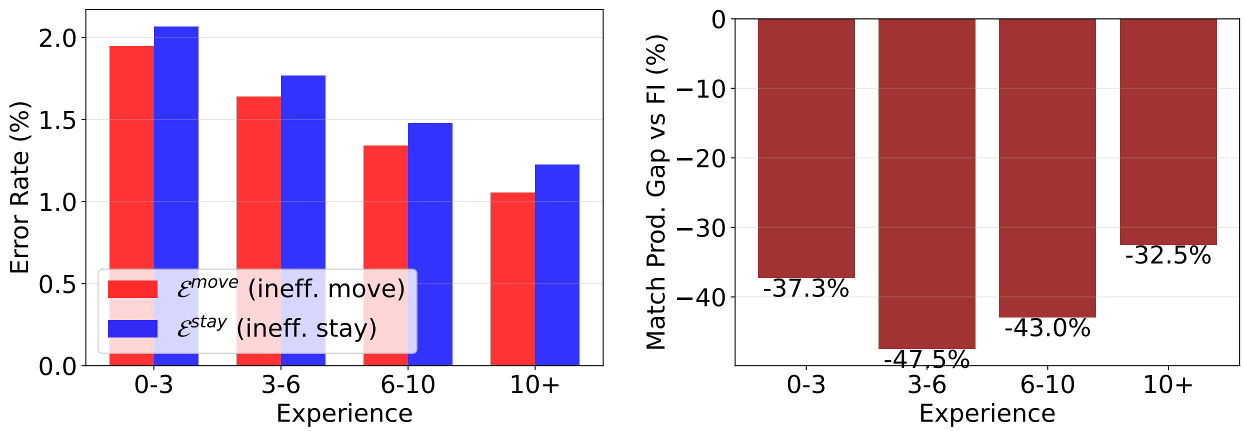
$$\mathcal{E}_t^{move} \equiv \{\text{Offer}_t = 1\} \cap \{d_t = \text{move}\} \cap \{d_t^{FI} \neq \text{move}\},$$

$$\mathcal{E}_t^{stay} \equiv \{\text{Offer}_t = 1\} \cap \{d_t \neq \text{move}\} \cap \{d_t^{FI} = \text{move}\},$$

and we report the corresponding conditional error rates $\Pr(\mathcal{E}_t^{move} \mid \text{Offer}_t = 1, x_t \in \mathcal{X})$ and $\Pr(\mathcal{E}_t^{stay} \mid \text{Offer}_t = 1, x_t \in \mathcal{X})$ by experience. These rates are computed as the number of respective errors divided by the number of offer observations in the bin. Figure 5a shows that the error rate is declining with experience and reaches about $\mathcal{E}_t^{move} = \mathcal{E}_t^{stay}$=2% at 0-3 years of experience and slightly above 1% at over 10 years of experience.

Match productivity and output gaps. To assess the implications of these errors for output, we compare realized match productivity among employed workers across economies. For

Figure 5: Output Effects of Learning



(a) Error Rates (b) Match Productivity Difference

Notes: Panel (a) reports misallocation rates among employed workers who receive an on-the-job offer at time t. An "erroneous move" occurs when the learning economy chooses to move but the full-information (FI) benchmark would stay; an "erroneous stay" occurs when the learning economy does not move but the FI benchmark would move. The FI benchmark is a counterfactual simulation that differs in the learning parameter $\sigma_{A0} \approx 0$ and in the information set at the offer decision: it uses the realized match component to apply the FI move rule for offer recipients and it accepts all offers out of unemployment (keeping the same exogenous separation process and offer arrival rates). Panel (b) reports the percent gap in mean realized match productivity among employed workers between the learning and FI simulations by experience group.

each experience bin, we report $\mathrm{E}[m_t \mid E_t = 1]^L$ and $\mathrm{E}[m_t \mid E_t = 1]^{FI}$, computed from the learning and FI simulations, respectively. Figure 5b reports the percent difference

$$\Delta m(x) \equiv 100 \times \frac{\mathrm{E}[m_t \mid E_t = 1, x_t \in \mathcal{X}]^L - \mathrm{E}[m_t \mid E_t = 1, x_t \in \mathcal{X}]^{FI}}{\left|\mathrm{E}[m_t \mid E_t = 1, x_t \in \mathcal{X}]^{FI}\right|}.$$

We see that realized match productivity is substantially lower under learning than under full information throughout the life cycle. The gap is about 37.3% for workers with 0–3 years of experience, 47.5% for 3–6 years, 43.0% for 6–10 years, and 32.5% for 10+ years. Thus, the productivity loss is large at all ages and is most pronounced in early-to-mid career rather than strictly at labor-market entry. These match-quality losses translate into lower aggregate output under learning frictions, with the burden concentrated on workers who still face substantial uncertainty and who are most exposed to inefficient mobility decisions.

To place the magnitude of these losses in perspective, note that the the output cost of learning frictions (1.3% of output) is of a similar order as the welfare cost of search frictions estimated in related frameworks. Lise et al. (2016) estimate that eliminating search frictions would raise welfare by 3-5% in the U.S. labor market, while Jarosch (2023) finds that the present value earnings loss from an average job displacement is 15% in Germany. Our estimate captures a distinct source of inefficiency - misallocation due to imperfect information rather than search frictions per se - and suggests that informational frictions are quantitatively important for aggregate productivity. The fact that the match-productivity gap peaks at intermediate experience (3–6 years) rather than at entry reflects that the most consequential mobility decisions occur after workers have begun climbing the job ladder but before beliefs have tightened sufficiently to guide reallocation efficiently.

7.3 Counterfactual policies

This section evaluates two counterfactual policies in the estimated economy. First, we study an "apprenticeship" policy that reduces initial uncertainty about worker ability, motivated by systems that provide certified pre-market information about skills. Second, we vary the worker bargaining weight α, motivated by changes in workers' bargaining position. In both exercises, we hold fixed all other primitives and recompute equilibrium objects, and we simulate long panels using a common random seed across counterfactuals to reduce Monte Carlo noise.

For each counterfactual, we report the percentage change in output relative to the baseline and decompose it into extensive and intensive components:

$$\Delta Y = \underbrace{\frac{(e - e_0)\,\bar{y}_0}{Y_0} \cdot 100}_{\text{extensive margin}} + \underbrace{\frac{e\,(\bar{y} - \bar{y}_0)}{Y_0} \cdot 100}_{\text{intensive margin}}. \tag{7}$$

Apprenticeships: reducing initial uncertainty. We model an apprenticeship regime as a mean-preserving reduction in the prior variance of worker ability at labor-market entry. Relative to the baseline prior $A_{i,0} \sim \mathcal{N}(\bar{a}, \sigma_{A0}^2)$, the apprenticeship economy sets

$$\sigma_{A0}^{2,\text{appr}}(\chi) = (1 - \chi)\,\sigma_{A0}^2, \qquad \chi \in [0, 1),$$

holding fixed the distribution of true ability $a_i \sim \mathcal{N}(\bar{a}, \sigma_a^2)$ and all other primitives. The parameter χ indexes the fraction of initial uncertainty resolved by certification.

For each χ, we solve the model and simulate the implied economy. We record: (i) aggregate output $Y(\chi)$ and its decomposition (7) and (ii) early-career within-job wage instability, measured by $\text{SD}(\Delta w_{t+1} \mid \text{stayer}, x_t \leq 3)$ in percent. Figure 6 summarizes the results.

Panel (a) plots the extensive and intensive contributions in (7). Reducing initial uncertainty lowers output rather than raising it. The effect is monotone in χ and is driven almost entirely by the extensive margin, with only a small additional intensive-margin contribution. Economically, better pre-market information makes workers more selective at labor-market entry and reduces the role of experimentation, so equilibrium employment falls slightly in the current calibration. Thus, apprenticeship-style certification improves information but does not generate a positive output effect here.

Panel (b) shows that the same policy substantially reduces early-career within-job wage instability. As χ rises, the standard deviation of early-career stayer wage changes declines markedly, from a little above 10% in the baseline to below 8% at the strongest counterfactual. The calibration therefore implies a trade-off: reducing initial uncertainty compresses early-career wage risk, but it does so at a modest output cost. In the model, improved certification stabilizes wages by reducing the scope for belief revisions early in the career, but it also makes workers less willing to accept marginal jobs, which lowers employment.

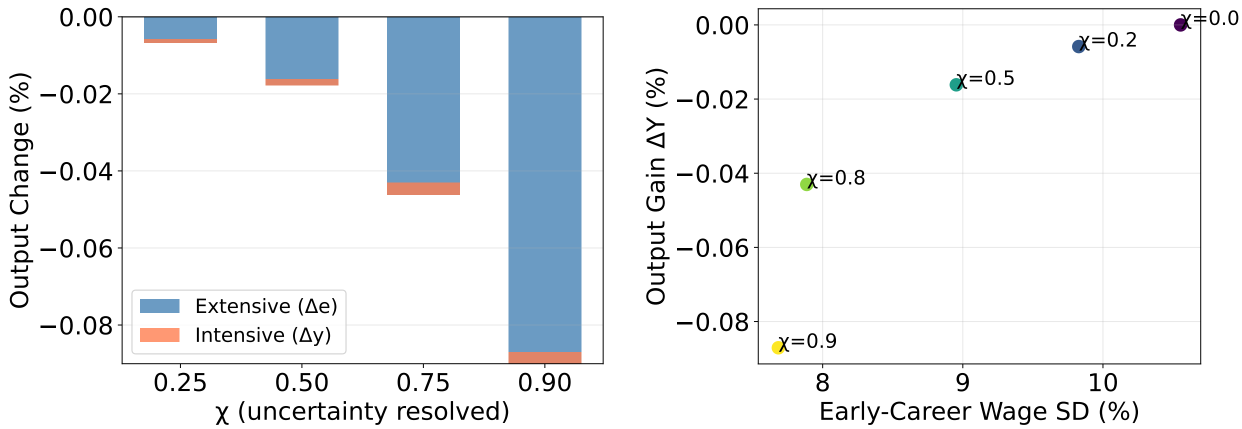
This result contrasts with the standard signaling literature following Spence (1973), where better pre-market information unambiguously improves matching efficiency. In our framework, the opposite occurs because reducing uncertainty about worker ability also reduces the option value of experimentation: workers with precise beliefs reject marginal job offers that they would have accepted under greater uncertainty, and some of these rejected matches would have turned out to be productive. The policy implication is that certification systems—such as the apprenticeship programs prevalent in Germany, Austria, and Switzerland—may stabilize early-career wages but need not improve allocative efficiency, a distinction that is absent from models without on-the-job learning.

Worker bargaining power: varying α. We next vary the worker bargaining weight α on a grid around its estimated value, keeping all other parameters fixed. For each α, we solve and simulate the economy and compute: (i) aggregate output $Y(\alpha)$ and the decomposition (7) relative to the baseline α_0, and (ii) wage-change volatility for stayers early and late in the career, $\mathrm{SD}(\Delta w_{t+1} \mid \text{stayer}, x_t \leq 3)$ and $\mathrm{SD}(\Delta w_{t+1} \mid \text{stayer}, x_t > 6)$.

Figure 7 reports the results. Panel (a) decomposes $\Delta Y(\alpha)$ into extensive and intensive margins. Panel (b) shows how stayer wage instability varies with bargaining power over the life cycle. We find that lower α increases output substantially but also raises wage volatility, especially early in the career. For instance, at $\alpha = 0.3$, output increases by about 0.8%, mainly through the extensive margin, while the standard deviation of wage changes for early-career workers rises sharply and is close to twice its baseline level.

These results reflect two forces. First, lower bargaining power reduces workers' outside

Figure 6: Apprenticeships: output and wage instability



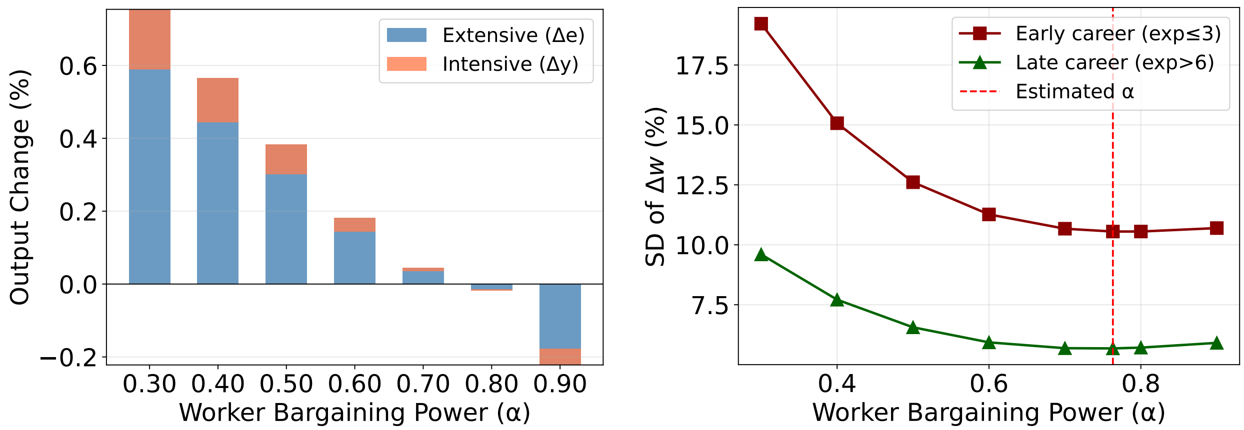
(a) Output decomposition (relative to baseline) (b) Early-career wage SD vs. output gain

Notes: Panel (a) reports the decomposition of the percentage output change $\Delta Y(\chi) = 100 \cdot (Y(\chi)/Y_0 - 1)$ into an extensive-margin component $\frac{(e(\chi)-e_0)\bar{y}_0}{Y_0} \cdot 100$ and an intensive-margin component $\frac{e(\chi)(\bar{y}(\chi)-\bar{y}_0)}{Y_0} \cdot 100$, where $Y = e\bar{y}$, $e = \Pr(E = 1)$, and $\bar{y} = \mathrm{E}[\tilde{y} \mid E = 1]$. Panel (b) plots early-career within-job wage instability against $\Delta Y(\chi)$, where wage instability is measured as $\mathrm{SD}(\Delta w_{t+1} \mid \text{stayer}, x_t \leq 3)$ (in percent). The apprenticeship policy reduces initial uncertainty about ability by setting $\sigma_{A0}^{2,\text{appr}}(\chi) = (1-\chi)\sigma_{A0}^2$, holding fixed the distribution of true ability and all other primitives. All objects are computed from simulated stationary panels of the model; the same simulation seed is used across values of χ to reduce Monte Carlo noise.

option value, making them less selective over job offers and thereby raising employment, the extensive margin effect. Second, when α is low, wages respond more strongly to outside offers through the renegotiation channel: a worker who receives an outside offer captures only a small share α of the resulting surplus gain, but the mere presence of the offer triggers a wage adjustment. This amplifies wage volatility, particularly early in careers when outside offers still need to be accumulated. Thus, policies that strengthen worker bargaining lead to two opposing forces: higher α reduces wage change variability but also lowers employment and aggregate output.

This trade-off connects to the broader debate on the role of labor market institutions in shaping wage dynamics. Cahuc et al. (2006) argued that between-employer competition, rather than bargaining power, is the primary determinant of wages in France. Our analysis adds a dynamic dimension: bargaining power not only determines the level of wages but also governs the *volatility* of wage changes over the career, because it controls the rate at which match-level shocks pass through to wages. In economies with strong worker bargaining, wages are smoother but employment is lower; in economies with weak bargaining, wages are volatile but more workers are employed. The estimated Italian economy, with $\alpha = 0.76$, sits at an intermediate point where both forces are active.

Figure 7: Bargaining power: output and wage instability



(a) Output decomposition (relative to $\hat{\alpha}$) (b) Stayer wage SD by experience

Notes: Panel (a) reports the decomposition of the percentage output change $\Delta Y(\alpha) = 100 \cdot (Y(\alpha)/Y_0 - 1)$ into extensive and intensive components as in (7), where the baseline 0 refers to the estimated α economy. Panel (b) reports stayer wage-change volatility by experience group, measured as $\mathrm{SD}(\Delta w_{t+1} \mid \text{stayer}, x_t \leq 3)$ and $\mathrm{SD}(\Delta w_{t+1} \mid \text{stayer}, x_t > 6)$ (in percent). Each point corresponds to a separate solve-and-simulate of the model holding all primitives fixed except the policy parameter (α). All statistics are computed from simulated stationary panels with a common random seed across counterfactual values to reduce Monte Carlo noise.

Summary. These exercises highlight three forces that are tightly linked in the estimated model. First, wage instability is shaped not only by learning but also by the evolution of the contract benchmark in the sequential-auction protocol. Second, with persistent match productivity, learning is history dependent: job changes reset the match prior and the match–ability covariance, so workers with the same experience can enter a job with different job-start uncertainty and therefore different subsequent wage dynamics. The variance decomposition shows that this history-dependent uncertainty is the dominant source of cross-worker heterogeneity in stayer wage-change volatility, while negotiation capital provides a quantitatively important stabilizing margin. Third, imperfect information is quantitatively consequential for efficiency: relative to a full-information benchmark, the learning economy exhibits misallocation among offer recipients and substantially lower realized match productivity, especially early in the life cycle. The counterfactual policies then reveal two distinct trade-offs. Reducing initial uncertainty through apprenticeship-style certification stabilizes early-career wages but modestly lowers output in the current calibration, whereas lowering worker bargaining power raises output primarily through the extensive margin but sharply increases early-career wage instability.

Taken together, these results show that the job ladder shapes wage dynamics not only through the standard channels of firm upgrading and rent extraction, but also through the informational content of job histories. The quantitative dominance of history-dependent learning over negotiation capital, the sizable output costs of imperfect information, and the non-trivial policy trade-offs between wage stability and employment underscore the importance of modeling learning and search frictions jointly rather than in isolation.

8 Conclusion

This paper documents a robust U-shaped relationship between within-job wage changes and subsequent job separations in matched employer-employee data from Italy, Germany, and Austria. Workers experiencing both wage cuts and wage gains are more likely to separate from their employer. The pattern pertains under a wide range of robustness checks but disappears once wage changes are standardized within tenure groups, indicating that it is primarily compositional rather than behavioral: workers at low rungs of the job ladder simultaneously face greater wage volatility and higher separation risk. We develop and estimate a random search model with learning, persistent match productivity, and on-the-job bargaining to account for this pattern and to study its quantitative implications.

The structural results point to three main conclusions. First, declining wage instability over the career reflects not only the accumulation of outside options, but also history-dependent learning: cross-worker differences in belief precision shaped by past job histories are the dominant source of heterogeneity in within-job wage-change volatility, while negotiation capital plays a stabilizing but secondary role. Second, learning frictions reduce aggregate output by 1.3% relative to a full-information benchmark, with the largest productivity losses arising at intermediate experience levels, when workers have started climbing the job ladder but beliefs remain too imprecise to guide reallocation efficiently. Third, policies that reduce uncertainty or alter bargaining power involve nontrivial trade-offs: apprenticeship-style certification stabilizes early-career wages but lowers output by reducing experimentation in marginal matches, while lower worker bargaining power raises output through employment but sharply increases wage instability.

Taken together, these findings underscore the importance of studying learning and search frictions jointly rather than in isolation. A natural next step is to extend the framework to settings with risk aversion or aggregate fluctuations, where the welfare costs of wage instability and learning frictions may be even larger.

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Online Appendices

A Additional Details: Empirics

A.1 Data Appendix

A.1.1 Italian Veneto Worker Histories

The Veneto Worker Histories (VWH) cover all wage workers in the private sector in the provinces Treviso and Vicenza in the North-East Italian region Veneto for the period 1975-2001.[25] It further contains the work history of all employer associated workers during the sampling period if those workers move out of the sampling provinces. The data set includes information on gender, age and residency of the workers. Information on the employer covers the age of the employer, the location of the seat of the employer and the sector of its economic activity. For each worker, the VWH contains information on all employment spells during the year, including total real earnings and time worked at the job as well as the qualification at the job (worker or manager, for instance) and the nature of the job (temporary or with undetermined duration) as well as the contract type. There is no information on education, yet the literature has argued that information on the qualification at the job provides a partial control for education levels (Galizzi and Lang, 1998). We construct the daily wage using total real wages (non-top coded) earned at the job and days at the job. The recorded income includes extraordinary wage payments such as overtime pay but excludes other types of payments that affect household income such as social security payments. Data on days worked is only consistently filled from 1982 onward which restricts the sample we are able to use under this definition.

A.1.2 German LIAB

The linked employer-employee dataset LIAB combines administrative records from the Federal Employment Agency (BA) with plant-level data from the Establishment Panel of the Institute of Employment Research (IAB) for the years 1993–2010.[26] For a disproportionately stratified sample of firms in operation during the years 2000–2008, over-representing large establishments, the data cover the full employment history of all employer-associated work-

[25] For further description of the data refer to Tattara and Valentini (2010), Leonardi and Pica (2013), Ibsen et al. (2008), Grinza (2021), Bartolucci et al. (2018), Serafinelli (2019).

[26] Further details on the data set can be found in Klosterhuber et al. (2013) and Fischer et al. (2014) for a detailed description as well as Card et al. (2013), Hirsch and Zwick (2015), Addison et al. (2008), John T. Addison (2010), Addison et al. (2015), Gürtzgen (2007).

ers in the years 1999–2009 and collect work histories as far back as 1993.[27] East German establishments enter the panel from 1996; the 1993–1995 observations therefore cover West Germany only.[28] There is both an upper ceiling and a lower floor on wages subject to social security contributions in Germany. For the upper ceiling two potentially binding thresholds (one each for East and West Germany) exist, depending on the social security organization that the worker belongs to. The data set includes information on employees subject to social security contributions and excludes civil servants, family workers and students in higher education. The main variables from the data set used in this study include information on the start and end of employment spells, the type of work (temporary, full-time), the age of the worker, the wage, the sector of economic activity of the employer as well as the occupation at the three digit level. We also exploit experience and tenure variables provided as part of the data that accurately measure each workers employment histories. The LIAB is furthermore unique among the three data sets in that it offers information on education. The wage information available in the LIAB is daily gross wages up to the earnings ceiling for social security contributions. Firm-level variables in the linked Establishment History Panel (BHP) are measured as of June 30 each year and thus represent point-in-time snapshots rather than annual flow measures. We deflate wages using the CPI deflator with base year 2010.

A.1.3 Austrian AMDB

The Austrian AMDB dataset is co-constructed by the federal ministry of economics and labor (BMWA) and the labor service institution AMS based on social security records.[29] It contains the universe of employment spells and social security benefits for Austrian workers during the time period 2000-2016 and covers start and end date, total earnings and days worked at each job for each month of the year. Moreover, the AMDB includes information on the economic sector at the 4-digit level and the work place location as well as age in 5 age groups. The recorded income is subject to a single, nationally uniform reporting limit. We adjust observed nominal wages using the CPI deflator with base year 2010.

[27] Sampling probabilities range from 0.11% for establishments with 1–4 employees to 91.3% for establishments with 5,000 or more employees (Fischer et al., 2014).

[28] Full coworker coverage is available only for establishments with a valid IAB survey interview in the relevant year (wave codes B/C in Fischer et al. 2014); establishments re-entering the panel after a period of exclusion receive a new identifier. Workers at non-panel firms appear in the LIAB via their employment histories but without complete coworker rosters. As a result, a full set of coworkers are only available at LIAB-sampled firms during the period 1999–2009.

[29] For a description of the data set, cf. here. For additional information, consider Zweimüller et al. (2009) and Borovičková (2022); Borovičková and Shimer (2025) using a similar data set.

A.2 Empirical Appendix

Table A.1: Sample Construction and Attrition

	Italy	**Germany**	**Austria**
Step 0: Keep i if entry age < 30	50.07	64.49	65.70
Step 1: Keep i if $19 \leq \text{age} \leq 63^{\star}$, men	49.88	40.47	49.28
Step 2: Drop i if $\exp(W_t) \leq 5$ (any t)*	0.12	0.76	0.95
Step 3: Drop i if $\lvert \Delta W_t \rvert \geq 1$ (any t)*	3.76	5.84	9.86
Step 4: Drop i if public sector (any t)*	5.30	4.08	20.05
Step 5: Drop i if $\text{jobs}_t \geq 10$ (any t)*	0.00	0.79	0.01
Step 6: Drop i if sex missing (any t)*	0.00	0.00	0.00
Step 7: Drop i if $\text{apprentice}_t = 1$ (in t)	5.58	0.17	N/A

Notes: The table reports the share of the remaining sample removed at each step of the sample construction procedure. The sample (already at the worker-year main spell level) is sequentially restricted as follows, implementing the selection procedure of Kline et al. (2020) (selection steps marked by $\star$), plus additional restrictions on age at entry, gender, and the removal of apprentices. Step 0 restricts the sample to individuals entering the labor market before age 30. Step 1 further restricts the sample to individuals aged 19–63 and to males. Step 2 drops individuals who ever receive very low wages (daily wages $\leq$ 5€). Step 3 removes individuals who ever experience absolute log wage changes greater than one between consecutive years. Step 4 excludes individuals who ever work in the public sector. Step 5 drops individuals with ten or more jobs within a year. Step 6 excludes individuals with missing gender information. Step 7 removes apprentices (not applied to Austria, where apprentices are already excluded in the raw data). Following Kline et al. (2020), all restrictions in steps 2 to 6 are applied at the individual level: if a condition is met in any year, the individual is entirely removed from the sample.

Table A.2: Summary Statistics by Country: Empirical Analysis Samples

	Italy			**Germany**			**Austria**		
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Age	31.47	5.37	31.00	33.17	5.16	33.00	32.33	5.31	32.00
Tenure at the employer	7.18	3.88	6.00	6.98	3.76	6.00	7.12	3.91	6.00
Tenure at the employer (IAB)				8.57	5.13	7.40			
Labor market experience	9.66	4.31	9.00	9.38	4.04	9.00	9.83	4.07	9.00
Labor market experience (IAB)				11.41	5.16	10.80			
Employer size	9.46	37.79	2.85				14.78	81.21	2.65
Employer size (TV & VI)	10.24	38.83	3.07						
Employer size (IAB)				207.60	860.52	41.97			
% change in log real wage	2.94	5.89	2.22	1.95	5.22	1.34	2.61	6.10	1.74
% separations	7.43	26.23	0.00	8.05	27.21	0.00	8.97	28.58	0.00
% separations into unemployment (EU)	0.96	9.76	0.00	1.03	10.10	0.00	1.96	13.86	0.00
% separations into employment (EE)	6.47	24.60	0.00	6.82	25.21	0.00	7.01	25.53	0.00
Obs.	1,645,579			1,229,924			2,928,498		

Notes: The table reports worker-level summary statistics for the three country samples. Entries labeled (IAB) refer to administratively provided German measures. Employer size is measured at the level of the available employer identifier. Employer size (TV & VI) reports employer size only for employers in Treviso and Vicenza, where the universe of employment relationships are observed. EU transitions encompass all separations that are followed by an unemployment spell of more than one month, EE transitions are the complement.

Table A.3: Sample Composition by Country: Empirical Analysis Samples

	Italy		**Germany**		**Austria**	
	Count	Mean	Count	Mean	Count	Mean
Workers	306,057		216,633		478,666	
Employers	68,129		82,231		97,823	
Manufacturing (workers)		56.30		54.29		38.76
Manufacturing (employers)		44.35		36.83		19.35
% Blue collar		68.78				
% White collar		30.31				
% Secondary-intermediary degree				87.88		
% University degree				9.83		
Obs.	1,645,579		1,229,924		2,928,498	

Notes: The table reports sample-composition statistics for the three country samples. Share variables are reported in percent.

Table A.4: Separation Rates by Age

	Italy		**Germany**		**Austria**	
	Mean	SD	Mean	SD	Mean	SD
Age 25						
% separations	10.64	30.84	9.99	29.99	13.98	34.68
Obs.	88,778		34,887		139,627	
Age 35						
% separations	5.64	23.06	7.91	26.99	8.58	28.00
Obs.	74,560		71,541		158,682	
Age 45						
% separations	4.13	19.90	4.88	21.54	7.23	25.91
Obs.	9,899		8,246		23,197	

Notes: The table reports mean separation rates and their standard deviations by age group (25, 35, and 45) and country. Reported values are expressed in percentage points.

Table A.5: Logit Estimates: Timing and Measurement of Wage Changes

	Italy			**Germany**			**Austria**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1st decile	1.20***	1.40***	1.34***	1.24***	1.84***	1.48***	1.38***	1.75***	1.53***
	(0.016)	(0.020)	(0.017)	(0.018)	(0.027)	(0.022)	(0.012)	(0.016)	(0.014)
2nd decile	1.07***	1.11***	1.18***	1.14***	1.51***	1.37***	1.24***	1.24***	1.39***
	(0.014)	(0.017)	(0.016)	(0.017)	(0.023)	(0.021)	(0.011)	(0.012)	(0.013)
3rd decile	1.04**	1.01	1.12***	1.12***	1.22***	1.35***	1.12***	1.08***	1.32***
	(0.014)	(0.016)	(0.015)	(0.017)	(0.019)	(0.020)	(0.010)	(0.011)	(0.012)
4th decile	1.00	1.00	1.07***	1.17***	1.26***	1.29***	1.06***	1.04***	1.16***
	(.)	(.)	(0.015)	(0.018)	(0.020)	(0.020)	(0.0099)	(0.011)	(0.011)
5th decile	1.01	1.00	1.03*	1.05***	1.07***	1.14***	1.00	1.00	1.06***
	(0.014)	(0.016)	(0.014)	(0.016)	(0.017)	(0.018)	(0.0095)	(.)	(0.010)
6th decile	1.04*	1.10***	1.00	1.03*	1.00	1.05**	1.00	1.08***	1.00
	(0.014)	(0.017)	(.)	(0.016)	(.)	(0.017)	(.)	(0.011)	(.)
7th decile	1.03*	1.24***	1.00	1.01	1.01	1.00	1.01	1.13***	1.03**
	(0.014)	(0.019)	(0.014)	(0.016)	(0.016)	(.)	(0.0096)	(0.011)	(0.010)
8th decile	1.05***	1.47***	1.01	1.00	1.04*	1.00	1.04***	1.25***	1.06***
	(0.014)	(0.021)	(0.014)	(.)	(0.017)	(0.016)	(0.0099)	(0.012)	(0.010)
9th decile	1.06***	1.87***	1.02	1.03	1.16***	1.06***	1.06***	1.49***	1.10***
	(0.014)	(0.026)	(0.014)	(0.016)	(0.018)	(0.017)	(0.0100)	(0.014)	(0.011)
10th decile	1.10***	3.45***	1.10***	1.21***	1.58***	1.23***	1.10***	2.32***	1.16***
	(0.015)	(0.044)	(0.015)	(0.018)	(0.024)	(0.019)	(0.010)	(0.021)	(0.011)
Obs.	1,645,579	1,645,579	1,645,579	1,229,924	1,229,924	1,229,924	2,928,498	2,928,498	2,928,498
Wage-change measure	Observed	Observed	Residual	Observed	Observed	Residual	Observed	Observed	Residual
Wage-change timing	$t-1$	t	$t-1$	$t-1$	t	$t-1$	$t-1$	t	$t-1$

Notes: The table reports odds ratios from logit regressions of separation in year t on deciles of wage changes. Columns (1), (2), (4), (5), (7), and (8) use observed wage changes, while columns (3), (6), and (9) use residualized wage changes. Columns (1), (3), (4), (6), (7), and (9) use lagged wage changes, whereas columns (2), (5), and (8) use contemporaneous wage changes. The omitted category is the lowest separation hazard wage-change bin. Residualized wage changes are obtained after controlling for year fixed effects, lagged tenure, lagged experience, lagged age, industry dummies and where available occupation dummies. Standard errors are reported in parentheses.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.6: Wage Changes and Subsequent Separations: Linear Probability Model with Linear Term Only

	Italy		**Germany**		**Austria**	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔW_{t-1}	-0.015***	-0.012**	-0.028***	-0.086***	-0.078***	-0.098***
	(0.0036)	(0.0036)	(0.0049)	(0.0050)	(0.0028)	(0.0029)
W_{t-1}		-0.028***		0.0029**		-0.039***
		(0.00077)		(0.00096)		(0.00062)
Exp_{t-1}		0.00033***		0.00019*		0.0028***
		(0.000067)		(0.000084)		(0.000060)
Ten_{t-1}		-0.0056***		-0.0074***		-0.0096***
		(0.000070)		(0.000088)		(0.000060)
Obs.	1,645,579	1,645,579	1,229,924	1,229,924	2,928,498	2,928,498

Notes: The table reports coefficients from linear probability models of separation in year t on lagged wage changes. The estimating equation is Equation (3). Columns (1), (3), and (5) have no controls. Columns (2), (4), and (6) control for lagged log wage, lagged experience, lagged tenure, lagged employer size, and lagged employer-size growth. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.7: Wage Changes and Subsequent Separations by Transition Type

	Italy			**Germany**			**Austria**		
	Baseline (1)	E2E (2)	E2U (3)	Baseline (4)	E2E (5)	E2U (6)	Baseline (7)	E2E (8)	E2U (9)
ΔW_{t-1}	-0.051***	-0.040***	-0.012***	-0.092***	-0.058***	-0.027***	-0.120***	-0.087***	-0.038***
	(0.0050)	(0.0047)	(0.0019)	(0.0060)	(0.0055)	(0.0022)	(0.0036)	(0.0032)	(0.0018)
ΔW_{t-1}^2	0.960***	0.780***	0.170***	1.290***	1.000***	0.240***	0.920***	0.620***	0.290***
	(0.040)	(0.038)	(0.015)	(0.060)	(0.055)	(0.022)	(0.028)	(0.025)	(0.014)
W_{t-1}	-0.061***	-0.046***	-0.015***	-0.027***	0.001	-0.025***	-0.056***	-0.029***	-0.027***
	(0.00072)	(0.00068)	(0.00027)	(0.00075)	(0.00070)	(0.00028)	(0.00056)	(0.00050)	(0.00027)
Obs.	1,645,579	1,645,579	1,645,579	1,229,924	1,229,924	1,229,924	2,928,498	2,928,498	2,928,498

Notes: The table reports coefficients from linear probability models of separation in year t on lagged wage changes and lagged log wages. Columns (1), (4), and (7) use the baseline separation indicator. Columns (2), (5), and (8) use as dependent variable an indicator for employment-to-employment (E2E) transitions, defined as job changes followed by an interruption of less than one month. Columns (3), (6), and (9) use as dependent variable an indicator for employment-to-unemployment (E2U) transitions, defined as job changes followed by an interruption of more than one month. Robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.8: Wage Changes and Subsequent Separations by Transition Type

		1 month def.		**3 month def.**	
	Baseline	Layoff	Quit	Layoff	Quit
	(1)	(2)	(3)	(4)	(5)
ΔW_{t-1}	-0.092***	-0.022***	-0.070***	-0.024***	-0.068***
	(0.0060)	(0.0019)	(0.0057)	(0.0020)	(0.0057)
ΔW^2_{t-1}	1.29***	0.17***	1.12***	0.19***	1.10***
	(0.060)	(0.019)	(0.057)	(0.020)	(0.057)
W_{t-1}	-0.027***	-0.019***	-0.0072***	-0.021***	-0.0061***
	(0.00075)	(0.00024)	(0.00072)	(0.00025)	(0.00072)
Obs.	1,229,924	1,229,924	1,229,924	1,229,924	1,229,924

Notes: The table reports coefficients from linear probability models of separation in year t on lagged wage changes and lagged log wages. Separations are divided in likely layoffs and quits, where a layoff is defined as receiving unemployment benefits within one month (three months) of separation. Quits are defined as the complement. Columns (1) uses the baseline separation indicator. Columns (2) and (4) use as dependent variable an indicator for likely layoff transitions. Columns (3) and (5) use as dependent variable an indicator for likely quit transitions. Columns (2) and (3) classify transitions using a one-month interruption threshold, while Columns (4) and (5) use a three-month interruption threshold. Robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.9: Wage Changes and Subsequent Separations: Controlling for Occupational Wage Position

	Italy		**Germany**		**Austria**	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔW_{t-1}	-0.051***	-0.051***	-0.092***	-0.10***	-0.12***	-0.13***
	(0.0052)	(0.0052)	(0.0062)	(0.0062)	(0.0039)	(0.0039)
ΔW^2_{t-1}	0.96***	0.96***	1.29***	1.28***	0.92***	0.95***
	(0.042)	(0.042)	(0.063)	(0.063)	(0.030)	(0.030)
W_{t-1}	-0.061***	-0.052***	-0.027***	0.020***	-0.056***	-0.11***
	(0.00070)	(0.0012)	(0.00087)	(0.0012)	(0.00059)	(0.0011)
$W_{t-1} - \mu(W_{t-1})^s$		-0.015***		-0.078***		0.068***
		(0.0015)		(0.0015)		(0.0013)
$(W_{t-1} - \mu(W_{t-1})^s)^2$		0.013***		0.048***		-0.0034**
		(0.0015)		(0.0022)		(0.0011)
Obs.	1,645,579	1,645,579	1,229,924	1,229,924	2,928,498	2,928,498

Notes: The table reports coefficients from linear probability models of separation in year t on lagged wage changes and lagged log wages. Columns (1), (3), and (5) report the baseline specification. Columns (2), (4), and (6) additionally control for the worker's lagged relative wage position within occupation, entered linearly and quadratically. For Austria, where occupation is not observed, the corresponding control is based on the worker's position within the sectoral wage distribution. Robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.10: Wage Changes, Occupational Switching, and Separations

	Italy		**Germany**		**Austria**	
	Δ Occ. (1)	Sep. (2)	Δ Occ. (3)	Sep. (4)	Δ Sec. (5)	Sep. (6)
ΔW_{t-1}	0.015***	-0.051***	-0.056***	-0.10***	-0.047***	-0.13***
	(0.0033)	(0.0052)	(0.0049)	(0.0062)	(0.0024)	(0.0039)
ΔW_{t-1}^2	0.68***	0.96***	0.94***	1.28***	0.35***	0.95***
	(0.029)	(0.042)	(0.050)	(0.063)	(0.018)	(0.030)
W_{t-1}	-0.0063***	-0.052***	-0.0083***	0.020***	-0.030***	-0.11***
	(0.00086)	(0.0012)	(0.00085)	(0.0012)	(0.00064)	(0.0011)
$W_{t-1} - \mu(W_{t-1})^s$	-0.0011	-0.015***	0.0019	-0.078***	0.013***	0.068***
	(0.0011)	(0.0015)	(0.0011)	(0.0015)	(0.00074)	(0.0013)
$(W_{t-1} - \mu(W_{t-1})^s)^2$	0.080***	0.013***	0.051***	0.048***	0.000028	-0.0034**
	(0.0017)	(0.0015)	(0.0018)	(0.0022)	(0.00065)	(0.0011)
Obs.	1,645,579	1,645,579	1,229,924	1,229,924	2,928,498	2,928,498

Notes: The table reports coefficients from linear probability models relating lagged wage changes to occupational/sectoral switching and separation in year t. Columns (1), (3), and (5) use as dependent variable an indicator for an occupational/sectoral change; for Austria, the corresponding outcome is a sectoral change. Columns (2), (4), and (6) use as dependent variable an indicator for separation. All specifications additionally control for the worker's lagged relative wage position within occupation, entered linearly and quadratically. For Austria, the corresponding control is based on the worker's position within the sectoral wage distribution. Robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.11: Wage Gains upon Job-to-Job Mobility

	Italy	**Germany**	**Austria**
	(1)	(2)	(3)
1st decile	0.94*	0.85***	0.95**
	(0.024)	(0.024)	(0.017)
2nd decile	0.93**	0.91**	0.98
	(0.025)	(0.026)	(0.017)
3rd decile	1.00	0.75***	0.96*
	(.)	(0.022)	(0.018)
4th decile	0.95	0.60***	0.99
	(0.026)	(0.017)	(0.018)
5th decile	0.97	0.93*	1.00
	(0.026)	(0.028)	(.)
6th decile	0.93**	1.00	0.97
	(0.025)	(.)	(0.018)
7th decile	0.86***	0.98	0.92***
	(0.023)	(0.029)	(0.017)
8th decile	0.83***	0.96	0.89***
	(0.022)	(0.029)	(0.016)
9th decile	0.77***	0.94*	0.85***
	(0.020)	(0.028)	(0.016)
10th decile	0.71***	0.85***	0.77***
	(0.019)	(0.024)	(0.014)
Obs.	122,264	98,957	262,694
Mean dep. var.	0.60	0.56	0.59

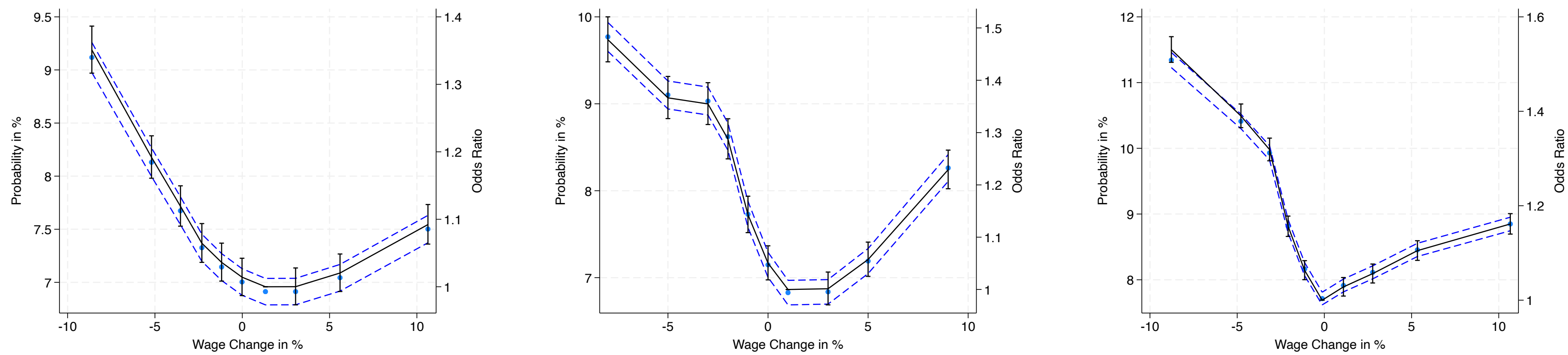
Notes: The table reports odds ratios from logit regressions of an indicator for positive wage growth upon job mobility on deciles of lagged wage changes. The sample is restricted to job switchers. The omitted category is the wage-change bin with the highest share of workers experiencing wage growth upon job moility. Standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.12: Wage Changes and Subsequent Separations: Linear Probability Model, Sample Robustness

	Germany						**Italy**			
	Excl. part-time		**West**		**East**		**All Veneto**		**Treviso & Vicenza**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔW_{t-1}	-0.100***	-0.160***	-0.066***	-0.130***	-0.200***	-0.290***	-0.051***	-0.086***	-0.081***	-0.120***
	(0.0063)	(0.0063)	(0.0067)	(0.0068)	(0.015)	(0.016)	(0.0052)	(0.0052)	(0.0085)	(0.0085)
ΔW^2_{t-1}	1.350***	1.120***	1.080***	0.920***	2.220***	1.840***	0.960***	0.840***	1.080***	0.940***
	(0.066)	(0.066)	(0.069)	(0.069)	(0.16)	(0.16)	(0.042)	(0.041)	(0.067)	(0.067)
W_{t-1}	-0.019***	0.012***	-0.022***	0.013***	-0.028***	-0.0081***	-0.061***	-0.029***	-0.056***	-0.028***
	(0.00088)	(0.00098)	(0.0011)	(0.0012)	(0.0020)	(0.0021)	(0.0007)	(0.0008)	(0.0012)	(0.0013)
Exp_{t-1}		0.00018*		0.00055***		-0.0036***		0.00038***		0.00046***
		(0.000085)		(0.000097)		(0.00020)		(0.00007)		(0.00010)
Ten_{t-1}		-0.0073***		-0.0072***		-0.0080***		-0.0056***		-0.0062***
		(0.000089)		(0.00010)		(0.00018)		(0.00007)		(0.00011)
Obs.	1,208,529	1,208,529	989,989	989,989	239,935	239,935	1,645,579	1,645,579	698,605	698,605

Notes: The table reports coefficients from linear probability models of separation in year t on lagged wage changes. The estimating equation is Equation (3). Columns (1)–(2) use the German sample excluding part-time workers based on LIAB information. Columns (3)–(6) report results separately for West and East Germany. Columns (7)–(10) use Italian data, where columns (9)–(10) restrict attention to the provinces of Treviso and Vicenza, for which the universe of employment relationships is observed. Odd-numbered columns include lagged log wages as controls. Even-numbered columns additionally control for lagged experience, lagged tenure, lagged employer size, and lagged employer-size growth. Robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure A.1: Residual Wage Changes and Subsequent Separations



(a) Italy

(b) Germany

(c) Austria

Notes: The figure plots the separation rate in year t against residualized wage changes in year $t-1$ by country. The solid line and markers show non-parametric within-bin estimates of the separation rate (left axis). The dashed line reports the odds ratio of separation relative to the median residual wage-change bin from the corresponding logit specification (right axis). Error bars are based on the linear within-bin predictor of separation rates for the non-parametric specification. Each marker corresponds to one wage-change bin in the country-specific sample and represents about 120K observations for Germany, 160K for Italy and 290K for Austria.

B Additional Details: Theory

B.1 Baseline model: Variance of wage changes for stayers and movers

Setting. Output is

$$y_{i,j,t} = \mu_j + a_i + \eta_{i,j,t}, \qquad \eta_{i,j,t} \sim \mathcal{N}(0, \sigma_\eta^2),$$

and the (common) prior at labor-market entry is $a_i \sim \mathcal{N}(A_0, \sigma_{A0}^2)$. Let $\tilde{y}_t \equiv y_t - \mu_j$ denote output net of firm productivity.

Bayesian updating. Let $A_t \equiv \mathrm{E}[a_i \mid \mathcal{I}_t]$ and $\sigma_{a,t}^2 \equiv \mathrm{Var}(a_i \mid \mathcal{I}_t)$, where $\mathcal{I}_t = (\mathcal{I}_{t-1}, y_t)$ is information up to period t. Standard conjugate updating implies

$$A_t = A_{t-1} + K_{t-1}\,(\tilde{y}_t - A_{t-1}), \qquad K_{t-1} \equiv \frac{\sigma_{a,t-1}^2}{\sigma_{a,t-1}^2 + \sigma_\eta^2}, \tag{8}$$

and posterior precision is additive:

$$\frac{1}{\sigma_{a,t}^2} = \frac{1}{\sigma_{A0}^2} + \frac{t}{\sigma_\eta^2} \quad \Longrightarrow \quad \sigma_{a,t}^2 = \frac{\sigma_{A0}^2}{1 + t\,(\sigma_{A0}^2/\sigma_\eta^2)}. \tag{9}$$

Define the signal-to-noise ratio $s_t \equiv \sigma_{a,t}^2/\sigma_\eta^2$, so $s_t = s_0/(1 + s_0 t)$.

Wage setting. Under the spot-wage normalization in the baseline model, the period-t wage for a worker employed at firm j is

$$w_t = \mathrm{E}[y_t \mid \mu_j, \mathcal{I}_{t-1}] = \mu_j + A_{t-1}.$$

Hence for a stayer (same firm between t and t+1),

$$\Delta w_t \equiv w_{t+1} - w_t = A_t - A_{t-1}.$$

We index Δw_t by the experience level t at which the belief revision occurs, so that V_t and p_t share the same subscript throughout. In the data, the corresponding object is the wage change observed between years t and $t + 1$.

Proposition B.1 (Stayers)**.** *Conditional on experience t and staying with the same firm,*

$$\Delta w_t = K_{t-1}\big((a_i - A_{t-1}) + \eta_t\big),$$

and the cross-sectional variance of wage changes is

$$V_t \equiv \mathrm{Var}(\Delta w_t \mid \mathit{stay}, t) = \sigma_\eta^2 \, \frac{s_{t-1}^2}{1+s_{t-1}} = \frac{\sigma_\eta^2 \, s_0^2}{\big(1+s_0(t-1)\big)\big(1+s_0 t\big)}. \tag{10}$$

Moreover, $\{V_t\}$ *is strictly decreasing in* t *and satisfies* $V_t \to 0$ *as* $t \to \infty$.

Proof sketch: The first display follows from (8) and $\tilde{y}_t = a_i + \eta_t$. Conditional on $\mathcal{I}_{t-1}$, the forecast error satisfies $(a_i - A_{t-1}) \sim \mathcal{N}(0, \sigma_{a,t-1}^2)$ and is independent of η_t, so

$$\mathrm{Var}(\Delta w_t \mid \text{stay}, t) = K_{t-1}^2(\sigma_{a,t-1}^2 + \sigma_\eta^2) = \frac{\sigma_{a,t-1}^4}{\sigma_{a,t-1}^2 + \sigma_\eta^2} = \sigma_\eta^2 \, \frac{s_{t-1}^2}{1+s_{t-1}}.$$

Substituting $s_{t-1} = s_0/(1+s_0(t-1))$ yields (10); monotonicity and the limit follow because s_{t-1} decreases to zero.

B.2 Baseline model: Composition-induced U-shape

Setting Let

$$X_t \equiv \Delta w_t, \qquad Y_t \equiv \mathbf{1}\{\text{separate between } t \text{ and } t{+}1\}.$$

Assume that conditional on experience t,

$$\mathrm{E}[X_t \mid t] = 0, \quad \mathrm{Var}(X_t \mid t) = V_t, \quad Y_t \mid t \sim \mathrm{Bernoulli}(p_t), \quad X_t \perp Y_t \mid t,$$

and let π_t denote the share of stayer observations at experience t.

Model-implied objects. In the baseline learning model,

$$V_t = \mathrm{Var}(\Delta w_t \mid \text{stay}, t) = \frac{\sigma_\eta^2 s_0^2}{\big(1+s_0(t-1)\big)\big(1+s_0 t\big)}, \tag{11}$$

so V_t declines with experience as beliefs about ability become more precise. The separation probability at experience t can be written as

$$p_t = \delta + (1-\delta)\Big(p_t^{EU} + \kappa\lambda\, q_t\Big), \qquad q_t \equiv \mathrm{E}[1 - F_\mu(\mu) \mid \text{employed at } t]\,, \tag{12}$$

and falls with experience under standard job-ladder selection as the distribution of μ among employed workers shifts upward over time, lowering q_t.

Proposition B.2. *In the pooled population regression* $Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \varepsilon$, $\beta_1 = 0$ *and*

$$\beta_2 = \frac{\mathrm{Cov}(X^2, Y)}{\mathrm{Var}(X^2)} = \frac{\mathrm{Cov}_\pi(V_t, p_t)}{\mathrm{Var}(X^2)}.$$

If $\{V_t\}$ *and* $\{p_t\}$ *are both weakly decreasing in* t *and nondegenerate under weights* $\{\pi_t\}$*, then* $\beta_2 > 0$*.*

Proof sketch: By $X \perp Y \mid t$, $\mathrm{Cov}(X^2, Y) = \mathrm{Cov}(\mathrm{E}[X^2 \mid t], \mathrm{E}[Y \mid t]) = \mathrm{Cov}_\pi(V_t, p_t)$. Moreover $\mathrm{Var}(X^2) > 0$ whenever V_t is nondegenerate; under normality, $\mathrm{E}[X^4 \mid t] = 3V_t^2$, which yields the closed-form denominator used in the text. Finally, monotone V_t and p_t imply $\mathrm{Cov}_\pi(V_t, p_t) > 0$.

Corollary B.2.1. *Let* $Z_t \equiv X_t/\sqrt{V_t}$*. Then in the pooled regression* $Y = \alpha_0 + \alpha_2 Z^2 + u$*, one has* $\alpha_2 = 0$*.*

Proof sketch: Since $Z_t^2 \mid t$ has mean one for all t, we have $\mathrm{Cov}_\pi(\mathrm{E}[Z_t^2 \mid t],\, p_t) = \mathrm{Cov}_\pi(1, p_t) = 0$, so $\alpha_2 = 0$ by the same argument as Proposition B.2.

B.3 Learning Process with Match Productivity

Setting. In each period, log output for worker i at firm j is

$$y_{i,j,t} \;=\; \mu_j \;+\; a_i \;+\; m_{i,j,t},$$

where a_i is the worker's intrinsic (time-invariant) productivity and $m_{i,j,t}$ is a match-specific component that follows

$$m_{i,j,t} \;=\; \rho\, m_{i,j,t-1} \;+\; \eta_{i,j,t}, \qquad \eta_{i,j,t} \sim \mathcal{N}(0, \sigma_\eta^2).$$

At job start, agents hold the prior $m_{i,j,0} \sim \mathcal{N}(0, \sigma_{m0}^2)$ with $\sigma_{m0}^2 = \sigma_\eta^2/(1-\rho^2)$, so the prior equals the unconditional variance of the AR(1) process.

State-space representation. The output equation and the law of motion can be cast as a linear Gaussian filtering problem. Let the latent state be $\theta_{i,j,t} \equiv \big(m_{i,j,t},\, a_i\big)^\top$. The observation and transition equations are

$$\underbrace{y_{i,j,t} - \mu_j}_{\equiv \tilde{y}_{i,j,t}} \;=\; \underbrace{\begin{bmatrix} 1 & 1 \end{bmatrix}}_{H} \theta_{i,j,t}, \qquad \theta_{i,j,t} \;=\; \underbrace{\begin{bmatrix} \rho & 0 \\ 0 & 1 \end{bmatrix}}_{\Phi} \theta_{i,j,t-1} \;+\; \underbrace{\begin{bmatrix} \eta_{i,j,t} \\ 0 \end{bmatrix}}_{\text{process noise}},$$

with process-noise covariance $Q \equiv \mathrm{diag}(\sigma_\eta^2, 0)$. Because there is no additional measurement error (i.e. the observation-noise variance is $\sigma_\varepsilon^2 = 0$), all randomness enters through $\eta_{i,j,t}$ in the state equation.[30]

Let $\mathcal{I}_t$ denote information up to and including y_t (so $\mathcal{I}_t = (\mathcal{I}_{t-1}, y_t)$). We track the filtered means $\hat{m}_{i,j,t} \equiv \mathbb{E}[m_{i,j,t} \mid \mathcal{I}_t]$ and $A_{i,t} \equiv \mathbb{E}[a_i \mid \mathcal{I}_t]$, together with the filtered covariance matrix

$$P_{t|t} \;\equiv\; \begin{bmatrix} P_{m,t} & C_t \\ C_t & P_{a,t} \end{bmatrix} \;=\; \mathrm{Var}\big((m_{i,j,t},\, a_i)^\top \mid \mathcal{I}_t\big),$$

where we suppress the subscripts i, j when context permits.

Prediction step (before observing y_t). If the worker remains in the same job at t, the predicted state and covariance are

$$\begin{bmatrix} \hat{m}_{t|t-1} \\ A_{t|t-1} \end{bmatrix} = \Phi \begin{bmatrix} \hat{m}_{t-1|t-1} \\ A_{t-1|t-1} \end{bmatrix} = \begin{bmatrix} \rho\, \hat{m}_{t-1|t-1} \\ A_{t-1|t-1} \end{bmatrix},$$

$$P_{t|t-1} = \Phi\, P_{t-1|t-1}\, \Phi^\top + Q = \begin{bmatrix} \rho^2 P_{m,t-1} + \sigma_\eta^2 & \rho\, C_{t-1} \\ \rho\, C_{t-1} & P_{a,t-1} \end{bmatrix}.$$

When a new job starts at period t, the firm draw μ_j resets and the match prior is reinitialized, while beliefs about a_i carry over from the previous job. Specifically, at job start:

$$\hat{m}_{t|t-1} = 0, \quad P_{m,t|t-1} = \sigma_{m0}^2, \quad C_{t|t-1} = 0, \quad A_{t|t-1} = A_{t-1|t-1}, \quad P_{a,t|t-1} = P_{a,t-1}.$$

Update step (after observing y_t). Define the innovation

$$\xi_t \;\equiv\; \tilde{y}_t - H \begin{bmatrix} \hat{m}_{t|t-1} \\ A_{t|t-1} \end{bmatrix}$$

and its variance

$$\Omega_t \;\equiv\; H\, P_{t|t-1}\, H^\top + \sigma_\varepsilon^2 \;=\; P_{m,t|t-1} + P_{a,t|t-1} + 2\, C_{t|t-1}. \tag{13}$$

[30] Setting $\sigma_\varepsilon^2 > 0$ would add an i.i.d. measurement-error term $\varepsilon_{i,j,t}$ to the observation equation and replace every occurrence of $\sigma_\varepsilon^2 = 0$ below with the appropriate positive value. We maintain $\sigma_\varepsilon^2 = 0$ throughout.

The Kalman gain and filtered-mean updates are

$$K_t \;=\; P_{t|t-1}\, H^\top\, \Omega_t^{-1} = \begin{bmatrix} K_{m,t} \\ K_{a,t} \end{bmatrix}, \qquad \begin{bmatrix} \hat{m}_{t|t} \\ A_{t|t} \end{bmatrix} = \begin{bmatrix} \hat{m}_{t|t-1} \\ A_{t|t-1} \end{bmatrix} + K_t\, \xi_t,$$

with component gains

$$K_{m,t} = \frac{P_{m,t|t-1} + C_{t|t-1}}{\Omega_t}, \qquad K_{a,t} = \frac{P_{a,t|t-1} + C_{t|t-1}}{\Omega_t}.$$

The deterministic covariance updates are

$$\begin{aligned} P_{m,t} \;&=\; P_{m,t|t-1} \;-\; \frac{(P_{m,t|t-1} + C_{t|t-1})^2}{\Omega_t}, \\ P_{a,t} \;&=\; P_{a,t|t-1} \;-\; \frac{(P_{a,t|t-1} + C_{t|t-1})^2}{\Omega_t}, \\ C_t \;&=\; C_{t|t-1} \;-\; \frac{(P_{m,t|t-1} + C_{t|t-1})(P_{a,t|t-1} + C_{t|t-1})}{\Omega_t}. \end{aligned} \tag{14}$$

Note that the Kalman gain K_t here generalizes the scalar Bayesian gain K_{t-1} defined in equation (8) of Appendix B.1: in the baseline model ($\rho = 0$, no separate match component), the ability gain $K_{a,t}$ reduces to K_{t-1}.

Deterministic variance dynamics. The sequences $\{P_{m,t}, P_{a,t}, C_t\}$ are deterministic functions of (i) the initial job-start priors (σ^2_{m0}, $P_{a,\text{in}}$), (ii) the parameters (ρ, σ^2_η), and (iii) the dates of job starts. Within a given job, $(P_{m,t}, P_{a,t}, C_t)$ depend only on job tenure τ, not on realized signals. Across jobs, $P_{a,t}$ depends on the history of past job lengths, because each job reset changes how much information about a_i can be extracted before the next reset.

Lemma B.3 (Random-walk match productivity and lack of learning)**.** *Suppose match productivity follows a random walk ($\rho = 1$),*

$$m_t = m_{t-1} + \eta_t, \qquad \eta_t \sim \mathcal{N}(0, \sigma^2_\eta),$$

and the only observed signal is $\tilde{y}_t \equiv y_t - \mu = a + m_t$ (i.e. there is no observation noise, $\sigma^2_\varepsilon = 0$). Then the output history $\{\tilde{y}_s\}_{s\le t}$ identifies only the increments $\{m_s - m_0\}_{s\le t}$ and the sum $a + m_0$, but does not separately identify (a, m_0). Consequently, posterior uncertainty about the decomposition between ability and the match level does not vanish with tenure.

Moreover, under the spot-wage normalization $w_t = \mathrm{E}[y_t \mid \mathcal{I}_{t-1}]$, wage changes for job stayers *satisfy*

$$\Delta w_{t+1} = w_{t+1} - w_t = \eta_t,$$

so the stayer wage-change variance is constant:

$$\mathrm{Var}(\Delta w_{t+1} \mid \textit{stay}, t) = \sigma_\eta^2 \quad \textit{for all } t.$$

In particular, the experience profile $\{V_t\}$ *is flat when* $\rho = 1$*, and therefore the composition channel in Appendix B.2 yields* $\beta_2 = 0$*.*

Proof sketch: With $\rho = 1$ and $\sigma_\varepsilon^2 = 0$, successive output differences satisfy $\tilde{y}_t - \tilde{y}_{t-1} = m_t - m_{t-1} = \eta_t$, so the data reveal the innovation sequence $\{\eta_s\}_{s \le t}$ and hence $\{m_t - m_0\}$, but never pin down the level decomposition between a and m_0 (only $a + m_0$ is identified). Under the spot-wage normalization,

$$w_t = \mathrm{E}[y_t \mid \mathcal{I}_{t-1}] = \mu + \mathrm{E}[a + m_0 \mid \mathcal{I}_{t-1}] + \sum_{s=1}^{t-1} \eta_s,$$

so $\Delta w_{t+1} = \eta_t$ and $\mathrm{Var}(\Delta w_{t+1} \mid \mathrm{stay}, t) = \sigma_\eta^2$. Because Proposition B.2 implies $\beta_2 \propto \mathrm{Cov}_\pi(V_t, p_t)$, a constant V_t yields $\beta_2 = 0$.

Lemma B.4 (Mean reversion implies negative serial dependence)**.** *Assume*

1. *match productivity follows* $m_t = \rho m_{t-1} + \eta_t$ *with* $|\rho| < 1$ *and* $\eta_t \sim \mathcal{N}(0, \sigma_\eta^2)$ *i.i.d.;*
2. *ability is known (equivalently, beliefs about* a *are degenerate); and*
3. *under spot wages the period-*t *wage equals predicted output,* $w_t = \mu + a + \mathrm{E}[m_t \mid \mathcal{I}_{t-1}] = \mu + a + \rho\, m_{t-1}$*.*

Then wage changes satisfy

$$\Delta w_{t+1} = \rho(m_t - m_{t-1}) = \rho\big((\rho - 1)m_{t-1} + \eta_t\big),$$

and their lag-1 autocovariance is strictly negative:

$$\mathrm{Cov}(\Delta w_{t+1}, \Delta w_{t+2}) = -\,\frac{\rho^2(1-\rho)}{1+\rho}\,\sigma_\eta^2 \; < \; 0.$$

Proof sketch: Under stationarity, $\mathrm{Var}(m_t) = \sigma_\eta^2/(1-\rho^2)$ and $\mathrm{Cov}(m_{t-1}, m_t) = \rho\,\mathrm{Var}(m_t)$. Using $\Delta w_{t+1} = \rho\big((\rho-1)m_{t-1} + \eta_t\big)$ and $\Delta w_{t+2} = \rho\big((\rho-1)m_t + \eta_{t+1}\big)$, all cross-terms with

η_{t+1} vanish and $\text{Cov}(\eta_t, m_t) = \sigma_\eta^2$. A direct expansion yields

$$\text{Cov}(\Delta w_{t+1}, \Delta w_{t+2}) = \rho^2 \Big((\rho - 1)^2 \, \text{Cov}(m_{t-1}, m_t) + (\rho - 1) \, \text{Cov}(\eta_t, m_t) \Big) = -\frac{\rho^2 (1-\rho)}{1+\rho} \, \sigma_\eta^2.$$

B.4 Derivation Surplus Function Extended Model

Setting In the following, we report the surplus functions for the model with renegotiation of the surplus share. Let $V(J, I, M, R)$ denote the value of an employed worker I at firm J and match quality M with outside option R. Let N_t denote beliefs about match productivity and $M = \{N_{t-1}, \tau\}$ the match state, with τ job tenure. The worker's state vector stays $I = \{A_{t-1}, x_{t-1}\}$. Let $G^{I,J,M}(\cdot \mid I, M)$ denote the transition kernel for the updated belief state (I', M') induced by observing output while employed at firm J with current states I, M. Moreover, denote by $U(I)$ and $P(J, I, M, R)$ the value of an unemployed worker and the value of a job to the firm, respectively. Further, denote by $S(J, I, M) = P(J, I, M, R) + V(J, I, M, R) - U(I)$ the joint surplus of the match. Due to the invariance of total surplus to the sharing agreement, the surplus function is independent of the outside option R, as in Jarosch (2023).

Negotiation and Events In this environment, there is the following set of mobility situations. If workers match with a firm J out of unemployment, their outside option is zero and they enter the match if the surplus at the firm exceeds zero. Let M^0 denote the job-start prior belief for the match component: $E[m] = 0$, $Var(m) = \sigma_{m0}^2$. We denote this case as $\mathcal{M}_0 : \{S(J, I, M^0) > 0\}$. The worker then receives $V(J, I, M^0, \emptyset) - U(I) = \alpha S(J, I, M^0)$.

Timing is as follows. After output is observed and beliefs update from (I, M) to (I', M'), and conditional on no exogenous separation, an outside offer J' (if any) is realized and the worker chooses the best of unemployment, staying, or moving. Hence the relevant continuation value of the incumbent at the decision point is $S^+(J, I', M') = \max\{S(J, I', M'), 0\}$.

If workers receive an outside offer J' during on-the-job search, they can leave their current firm J to receive

$$V(J', I', M^0, R') - U(I') \;=\; R' + \alpha\big(S(J', I', M^0) - R'\big), \qquad R' = S^+(J, I', M'),$$

i.e. the outside option at the new firm equals the value of the maximal feasible bid at the origin firm. The worker will move to J' if the total surplus at the new firm exceeds the incumbent continuation value. We denote the set of firms J' for which the worker will move as

$$\mathcal{M}_2 : \{S(J', I', M^0) > S^+(J, I', M')\}.$$

If moving to the new firm is not optimal, then workers with previous outside option R can still renegotiate their current surplus share to obtain $V(J, I', M', R) - U(I') = R + \alpha(S(J, I', M') - R)$. This strategy is optimal if the surplus at the previous outside option is lower than the surplus at the outside offer, hence for the set of firms

$$\mathcal{M}_3 : \{R < S(J', I', M^0) < S^+(J, I', M')\}.$$

Finally, in the presence of learning, it is possible that the belief about the quality of the match changes such that the worker's or firm's incentive constraints are violated. In this case, we assume that workers and firms renegotiate their contract to satisfy the incentive compatibility constraints $0 < V(J, I, M, R) - U(I) < S(J, I, M)$. Specifically, we assume that the worker gets all the surplus ($V(J, I, M, R) - U(I) = S(J, I, M)$) whenever the firm's constraint is violated (if $V(J, I, M, R) - U(I) > S(J, I, M)$) and conversely the firm receives the total surplus whenever the worker's incentive constraint is violated ($V(J, I, M, R) - U(I) = 0$ if $V(J, I, M, R) - U(I) < 0$). Overall, separations in this model arise (i) through switching employers after on-the-job search or (ii) by choosing unemployment at the decision point.

Worker Value The value of the match to the worker with outside option R is composed of the wage payment and the continuation value of staying with the firm or moving upon receiving an outside offer. Similarly, the worker receives the unemployment value $U(I')$ if the worker chooses unemployment at the decision point. In addition, when receiving an outside offer that leads to surplus renegotiation ($\mathcal{M}_3$), the worker can change the outside option.

$$\begin{aligned} V(J, I, M, R) &= w(J, I, M, R) + \beta\delta \int U(I')\, dG^{I,J,M}(I', M') \\ &+ \beta(1-\delta) \int \Bigg[\kappa\lambda \bigg(\int_{\mathcal{M}_2} V(J', I', M^0, R')\, dF(J') + \int_{\mathcal{M}_3} V(J, I', M', R'')\, dF(J') \bigg) \\ &+ \bigg(1 - \kappa\lambda \int_{\mathcal{M}_2 \cup \mathcal{M}_3} dF(J')\bigg) \max\{\min\{V(J, I', M', R'), V(J, I', M', R)\}, U(I')\} \Bigg] \\ & dG^{I,J,M}(I', M'), \end{aligned}$$

with

$$R' = S^+(J, I', M'), \qquad R'' = S(J', I', M^0).$$

Using the bargaining protocol, we obtain

$$
\begin{aligned}
V(J,I,M,R) &= w(J,I,M,R) + \beta\delta \int U(I')\, dG^{I,J,M}(I',M') \\
&+ \beta(1-\delta) \int \Bigg[\kappa\lambda \bigg(\int_{\mathcal{M}_2} \Big(U(I') + R' + \alpha\big(S(J',I',M^0) - R'\big)\Big)\, dF(J') \\
&+ \int_{\mathcal{M}_3} \Big(U(I') + R'' + \alpha\big(S(J,I',M') - R''\big)\Big)\, dF(J') \bigg) \\
&+ \bigg(1 - \kappa\lambda \int_{\mathcal{M}_2 \cup \mathcal{M}_3} dF(J')\bigg) \bigg(U(I') \\
&+ \max\{\min\{R + \alpha(S(J,I',M') - R),\, S(J,I',M')\},\, 0\} \bigg) \Bigg]\, dG^{I,J,M}(I',M').
\end{aligned}
$$

This yields for the surplus to the worker:

$$
\begin{aligned}
V(J,I,M,R) - U(I) &= w(J,I,M,R) + \beta \int U(I')\, dG^{I,J,M}(I',M') - U(I) \\
&+ \beta(1-\delta) \int \Bigg[\kappa\lambda \bigg(\int_{\mathcal{M}_2} \Big(R' + \alpha\big(S(J',I',M^0) - R'\big)\Big)\, dF(J') \\
&+ \int_{\mathcal{M}_3} \Big(R'' + \alpha\big(S(J,I',M') - R''\big)\Big)\, dF(J') \bigg) \\
&+ \bigg(1 - \kappa\lambda \int_{\mathcal{M}_2 \cup \mathcal{M}_3} dF(J')\bigg) \\
&\quad \max\{\min\{R + \alpha(S(J,I',M') - R),\, S(J,I',M')\},\, 0\} \Bigg]\, dG^{I,J,M}(I',M').
\end{aligned}
$$

Firm Value The value to the firm is

$$
\begin{aligned}
P(J,I,M,R) &= E[y_{i,j}|J,I,M] - w(J,I,M,R) \\
&+ \beta(1-\delta) \int \Bigg[\kappa\lambda \int_{\mathcal{M}_3} \Big((1-\alpha)\big(S(J,I',M') - S(J',I',M^0)\big)\Big)\, dF(J') \\
&+ \bigg(1 - \kappa\lambda \int_{\mathcal{M}_2 \cup \mathcal{M}_3} dF(J')\bigg) \\
&\quad \min\{\max\{(1-\alpha)\left(S(J,I',M') - R\right), 0\},\, S^+(J,I',M')\} \Bigg]\, dG^{I,J,M}(I',M').
\end{aligned}
$$

Joint surplus The joint surplus is hence (dropping the negotiation position due to the invariance of total surplus to the sharing arrangement)

$$\begin{aligned} S(J,I,M) &= E[y_{i,j}|J,I,M] + \beta \int U(I')\, dG^{I,J,M}(I',M') - U(I) \\ &+ \beta(1-\delta) \int \left[S^+(J,I',M') + \kappa\lambda\alpha \int \left(S^+(J',I',M^0) - S^+(J,I',M') \right)^+ dF(J') \right] \\ & dG^{I,J,M}(I',M'). \end{aligned}$$

Moreover, the worker's value of unemployment is changed only by the bargaining parameter α:

$$U(I) = z + \beta\lambda\alpha \int S^+(J',I,M^0)\, dF(J') + \beta U(I).$$

We can bring together both equations to yield

$$\begin{aligned} S(J,I,M) &= E[y_{i,j}|J,I,M] - z + \beta \int (U(I') - U(I))\, dG^{I,J,M}(I',M') - \beta\lambda\alpha \int S^+(J',I,M^0)\, dF(J') \\ &+ \beta(1-\delta) \int \left[S^+(J,I',M') + \kappa\lambda\alpha \int \left(S^+(J',I',M^0) - S^+(J,I',M') \right)^+ dF(J') \right] \\ & dG^{I,J,M}(I',M'). \end{aligned}$$

Note that for $\alpha = 1$, we recover the surplus equation in the baseline model.

Using the contracting rule, together with the equation for the surplus of the match to the worker, we obtain for wages $w(J,I,M,R)$

$$\begin{aligned} w(J,I,M,R) &= R + \alpha(S(J,I,M) - R) - \beta \int U(I')\, dG^{I,J,M}(I',M') + U(I) \\ &- \beta(1-\delta) \int \Bigg[\kappa\lambda \bigg(\int_{\mathcal{M}_2} \Big(R' + \alpha\big(S(J',I',M^0) - R'\big)\Big)\, dF(J') \\ &+ \int_{\mathcal{M}_3} \Big(R'' + \alpha\big(S(J,I',M') - R''\big)\Big)\, dF(J') \bigg) + \bigg(1 - \kappa\lambda \int_{\mathcal{M}_2 \cup \mathcal{M}_3} dF(J') \bigg) \\ & \max\{\min\{R + \alpha(S(J,I',M') - R),\ S(J,I',M')\}, 0\} \Bigg]\, dG^{I,J,M}(I',M'). \end{aligned}$$

with $\mathcal{M}_2 : \{S(J',I',M^0) > S^+(J,I',M')\}$, $\mathcal{M}_3 : \{R < S(J',I',M^0) < S^+(J,I',M')\}$, and $S^+ = \max\{S, 0\}$.

B.5 Surplus Operator and Contraction

Under the within-period timing adopted in the main text, the unemployment value and joint surplus satisfy

$$U(I) = z \; + \; \beta\, U(I) \; + \; \beta\, \alpha\, \lambda \int S^{+}(J', I, M^{0})\, dF(J'), \tag{U}$$

$$\begin{aligned} S(J, I, M) = E[y_{ij}|J, I, M] - z \; + \; \beta \int \big(U(I') - U(I)\big)\, dG^{I,J,M}(I', M') \\ - \beta\, \alpha\, \lambda \int S^{+}(J', I, M^{0})\, dF(J') + \beta(1-\delta) \int \Bigg[S^{+}(J, I', M') \\ + \kappa\lambda\alpha \int \Big(S^{+}(J', I', M^{0}) - S^{+}(J, I', M') \Big)^{+} dF(J') \Bigg] dG^{I,J,M}(I', M'). \end{aligned} \tag{S}$$

where $S^{+}(J, I, M) := \max\{S(J, I, M), 0\}$, M^{0} is the job-start match prior, and G is the transition kernel for (I', M') induced by learning. Solving (U) for $U(I)$ yields the closed form

$$U(I) = \frac{z}{1-\beta} + \frac{\beta\alpha\lambda}{1-\beta} \int S^{+}(J', I, M^{0})\, dF(J'). \tag{15}$$

Surplus operator. Substituting (15) into (S) expresses the right-hand side of (S) as a mapping of the surplus function alone. Define the operator T on bounded measurable functions S by

$$\begin{aligned} (TS)(J, I, M) := \mathrm{E}[y_{ij}|J, I, M] - z \; + \; \beta \int \big(U_S(I') - U_S(I)\big)\, dG^{I,J,M}(I', M') \\ - \; \beta\alpha\lambda \int S^{+}(J', I, M^{0})\, dF(J') + \beta(1-\delta) \int \Bigg[S^{+}(J, I', M') \\ + \kappa\lambda\alpha \int \Big(S^{+}(J', I', M^{0}) - S^{+}(J, I', M') \Big)^{+} dF(J') \Bigg] dG^{I,J,M}(I', M'), \end{aligned} \tag{16}$$

where $U_S(I)$ denotes the right-hand side of (15) evaluated at S. A fixed point of T is a surplus function consistent with (U)–(S).

Proposition B.5. *If*

$$\beta(1-\delta)\big(1 + 2\kappa\lambda\alpha\big) \; + \; \frac{\beta\alpha\lambda(1+\beta)}{1-\beta} \; < \; 1, \tag{17}$$

then T is a contraction on the space of bounded measurable functions equipped with the sup norm. In particular, there exists a unique surplus function $S^{\star}$ satisfying (S), and the corresponding unemployment value $U^{\star}$ is uniquely determined by (15).

Proof sketch: We bound $\|TS - T\tilde{S}\|_\infty$ for arbitrary bounded $S, \tilde{S}$. Throughout, we use the elementary inequalities

$$|x^+ - y^+| \le |x - y|, \qquad \big|(x-y)^+ - (x'-y')^+\big| \le |x - x'| + |y - y'|. \tag{18}$$

Continuation terms. The first inequality in (18) applied to $S^+(J, I', M')$ contributes a factor $\beta(1-\delta)$. For the on-the-job option value, apply the second inequality with $x = S^+(J', I', M^0)$ and $y = S^+(J, I', M')$; after a further application of the first inequality to each argument, this contributes $\beta(1-\delta) \cdot 2\kappa\lambda\alpha$. Together, the continuation terms satisfy a Lipschitz bound with modulus $\beta(1-\delta)(1 + 2\kappa\lambda\alpha)$.

Unemployment-value terms. The closed form (15) implies that U_S is Lipschitz in S^+ with modulus $\beta\alpha\lambda/(1-\beta)$. The term $\beta\int(U_S(I') - U_S(I))\,dG$ and the unemployment option $-\beta\alpha\lambda\int S^+dF$ together contribute at most $\beta\alpha\lambda(1+\beta)/(1-\beta)$ to the Lipschitz modulus.

Combining. Adding both bounds,

$$\|TS - T\tilde{S}\|_\infty \;\le\; \underbrace{\left(\beta(1-\delta)\big(1 + 2\kappa\lambda\alpha\big) \;+\; \frac{\beta\alpha\lambda(1+\beta)}{1-\beta}\right)}_{<1 \text{ by } (17)} \|S - \tilde{S}\|_\infty,$$

so T is a contraction. Existence and uniqueness of $S^\star$ follow from the Banach fixed-point theorem; $U^\star$ is then pinned down by (15).

Condition (17) has a transparent economic interpretation. The first term, $\beta(1-\delta)(1+2\kappa\lambda\alpha)$, bounds the discounted probability that a match survives and is potentially revised through on-the-job search. The second term, $\beta\alpha\lambda(1+\beta)/(1-\beta)$, captures the feedback of surplus into the unemployment value. Condition (17) is sufficient but not necessary. In practice, we verify existence and uniqueness numerically by confirming that the iterative algorithm converges to the same fixed point from multiple initial conditions.

C Additional Details: Estimation

C.1 Estimation Sample Comparison

Table A.13: Wage Changes and Subsequent Separations Across Samples

	Empirical	**Estimation**
	(1)	(2)
ΔW_{t-1}	-0.072***	-0.069***
	(0.0082)	(0.0076)
ΔW^2_{t-1}	0.970***	0.998***
	(0.060)	(0.058)
W_{t-1}	-0.073***	-0.075***
	(0.0013)	(0.0013)
Obs.	849,343	877,039

Notes: The table reports coefficients from linear probability models of separation in year t on lagged wage changes for Italy. Column (1) uses the empirical sample, while column (2) uses the structural estimation sample. Standard errors are reported in parentheses. The sample is restricted to workers with at most 10 years of experience. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.2 Details for SMM and Standard-Error Computation

We estimate the vector of internally estimated parameters

$$\Theta = \left\{\sigma^2_\mu, \sigma^2_\eta, \bar{a}, \sigma^2_a, \sigma^2_{A0}, \rho, \lambda, \kappa, \delta, z, \alpha\right\},$$

taking the discount factor β as externally calibrated (Section 6.1). The estimates are obtained by simulated method of moments (SMM). Let $m^{\text{data}} \in \mathbb{R}^K$ denote the vector of empirical target moments and $m^{\text{sim}}(\Theta) \in \mathbb{R}^K$ the corresponding model-implied moments computed from simulated data generated under Θ. We choose $\hat{\Theta}$ to minimize the weighted quadratic distance

$$\hat{\Theta} \;=\; \arg\min_{\Theta}\; L(\Theta), \qquad L(\Theta) \;\equiv\; \left(m^{\text{sim}}(\Theta) - m^{\text{data}}\right)^\top W \left(m^{\text{sim}}(\Theta) - m^{\text{data}}\right), \tag{19}$$

where W is a diagonal weighting matrix. All moments receive unit weight, except for the pooled U-shape moment $\hat{\beta}_2$, which is assigned a large weight in order to match it closely in the minimization of (19).[31]

[31] Equivalently, this can be viewed as imposing a near-equality constraint on $\hat{\beta}_2$ while fitting the remaining moments in a least-squares sense.

To find $\hat{\Theta}$, we follow Lise (2013) and Lise et al. (2016) in using a Metropolis–Hastings algorithm to explore the parameter space and reduce $L(\Theta)$. Starting from an initial parameter vector Θ_0, we generate N_{chains} independent chains $(\Theta_0, \ldots, \Theta_N)$. At each iteration j, we draw a candidate Θ' from $\mathcal{N}(\Theta_j, \Sigma)$, where Σ is a diagonal scaling matrix proportional to Θ_0. If $L(\Theta') < L(\Theta_j)$, we accept the candidate and set $\Theta_{j+1} = \Theta'$. Otherwise, we accept Θ' with probability $\exp\big(-A(L(\Theta') - L(\Theta_j))\big)$, where A is a tuning parameter chosen to achieve an average acceptance rate of approximately 25–40%, as suggested by Gelman et al. (2003). We select the global minimum across all chains and iterations as our estimate $\hat{\Theta}$. To enforce parameter constraints, we re-parametrize standard deviations in logs to ensure positivity and map rates and probabilities to the unit interval using a logit transform. The optimizer therefore searches over an unconstrained vector, which is then mapped back to economically meaningful parameters Θ before solving and simulating the model. In practice, we estimate $N_{\text{chains}} = 616$ independent chains with length 100 each.

To construct standard errors, we cast the SMM estimator in terms of GMM under standard regularity conditions (see, e.g., Honoré et al., 2020). Under these conditions,

$$\hat{\Theta} \xrightarrow{d} \mathcal{N}(\Theta^*, \Sigma_\Theta),$$

where

$$\Sigma_\Theta = (G'WG)^{-1}G'WSWG(G'WG)^{-1}.$$

Here, S is a diagonal matrix containing the variances of the empirical moments, which we estimate via bootstrap resampling of the underlying worker-level panel data. The matrix G is the $K \times \dim(\Theta)$ Jacobian of the simulated moments with respect to the parameters, $\partial m^{\text{sim}}(\Theta)/\partial\Theta'$, evaluated at $\hat{\Theta}$. We compute G numerically using central finite differences around the estimated parameter vector.

C.3 Additional Estimation Results

Table A.14: Local Sensitivity: Full set of moments

Moment	**Definition**	**Data**	**Baseline**	α	ρ	σ_{A0}
u	$\Pr(E_{it} = 0)$	7.70	7.82	6.62	7.52	7.79
EU	$\Pr(E \to U)$	2.26	5.44	5.18	5.14	5.40
EU+EE	$\Pr(E \to \text{Sep})$	16.02	17.50	17.99	17.33	17.43
$\text{E}[w_t]$	Mean wage	4.74	5.04	4.54	5.00	5.03
$\text{E}[w_t \mid \text{UE}]$	Mean wage UE	4.68	4.85	3.80	4.81	4.85
$\text{SD}(w_t \mid x{>}6)$	SD wages, high exp.	27.53	23.64	39.50	23.30	24.05
$\text{SD}(w_t \mid x{\leq}3)$	SD wages, low exp.	22.63	23.27	51.60	24.30	24.01
$\text{SD}(\Delta w_t \mid \text{stay}, x{\leq}3)$	SD Δw stayers, young	12.11	13.91	39.68	13.53	17.06
$\text{SD}(\Delta w_t \mid \text{stay}, 3{<}x{\leq}6)$	SD Δw stayers, mid	9.51	11.84	25.44	9.02	12.73
$\text{SD}(\Delta w_t \mid \text{move}, x{\leq}3)$	SD Δw movers, young	18.28	15.16	36.85	16.15	18.96
$\text{Corr}(\Delta w_t, \Delta w_{t+1})$	Autocorr. Δw stayers	−1.81	−3.83	−0.75	−4.26	−3.62
$\hat{\beta}_2$	U-shape coefficient	99.83	99.79	−18.74	82.77	77.78

Notes: Each experiment changes one parameter from its estimated value while holding all others fixed. In all three exercises, we change one parameter to the value 0.1 while keeping all other parameters at baseline. Baseline parameters: $\alpha = 0.763$, $\rho = 0.94$, $\sigma_{A0} = 0.061$. All moments are scaled by 100 except $\text{E}[w_t]$, $\text{E}[w_t|\text{UE}]$, and $\text{Corr}(\Delta w_t, \Delta w_{t+1})$ (scaled by 10). See Table 3 for details.