Worker Reallocation and the Wage Cyclicality of New Hires

Dominik Lukač* Andreas I. Mueller† Garyn Tan‡ Josef Zweimüller§

April 2026

Abstract

New hire wages are substantially more procyclical than incumbent wages, a pattern often interpreted as evidence that hiring wages are flexible. This paper examines whether this excess cyclicality reflects within-match wage adjustment or cyclical changes in the composition of firms and matches formed over the cycle. Using matched employer–employee administrative data covering the universe of Austrian private-sector employment from 1976 to 2018, we decompose new hire wage changes using AKM and time-varying AKM firm pay premia. Roughly 80 percent of the cyclicality of new hire wages is accounted for by the firm component: in expansions, workers are hired by higher premium firms, while in recessions this upgrading slows. For job-to-job hires, cyclicality is explained almost entirely by the firm component. For hires from non-employment, controlling for origin-firm selection reduces the remaining residual cyclicality to about 12 percent of the total. We show that the firm component in the micro wage regressions maps directly to the between-firm reallocation term in an aggregate decomposition of firm pay premia. Overall, the high measured cyclicality of new hire wages largely reflects reallocation across firms rather than within-match wage adjustment.

*Yale University, dominik.lukac@yale.edu
†University of Zurich, andreas.mueller@econ.uzh.ch
‡University of Zurich, garyn.tan@econ.uzh.ch
§University of Zurich, josef.zweimueller@econ.uzh.ch

1 Introduction

A long-standing finding in labor economics is that the wages of new hires are substantially more procyclical than the wages of incumbent workers. This gap is central for macroeconomic models because wages in newly formed matches help determine the marginal cost of hiring; if hiring wages adjust flexibly over the business cycle, wage rigidity has limited scope to amplify unemployment fluctuations (Pissarides, 2009). However, the observed procyclicality of new hire wages may reflect not only changes in wages offered within matches, but also cyclical reallocation of workers across firms with different pay premia. Distinguishing between wage adjustment and reallocation is therefore essential for interpreting what the cyclicality of hiring wages implies about wage rigidity.

In this paper, we show that the cyclicality of new hire wages is largely a reallocation phenomenon. Using matched employer–employee administrative data covering the universe of Austrian private-sector employment from 1976 to 2018, we find that most of the cyclicality of wages at hiring is accounted for by movements across firms with different pay premia rather than by within-match wage adjustment. As a result, measured hiring-wage cyclicality primarily reflects cyclical changes in where workers are hired, and therefore is not a direct measure of wage flexibility in newly formed matches.

Our analysis utilises a long panel of matched employer–employee data covering multiple business cycles. We measure wage changes at job start in first differences relative to the worker's last observed wage and estimate their cyclicality with respect to changes in the national unemployment rate. To separate reallocation from other sources of wage variation, we decompose wage changes using the AKM framework of Abowd, Kramarz, and Margolis (1999) and a time-varying extension (TV-AKM) that allows firm pay premia to evolve over time (Lachowska et al., 2023; Engbom, Moser, and Sauermann, 2023). This decomposition separates wage changes at hiring into a firm component, a component due to observables, and a residual component. We then further split the firm and residual components into destination and origin terms. This allows us to distinguish cyclical upgrading at the hiring firm from cyclical selection in the composition of origin firms.

Our main finding is that the firm component dominates the cyclicality of new hire wages. However, the drivers of wage cyclicality differ markedly between E–E and N–E transitions. For E–E transitions, the firm component accounts for nearly all of the observed cyclicality and is primarily attributable to the destination firm: expansions are characterized by stronger upgrading toward higher premium firms, while downturns reflect a collapse in job upgrading. For N–E transitions, the firm component accounts for around 80 percent of total cyclicality. Unlike E–E transitions, the firm component cyclicality is driven primarily by the origin firm, while the destination firm component appears relatively acyclical. We then show that around half of the remaining cyclical variation not attributable to the firm effect is still shaped by selection in the persistent component of the worker's match with the origin firm. Part of the residual cyclicality therefore still reflects reallocation. Once these origin-related components are removed, the remaining transitory cyclicality accounts for only about 12 percent of the total. The results are not driven by top-coding of wages, correlation between firm effects and transitions, estimation error in firm effects, or the choice of controls. Overall, our findings do not imply that within-match wage adjustment is absent, but they show that it accounts for only a limited share of the measured cyclicality of hiring wages in our setting.

We then show that this micro decomposition has a direct aggregate counterpart. Once samples are aligned and appropriate weights are used, the firm premium component in individual wage-change regressions maps directly to the between-firm reallocation term in an aggregate decomposition of changes in the average firm pay premium. This mapping links the wage cyclicality of new hires to the broader literature on cyclical worker reallocation across firms.

Applying this accounting framework, we find that aggregate movements in the average firm pay premium are strongly cyclical and are driven primarily by reallocation across incumbent firms. In downturns, the between-firm reallocation term shifts employment away from higher-paying firms, lowering the aggregate firm premium. Job-to-job reallocation accounts for the larger share of this cyclical movement, consistent with a collapse in upgrading along the firm pay ladder when labor market conditions deteriorate. Flows through non-employment are more nuanced: although hiring from non-employment shifts relatively toward higher premium firms in downturns, separations are disproportionately concentrated in the upper tail of the firm premium distribution, so the overall contribution of the N–E margin to the aggregate firm premium is negative. Overall, these aggregate reallocation patterns closely mirror the micro evidence, reflecting the dominant role of worker reallocation across firms with different pay premia in shaping wage cyclicality.

Our paper relates to several strands of the literature on wage cyclicality and labor market dynamics. A large empirical literature shows that wages of newly hired workers are substantially more procyclical than wages of incumbents, a pattern often interpreted as evidence that hiring wages are relatively flexible (Bils, 1985; Solon, Barsky, and Parker, 1994; Haefke, Sonntag, and van Rens, 2013; Pissarides, 2009). A central concern in this literature, however, is that measured cyclicality at hiring may reflect cyclical composition rather than wage adjustment within matches. Gertler, Huckfeldt, and Trigari (2020) argue that excess cyclicality of new hire wages largely reflects cyclical upgrading in match quality, in particular for hires from employment, and use the contrast in cyclicality between hires from employment and unemployment to infer composition effects. We complement and sharpen this view by using a long panel of linked employer–employee data to explicitly measure composition effects. In our data, most of the cyclicality of wages at hiring is accounted for by the firm component, implying that measured hiring-wage cyclicality primarily reflects where workers are hired rather than flexible wage setting within newly formed matches.

Our results also connect to the literature on cyclical upgrading, job ladders, and worker reallocation across firms. Models with on-the-job search imply that workers move toward better firms in expansions and that this upgrading weakens in downturns. Consistent with this mechanism, Haltiwanger et al. (2018) document a strongly procyclical firm wage ladder in job-to-job transitions, while Haltiwanger et al. (2025) show that the collapse of job-to-job reallocation in downturns lowers aggregate productivity growth. We build on this literature by showing that the same reallocation forces govern the cyclicality of wages at hiring. Using AKM and time-varying AKM decompositions (Abowd, Kramarz, and Margolis, 1999; Lachowska et al., 2023; Engbom, Moser, and Sauermann, 2023), we show that the firm component in micro wage-change regressions maps directly to the between-firm reallocation term in an aggregate decomposition of the average firm pay premium. This establishes a direct link between the wage cyclicality of new hires and the broader literature on cleansing, sullying, and cyclical worker reallocation.

The remainder of the paper is organized as follows. Section 2 describes the data and sample construction. Section 3 presents the wage cyclicality estimates and the AKM/TV-AKM decomposition. Section 4 links the micro decomposition to aggregate reallocation accounting and quantifies the contributions of job-to-job and non-employment flows. Section 5 concludes.

2 Data

Our primary data source is the Austrian Social Security Database (ASSD), a matched employer–employee administrative dataset covering the universe of private-sector employment relationships in Austria since 1972.[1] A detailed description is provided by Zweimüller et al. (2009). The central advantage of the ASSD for our purposes is that it combines long panel coverage spanning multiple business cycles with daily information on labor market state transitions. This structure is essential for identifying wage cyclicality and for measuring labor market transitions across repeated aggregate fluctuations.

The ASSD is constructed from social security records and contains complete spell information for all labor market states relevant for social insurance, including employment and registered unemployment. Employment spells are linked to unique firm identifiers, allowing us to construct a worker–firm panel with precise measures of mobility. For each worker–firm–year observation, the data record annual earnings derived from the social security contribution base, including supplementary payments. We construct daily wages by dividing annual earnings by contribution days and deflate nominal wages using the consumer price index. Earnings are subject to statutory contribution ceilings, implying right-censoring at the top of the distribution. We also assess whether top-coding affects our decomposition results, using administrative tax records, which span a substantially shorter time period (our panel is from 2002 to 2012) but which contain uncensored earnings.

2.1 Sample and variable construction

We restrict the sample to male workers aged 25–59 over the period 1976–2018. Because hours worked are not observed, this restriction is intended to capture a sub-population with high

[1] Observations in the earliest years are known to be less reliable.

full-time attachment and stable labor market participation. We define job-to-job transitions (E–E) as moves directly between employers and transitions from non-employment to employment (N–E) as hires following a spell of registered unemployment or other non-employment. Observations of recall employment (workers returning to the same employer) are excluded. Wage changes for new hires are computed relative to the last observed wage at the origin firm. We measure aggregate labor market conditions with the national unemployment rate.

3 The wage cyclicality of new hires

3.1 Measuring wage cyclicality

We begin by measuring the cyclicality of new hire wages using the standard regression framework introduced by Bils (1985):

$$\begin{aligned}\Delta \ln wage_{it} = \beta_0 + \beta^{UR} \times \Delta UR_t + \sum_m \beta^m \times \mathbb{1}\{Hire^m(it)\} \\ + \sum_m \beta^{m,UR} \times \mathbb{1}\{Hire^m(it)\} \times \Delta UR_t + \mathbf{X}_{it}\gamma + \varepsilon_{it}\end{aligned} \tag{1}$$

where $\Delta \ln wage_{it}$ is the first difference in log real wages for worker i (scaled by 100 for convenience), ΔUR_t is the change in the national unemployment rate, and $\mathbb{1}\{Hire^m(it)\}$ indicates that worker i is newly hired at t through hiring margin m. We distinguish between two margins: job-to-job transitions (m = E–E) and hires from non-employment (m = N–E). A subtle feature of the outcome variable is that $\Delta \ln wage_{it}$ refers to the first difference in *observed* wages. For the vast majority of observations, wages are observed in consecutive years, so the first difference corresponds to the changes between t and $t-1$. For workers who experience non-employment spells longer than twelve months, the difference is calculated relative to the last wage observed at the worker's origin firm. To account for this feature of the data, the regression also includes controls indicating the years since the last wage observation. Other controls include a white collar job indicator and quadratics in age and work experience.[2] We cluster standard errors by year, the same level as the regressor of interest.[3]

The coefficients of interest are β^{UR}, which captures the cyclicality of incumbent workers (stayers), and $\beta^{m,UR}$, which captures the additional cyclicality of wage changes for new hires

[2] We measure age and work experience relative to reference levels equal to their sample means (39 and 16 years respectively)

[3] Because the unemployment rate varies only at the year level, standard errors clustered at the individual-level are inappropriate. As pointed out by Moulton (1986), cross-sectional correlation in regression residuals leads to downward-biased standard errors when clustering is not aligned with the level of variation of the regressor. Intuitively, additional individual observations within a given year provide limited independent information about aggregate shocks. We therefore cluster standard errors by year, which allows for arbitrary cross-individual correlation within years. The rule of thumb is to have a sufficiently large number of clusters; our sample includes 43 year-clusters in the 1976–2018 period.

of type m.

Table 1 reports the estimates. The outcome $\Delta \ln wage_{it}$ is the change in log real wages, scaled by 100, so coefficients can be interpreted as semi-elasticities. Columns (1) and (2) report estimates for the full sample of workers. Column (1) pools all new hires to estimate cyclicality (relative to incumbents) at the hiring margin. The coefficient on ΔUR is small and statistically insignificant, indicating that incumbent wages are not cyclical. In contrast, wages at the hiring margin are strongly procyclical: a one percentage point increase in the unemployment rate is associated with an approximately 1.8 percent decline in wages of new hires relative to incumbents.

Column (2) separates new hires into job-to-job transitions (E–E) and hires from non-employment (N–E). For E–E hires, the additional cyclicality is −1.3, and for N–E hires the corresponding estimate is −1.9. Thus, both margins exhibit substantial procyclicality, although the estimated cyclicality for N–E hires exceeds that for E–E hires by around 50 percent. Columns (3) and (4) repeat these specifications restricting the sample to movers only (these regressions are estimated without a constant). The estimates are quantitatively similar. We focus on the mover-only specifications in the subsequent analysis, as the decomposition of wage changes into firm and other components is defined for workers with observed transitions.

Table 1
Real wage cyclicality

	All workers		Movers	
	(1)	(2)	(3)	(4)
Δ UR	0.134	0.135		
	(0.279)	(0.279)		
Hire $\times\Delta$ UR	-1.771***		-1.609***	
	(0.358)		(0.429)	
E-E $\times\Delta$ UR		-1.261***		-1.048***
		(0.337)		(0.385)
N-E $\times\Delta$ UR		-1.869***		-1.728***
		(0.412)		(0.473)
Hire	0.776***		-0.051	
	(0.129)		(0.240)	
E-E		3.210***		2.828***
		(0.150)		(0.207)
N-E		-1.748***		-2.353***
		(0.144)		(0.260)
N	39,687,922	39,687,922	3,784,559	3,784,559

*Notes: The dependent variable is the first difference in log real wages, multiplied by 100. Columns (1) and (2) use the full sample and include a constant in the regression; Columns (3) and (4) restrict the sample to movers and do not include a constant. All specifications include controls for years since last wage observation, a white-collar indicator and quadratics in age and work experience. Age and work experience are measured relative to reference levels equal to their sample means (39 and 16 years respectively). Standard errors are clustered by year. *** p<0.01, ** p<0.05, * p<0.1.*

3.2 Decomposition framework for wage cyclicality

The estimates in Table 1 confound the wage response with cyclical changes in the composition of matches. To isolate the underlying components, we develop a simple accounting framework that decomposes the cyclicality of new hires' real wages into firm and worker components, using the AKM framework of Abowd, Kramarz, and Margolis (1999):

$$\ln wage_{it} = \alpha_i + \psi_{j(it)t} + \mathbf{X}_{it}\zeta + \varepsilon_{it}. \tag{2}$$

where $j(it)$ is the function assigning worker i at time t to firm j. Under the conventional AKM framework, the firm fixed effect $\psi_{j(it)}$ is constant over time. We also implement a more flexible decomposition à la Lachowska et al. (2023) and Engbom, Moser, and Sauermann (2023), called TV-AKM, which allows for time-varying firm fixed effects. Under TV-AKM, within-firm variation in pay premia is identified by stayers (workers who remain at the same firm). Because the model is estimated on a dense mobility network of stayers and movers, the connected set in the TV-AKM specification remains only slightly smaller than in the conventional AKM framework, preserving broad sample coverage. Our control set $\mathbf{X}_{it}$ includes year dummies, a cubic in age and a cubic in tenure.[4]

The estimated components can then be used to decompose wage changes:

$$\Delta \ln wage_{it} = \Delta\hat{\psi}_{j(it)t} + \Delta\mathbf{X}_{it}\hat{\zeta} + \Delta\hat{\varepsilon}_{it} \tag{3}$$

The worker effect drops out, so wage changes of new hires reflect changes in firm effects, observable characteristics, and the residual. Analogously to Equation 1, we can estimate the cyclicality of each component of $x \in \{\hat{\psi}_{j(it)t}, \mathbf{X}_{it}\hat{\zeta}, \hat{\varepsilon}_{it}\}$:

$$\begin{aligned}\Delta x = \beta_0 + \beta^{UR} \times \Delta UR_t + \sum_m \beta^m \times \mathbb{1}\{Hire^m(it)\} \\ + \sum_m \beta^{m,UR} \times \mathbb{1}\{Hire^m(it)\} \times \Delta UR_t + \epsilon_{it}.\end{aligned} \tag{4}$$

This procedure allows us to attribute the cyclicality of new hire wages to between-firm reallocation, observable characteristics, and residual wage variation. We can further decompose the change in the firm effect into contributions from the destination and origin firms:

$$\begin{aligned}\Delta\psi_{j(it)t} = &\underbrace{(\psi_{j(it)t-1} - \bar{\psi}_{t-1})}_{\text{Destination}} - \underbrace{(\psi_{j(it-1)t-1} - \bar{\psi}_{t-1})}_{\text{Origin}} \\ &+ \underbrace{\psi_{j(it)t} - \psi_{j(it)t-1}}_{\text{Within}}\end{aligned} \tag{5}$$

The first two terms capture reallocation across firms with different pay premia, while the final term captures within-firm changes (zero by construction in the static AKM model). This decomposition allows us to distinguish cyclical wage movements arising from changes in the composition of hiring across firms from those driven by firm-level wage adjustment.

The more flexible TV-AKM specification is particularly useful in our setting. Estimated firm pay premia are highly persistent, with an AR(1) coefficient of 0.88 (see Figure A.5), but they are not constant over time. As a result, static AKM firm effects average over economically relevant variation in firm premia. In a long panel such as ours, allowing firm effects to evolve over time captures this variation directly.[5]

The residual component of wage cyclicality captures all variation not absorbed by firm

[4]Following Card, Heining, and Kline (2013a), we restrict the age profile to be flat at age 45. In the TV-AKM specification, the year dummies are absorbed by the firm-year effects.

[5]Estimating static firm premia over shorter panels limits the extent to which gradual drift in firm premia is averaged over. However, shorter panels do not in general eliminate concerns about time variation in firm premia, for example if firm premia also mean-revert over business-cycle horizons.

effects or observables, including persistent match-specific components as well as transitory shocks. To separate these channels, we further decompose ε_{it} following the standard AKM extension in Card, Heining, and Kline (2013b). The residual can be written as:

$$\varepsilon_{it} = u_{ij(it)} + \phi_{j(it)t} + \gamma_{it} + r_{it} \tag{6}$$

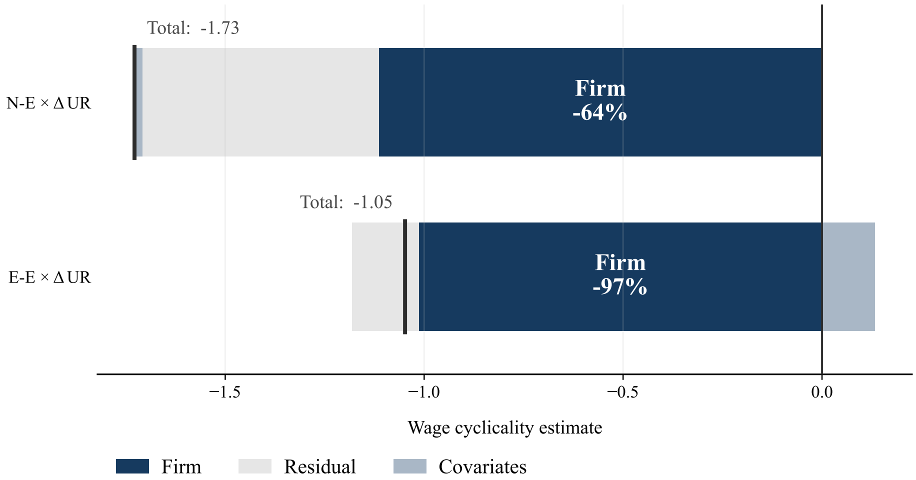
where $u_{ij(it)}$ are (time-invariant) firm-worker match effects, $\phi_{j(it)t}$ are firm shocks and γ_{it} is a unit root capturing drift in the portable component of $i's$ earning power. r_{it} describes remaining transitory shocks. Following Woodcock (2015), we assume $\phi_{j(it)t}, \gamma_{it}, r_{it}$ have zero mean and estimate $u_{ij(it)}$ as follows:

$$\hat{u}_{ij} = \frac{1}{T_{ij}} \sum_{t \in T_{ij}} \hat{\varepsilon}_{ijt}, \tag{7}$$

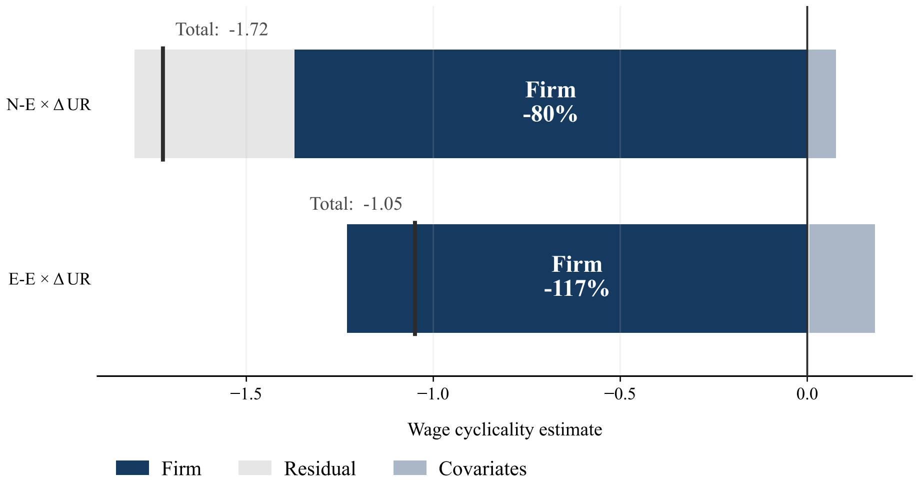
where T_{ij} denotes the duration of match (i, j). Intuitively, $\hat{u}_{ij}$ captures the persistent component of earnings that is specific to the worker–firm pair and not absorbed by worker effects or firm pay premia. In the context of new hires, these match effects capture persistent deviations from firm pay premia at job entry and may reflect firm-specific human capital, contract rigidities, or match productivity. Analogous to the decomposition of firm effects in Equation 5, we estimate the destination and origin components of the match effect.

3.3 Decomposition results

Figure 1 presents the decomposition of the estimated semi-elasticities for E–E and N–E hires under both the AKM and TV-AKM specifications (see Equation 4). The two approaches deliver similar results. For brevity, we mostly focus on the TV-AKM estimates in the discussion below, but highlight differences in the models where relevant. The figure summarises the main magnitudes, while Table 2 reports the full set of regression coefficients. By construction, the semi-elasticities of the firm, covariate, and residual components in Columns (2), (3), and (4) respectively sum to the total wage semi-elasticity reported in Column (1).



(a) AKM



(b) TV-AKM

Figure 1

Wage cyclicality decomposition

Notes: This figure reports the estimated semi-elasticities of wage cyclicality for movers, separately for job-to-job transitions (E–E) and hires from non-employment (N–E). Panel A uses the static AKM decomposition and Panel B uses the TV-AKM decomposition. In each panel, total wage cyclicality of movers is decomposed into the firm, covariate, and residual components as in Equation 4. The underlying regression coefficients are reported in Table 2.

Table 2
Movers' Real Wage Cyclicality Decomposition

		Decomposition		
	Movers (1)	Firm (2)	Covariates (3)	Residual (4)
Panel A: AKM				
E-E $\times \Delta$ UR	-1.048***	-1.013***	0.133	-0.168
	(0.385)	(0.341)	(0.290)	(0.186)
N-E $\times \Delta$ UR	-1.728***	-1.114***	-0.019	-0.594***
	(0.473)	(0.213)	(0.282)	(0.173)
E-E	2.828***	1.964***	-1.079***	1.942***
	(0.207)	(0.117)	(0.172)	(0.146)
N-E	-2.353***	-0.559***	-0.808***	-0.986***
	(0.260)	(0.106)	(0.156)	(0.108)
N	3,784,559	3,784,559	3,784,559	3,784,559
Panel B: TV-AKM				
E-E $\times \Delta$ UR	-1.049***	-1.231***	0.175	0.006
	(0.384)	(0.425)	(0.295)	(0.185)
N-E $\times \Delta$ UR	-1.723***	-1.372***	0.077	-0.427***
	(0.472)	(0.366)	(0.270)	(0.111)
E-E	2.825***	2.775***	-1.860***	1.909***
	(0.207)	(0.181)	(0.206)	(0.111)
N-E	-2.354***	-0.242	-1.535***	-0.577***
	(0.260)	(0.146)	(0.180)	(0.080)
N	3,777,950	3,777,950	3,777,950	3,777,950

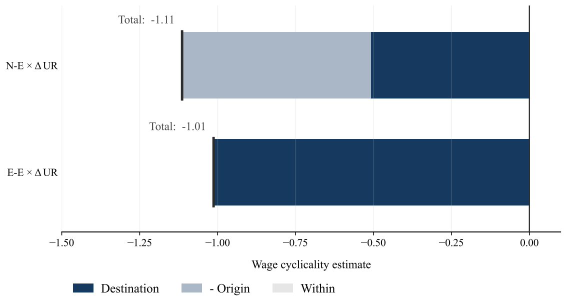
*Notes: This table reports estimates of Equation 4. Column (1) reports total wage cyclicality of movers. Columns (2)–(4) decompose this total into the firm, covariate, and residual components obtained from the AKM and TV-AKM wage decompositions. By construction, the estimates in Columns (2)–(4) sum to the total in Column (1). Standard errors are clustered by year. *** p<0.01, ** p<0.05, * p<0.1*

The figure makes clear that the dominant source of procyclicality operates through the firm effect component. For E–E transitions, the total semi-elasticity is -1.0, driven entirely by differences in firm pay premia (the covariate contribution slightly offsets the overall negative effect). Hence, the procyclicality of E–E wages reflects cyclical upgrading along the firm pay ladder rather than within-match wage adjustment.

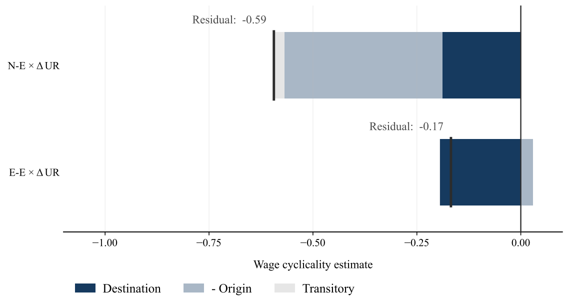
For hires from non-employment (N–E), the estimated total semi-elasticity among movers is -1.7. As illustrated in Figure 1, around 80 percent of this cyclicality is attributable to movements across firms, while the residual accounts for 25 percent (covariates account for 5 percent in the other direction). In contrast, the static AKM estimates attribute only 64 percent to the firm component. This gap suggests that a specification with time-varying firm premia is important for capturing the relevant cyclical variation: relative to static AKM, TV-AKM recovers more of the wage cyclicality associated with movements across firms rather than loading it into the residual.

To understand which parts of the firm and residual components drive these patterns, we next decompose these components into origin and destination terms. For the firm component, this decomposition follows Equation 5 and additionally isolates the within-firm component. For the residual, we first separate it into a persistent firm–worker match effect and a transitory component following Equations 6 and 7.

Panel A: AKM

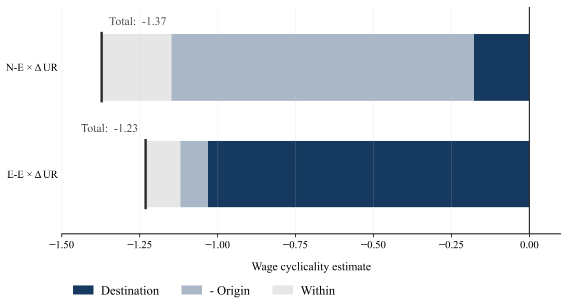


(A) Firm Effects

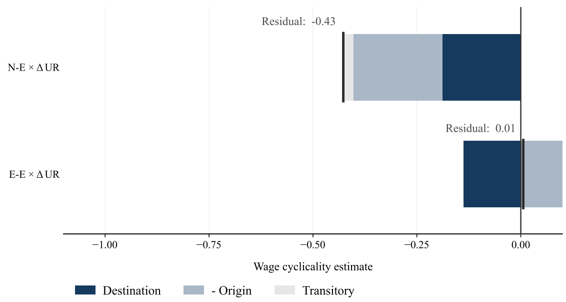


(B) Residuals

Panel B: TV-AKM



(C) Firm Effects



(D) Residuals

Figure 2
Firm and Residual Effects Decomposition

Notes: This figure further decomposes the firm and residual components of wage cyclicality for movers. The left panels decompose the firm effect into destination, origin, and within-firm components. The right panels decompose the residual into destination, origin, and transitory components. Panel A uses the static AKM decomposition and Panel B uses the TV-AKM decomposition. The underlying regression coefficients are reported in Table 3.

Table 3
Firm and Residual Effects Decomposition

	Firm (1)	Decomposition of Firm Effect: Destination (2)	Origin (3)	Within (4)	**Residual** (5)	Decomposition of Residual Effect: Destination (6)	Origin (7)	Transitory (8)
Panel A: AKM								
E-E ×Δ UR	-1.013***	-1.015***	-0.002	—	-0.168	-0.195	-0.029	-0.001
	(0.341)	(0.309)	(0.142)	—	(0.186)	(0.178)	(0.340)	(0.070)
N-E ×Δ UR	-1.114***	-0.508	0.606	—	-0.594***	-0.189	0.380**	-0.026
	(0.213)	(0.444)	(0.569)	—	(0.173)	(0.113)	(0.168)	(0.071)
E-E	1.964***	0.419	-1.546***	—	1.942***	-0.457***	-0.705***	1.694***
	(0.117)	(0.260)	(0.336)	—	(0.146)	(0.115)	(0.084)	(0.060)
N-E	-0.559***	-2.596***	-2.037***	—	-0.986***	-2.374***	0.041	1.429***
	(0.106)	(0.368)	(0.384)	—	(0.108)	(0.131)	(0.131)	(0.046)
N	3,784,559	3,784,559	3,784,559	—	3,784,559	3,784,559	3,784,559	3,784,559
Panel B: TV-AKM								
E-E ×Δ UR	-1.231***	-1.031***	0.089	-0.111	0.006	-0.138	-0.128	0.016
	(0.425)	(0.286)	(0.203)	(0.101)	(0.185)	(0.165)	(0.298)	(0.047)
N-E ×Δ UR	-1.372***	-0.179	0.969	-0.225	-0.427***	-0.188**	0.214	-0.025
	(0.366)	(0.732)	(0.866)	(0.178)	(0.111)	(0.084)	(0.131)	(0.060)
E-E	2.775***	1.151**	-1.401**	0.224***	1.909***	-0.143***	-0.747***	1.305***
	(0.181)	(0.453)	(0.533)	(0.068)	(0.111)	(0.049)	(0.046)	(0.053)
N-E	-0.242	-2.035***	-1.667**	0.126*	-0.577***	-1.710***	-0.231***	0.902***
	(0.146)	(0.613)	(0.629)	(0.073)	(0.080)	(0.060)	(0.057)	(0.042)
N	3,777,950	3,777,950	3,777,950	3,777,950	3,777,950	3,777,950	3,777,950	3,777,950

*Notes: This table reports estimates from the detailed decomposition of movers' wage cyclicality. Columns (2)–(4) decompose the firm component into destination, origin, and within-firm terms. Columns (6)–(8) decompose the residual component into destination, origin, and transitory terms. Panel A uses the static AKM decomposition. In the static model, the Within firm effect is zero by construction. Panel B uses the TV-AKM decomposition. Standard errors are clustered by year. *** p<0.01, ** p<0.05, * p<0.1*

The residual decomposition in Figure 2 shows that accounting for origin-related residual selection further reduces the remaining cyclicality of N–E hires. Under TV-AKM, the residual semi-elasticity falls from −0.43 to −0.21 when the persistent origin component is removed, leaving only the destination and transitory components; under AKM, it declines from −0.59 to −0.21 (Table 3). Relative to total wage cyclicality, this remaining component accounts for only 12 percent under both TV-AKM and AKM.

The relative importance of the origin and destination residual terms also differs sharply by transition type. For N–E hires, both the origin and destination residual contributions are negative, indicating that separations in downturns disproportionately occur from relatively favorable matches and are followed by transitions into worse matches. For E–E transitions, by contrast, the negative destination residual is largely offset by the origin component – in downturns, E–E transitions occur disproportionately to and from lower premia firms – so the net residual contribution is close to zero.

Turning to the firm effect decomposition, we find that the cyclicality of E–E wages is driven almost entirely by the destination firm. Under TV-AKM, the origin and within-firm contributions are relatively small. This pattern is consistent with a procyclical job ladder: during expansions, workers are more likely to move up the ladder via on-the-job search to higher-paying firms, while in downturns this upgrading channel weakens. For N–E hires, the pattern is different. Firm cyclicality is driven mainly by the origin firm rather than the destination firm: in downturns, workers hired from non-employment disproportionately come from higher premium firms. Comparing TV-AKM with static AKM, the decomposition of the firm component differs most clearly for N–E hires. Under TV-AKM, firm-driven cyclicality is concentrated in the origin firm; under static AKM, the destination firm plays a larger role. Thus, allowing firm premia to vary over time shifts the firm-effect decomposition of N–E wages away from destination-firm upgrading and toward origin-firm selection. In Section 4, we examine these compositional effects more comprehensively by analysing worker reallocation across firms at the aggregate level, and providing an explicit mapping between the micro regression results in this section and the broader literature on aggregate reallocation dynamics.

3.3.1 Alternative Specifications and Robustness

This subsection evaluates the robustness of the decomposition results to alternative implementations of the TV-AKM framework. The corresponding estimates are summarised in Figure 3 for both E–E and N–E hires.

Clustered firms. TV-AKM firm effects are estimated with sampling error that increases with the sparsity of the worker–firm mobility graph. While such noise does not bias the cyclicality estimates, it may inflate standard errors and mechanically amplify dispersion in firm premia. To address this concern, we follow Bonhomme, Lamadon, and Manresa (2019) and cluster firms into $k = 10$ synthetic firms using k-means on the distribution of wages. We then re-estimate the decomposition using these clustered firm effects.

The resulting cyclicality estimates are quantitatively very similar to the baseline. In particular, the firm component continues to account for the majority of the procyclicality of movers' wages on both the E–E and N–E margins. This indicates that the baseline results are not driven by noisily estimated firm effects and are robust to a substantially sparser worker–firm graph.

Worker controls. We augment the TV-AKM decomposition with additional controls for worker type (white/blue collar) and quadratic terms in age and labor market experience. Including these controls leaves the qualitative decomposition unchanged. The firm component remains the dominant contributor to wage cyclicality, and the residual component remains modest once origin and destination effects are separated. This suggests that cyclical composition along observable worker dimensions does not drive the main results.

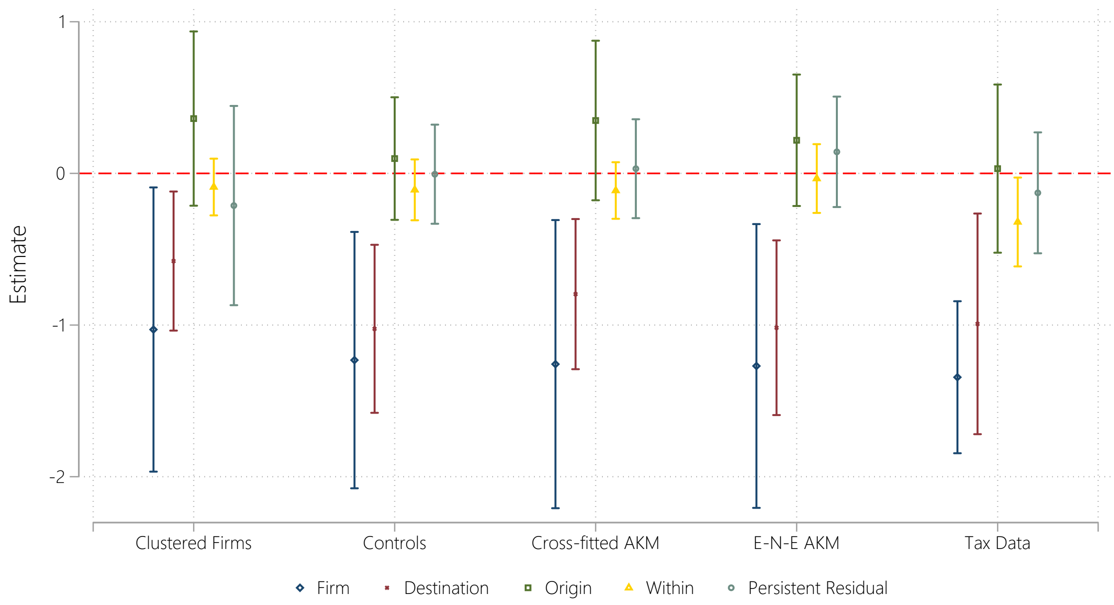
Cross-fitted TV-AKM. A potential concern is that the firm pay premia used in the decomposition are themselves identified from worker mobility. When we decompose movers' wage cyclicality using these estimated firm effects, an individual's wage change may both contribute to the estimation of the firm premium and be explained by it. To address this, we implement a cross-fitted TV-AKM procedure. We randomly assign workers to two separate groups, and estimate separate TV-AKMs. Although the TV-AKM effects are only identified within each group, the expected firm TV-AKM effects are the same due to random assignment. Given this, we normalize both sets such that $\bar{\hat{\psi}}^{k}_{j(it)t} = 0$. Next we assign all individuals from group 1 the estimated firm effects from group 2, and vice versa, i.e. $\hat{\psi}^{-i}_{j(it)t}$. Hence each worker is assigned firm effects estimated from the other group, ensuring that no observation contributes to the estimation of its own firm premium.

The cross-fitted estimates closely track the baseline TV-AKM results. The firm component of wage cyclicality remains strongly procyclical for both E–E and N–E hires. This indicates that the baseline findings are not an artefact of mechanical dependence between mobility and the estimation of firm effects.

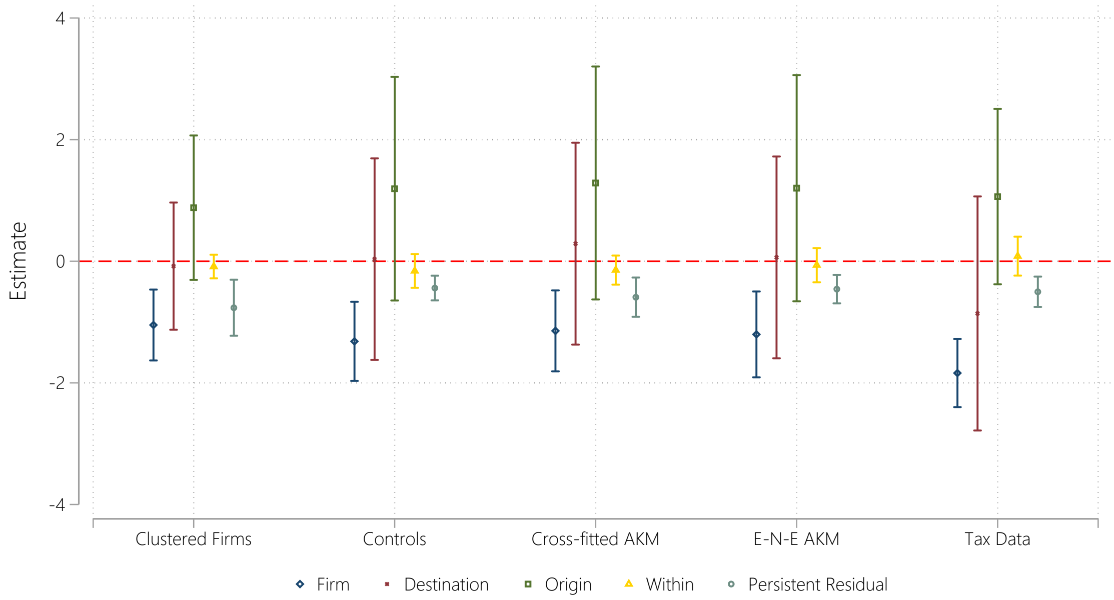
Endogenous mobility Endogenous mobility may bias the estimation of firm effects if match effects are systematically correlated with firm-to-firm transitions. In particular, in a job ladder environment with on-the-job search, E–E moves may reflect selective sorting across firms, inducing correlation between match effects and firm pay premia. To mitigate this concern, we estimate the TV-AKM model excluding E–E transitions.

The decomposition based on this E–N–E TV-AKM specification yields similar conclusions. The firm component remains the primary driver of movers' wage cyclicality. This suggests that endogenous sorting of match effects across firms does not overturn the central result that between-firm reallocation explains most of the observed procyclicality.

Replication with uncensored tax data. The main analysis uses social security records, which have the advantage of being available over a long time horizon (from 1975). The length of this panel is central for identifying wage cyclicality across multiple business cycles. A limitation of the data is that it is subject to censoring at the top of the wage distribution. To verify that censoring does not materially affect the results, we replicate the analysis using tax records covering 2002–2012, which provide exact, uncensored wage information. The estimated decomposition using tax data is quantitatively similar to the baseline. In particular, the firm component continues to account for the majority of the cyclicality of new hire wages. Hence, top-coding does not explain the baseline findings.



(A) $E - E \times \Delta UR$



(B) $N - E \times \Delta UR$

FIGURE 3

TV-AKM DECOMPOSITION OF WAGE CYCLICALITY: ALTERNATIVE SPECIFICATIONS

Notes: This figure reports the TV-AKM decomposition of movers' wage cyclicality under alternative specifications. Panel A shows estimates for job-to-job transitions (E–E) and Panel B shows estimates for hires from non-employment (N–E).

4 Relationship to worker reallocation literature

Section 3 showed that the procyclicality of new hire wages is driven primarily by worker reallocation across firms with different pay premia. This section embeds those micro-level results in the aggregate worker reallocation framework developed in the job creation and destruction literature. We first analyze how changes in the aggregate distribution of employment across firm pay premia evolve over the business cycle, following the aggregate decomposition methodologies of Haltiwanger et al. (2025). We then explicitly link these aggregate reallocation dynamics back to the micro wage regressions in Section 3, showing that these same aggregate reallocation dynamics largely govern the cyclicality of new hire wages.

4.1 Aggregate reallocation framework

We first develop a methodology for decomposing aggregate changes in firm pay premia into reallocation, entry, and exit components through poaching flows and hires out of non-employment. Our approach conceptually follows the decomposition of aggregate productivity in Haltiwanger et al. (2025).[6] Let $\bar{\psi}_t$ be the aggregate firm premium and π_{jt} denote firm j's employment share at time t. The change in $\bar{\psi}_t$ can be decomposed as follows:

$$\begin{aligned}\Delta\bar{\psi}_t = & \overbrace{\underbrace{\overbrace{\sum_{j\in\mathcal{J}_{t-1}\wedge j\in\mathcal{J}_t}(\psi_{jt-1}-\bar{\psi}_{t-1})\Delta\pi_{jt}}^{\text{Between}} + \overbrace{\sum_{j\in\mathcal{J}_{t-1}\wedge j\in\mathcal{J}_t}\Delta\psi_{jt}\Delta\pi_{jt}}^{\text{Cross}}}_{}}^{\text{Reallocation}} \\ & + \underbrace{\sum_{j\notin\mathcal{J}_{t-1}\wedge j\in\mathcal{J}_t}(\psi_{jt}-\bar{\psi}_{t-1})\pi_{jt} - \sum_{j\in\mathcal{J}_{t-1}\wedge j\notin\mathcal{J}_t}(\psi_{jt-1}-\bar{\psi}_{t-1})\pi_{jt-1}}_{\text{Net entry}} \\ \equiv & \ \theta_t^{Between} + \theta_t^{Cross} + \theta_t^{Netentry}\end{aligned} \tag{8}$$

The first two terms make up the reallocation component. The between term captures reallocation of employment shares across incumbent firms with different pay premia and is the key reallocation margin. The cross term captures the covariance between changes in employment shares and changes in firm pay premia among incumbents. It is zero by construction in the static AKM. The net entry term reflects compositional changes at the extensive firm margin (entry and exit).

Following Davis, Haltiwanger, and Schuh (1996), we calculate changes in employment shares using mid-point total employment: $\Delta\pi_{jt} = \frac{n_{jt}-n_{jt-1}}{n_t^{DFH}}$, where $n_t^{DFH} = \frac{1}{2}(N_{t-1}+N_t)$. Employment share changes can be additively decomposed into flow types:

[6] Our aggregate firm premium decomposition is conceptually analogous to the decomposition of aggregate productivity growth from Foster, Haltiwanger, and Krizan (2001), which in turn builds on Baily et al. (1992).

$$\Delta\pi_{jt} = \Delta\pi_{jt}^{poaching} + \Delta\pi_{jt}^{non-employment} + \Delta\pi_{jt}^{recalls} \tag{9}$$

We distinguish between poaching (E–E), non-employment (N–E), and recall flows.[7] For each flow margin, $m \in$ {poaching, non-employment, recalls}, we regress aggregate flows $\Delta\pi_t^m = \sum_j \Delta\pi_{jt}^m$ on the change in the aggregate unemployment rate.[8] Note that while by construction, aggregate poaching flows sum to zero, (i.e. $\sum_j \Delta\pi_{jt}^{poaching} = 0$), their contribution to $\Delta\bar{\psi}_t$ need not be zero.

$$\Delta\pi_t^m = \alpha_\pi^m + \beta_\pi^m \Delta UR_t + \epsilon_t. \tag{10}$$

Using additive separability of employment share changes from Equation 9, we can decompose the contributions of the between, cross, and net entry terms to the change in average firm effect further into channels driven by each hiring margin. For example, for $\theta_t^{Between}$:

$$\begin{aligned}\theta_t^{Between} &= \sum_{j\in\mathcal{J}_{t-1}\wedge j\in\mathcal{J}_t} (\psi_{jt-1} - \bar{\psi}_{t-1})(\Delta\pi_{jt}^{poaching} + \Delta\pi_{jt}^{non-employment} + \Delta\pi_{jt}^{recalls}) \\ &\equiv \theta_t^{Between,poaching} + \theta_t^{Between,non-employment} + \theta_t^{Between,recalls}.\end{aligned} \tag{11}$$

We analogously define the objects θ_t^{Cross} and $\theta_t^{Net\ entry}$. The effects of employment flows can then be mapped to changes in firm-effect components $x \in$ {Between, Cross, Net entry} as follows:

$$\theta_t^{x,m} = \alpha_\theta^{x,m} + \beta_\theta^{x,m} \Delta UR_t + \epsilon_t. \tag{12}$$

To identify cleansing and sullying effects, we partition incumbent firms according to their lagged pay premia. Firms above the median are designated high (H) rank, and firms below the median are designated low (L) rank. Using this partition, the between component in Equation (8) for a particular flow margin can be written as

[7]We refer to these as recall flows because they consist predominantly of recalls, though they may also include a small number of other transitions, such as movements to and from parental leave. We track these separately so that employment changes implied by worker flows exactly match changes in employment levels. Without doing so, approximation error would accumulate over time.

[8]We use a common index m to denote transition margins in both the micro and aggregate analyses, with m = E–E corresponding to poaching flows and m = N–E corresponding to flows from non-employment. While the wage cyclicality literature typically excludes recalls, aggregate reallocation studies rely on firm-level employment changes that do not separately identify them; with individual-level data, we can report recalls explicitly.

$$\begin{aligned}\theta_t^{Between,m} &= \sum_{j\in\mathcal{J}_{t-1}^H} (\psi_{j,t-1} - \bar{\psi}_{t-1})\,\Delta\pi_{jt}^m + \sum_{j\in\mathcal{J}_{t-1}^L} (\psi_{j,t-1} - \bar{\psi}_{t-1})\,\Delta\pi_{jt}^m \\ &\equiv \theta_t^{H,Between,m} + \theta_t^{L,Between,m}\end{aligned} \tag{13}$$

For high rank firms, the corresponding employment flows $\Delta\pi_t^{H,m} \equiv \sum_{j\in\mathcal{J}_{t-1}^H} \Delta\pi_{jt}^m$ summarise whether employment shifts toward or away from high rank firms through flow margin m. The term $\theta_t^{H,Between,m}$ maps these shifts into their contribution to changes in the aggregate firm premium. We estimate the cyclicality of these high and low rank components by running regressions analogous to Equations 10 and 12 separately for $\theta_t^{H,Between,m}$ and $\theta_t^{L,Between,m}$. In the worker reallocation literature, sullying effects during recessions occur primarily through collapse of the job ladder: that is, net poaching flows at high rank firms decline, generating a negative contribution of the between component ($\beta_\pi^{H,Between,E-E} < 0$ and $\beta_\theta^{Between,E-E} < 0$). Cleansing effects, by contrast, arise when separations increase disproportionately at low rank firms, shifting employment relatively towards high rank firms ($\beta_\pi^{L,Between,N-E} < \beta_\pi^{H,Between,N-E}$). In this case, the low rank contribution to the between component is positive ($\beta_\theta^{L,Between,N-E} > 0$). Although the high rank contribution may be negative if high rank firms also contract, cleansing implies that the former dominates the latter, such that $\beta_\theta^{L,Between,N-E} + \beta_\theta^{H,Between,N-E} > 0$.

4.1.1 Results

We start by estimating the cyclical impact of poaching versus non-employment flows on aggregate employment and the average firm pay premia. Table 4 reports the results, where Panel B estimates Equation 10 and Panel A estimates Equation 12. In Table 5, we first separate firms into high and low rank groups, and run analogous regressions to Equations 10 and 12. Below we discuss the results from both Tables on poaching and non-employment flows.

Poaching flows. As shown in Panel B of Table 4, by construction, poaching flows have no effect on aggregate employment. This is because poaching flows are E–E transitions – moves directly from one firm to another. Despite this, poaching flows contribute negatively to the average firm effect when the unemployment rate rises. A one ppt increase in the unemployment rate is associated with a statistically significant 0.0887 ppt decrease in the average firm effect (θ_t). During expansions, net poaching flows are directed toward higher premium firms, raising the average firm effect. In downturns, this channel reverses and net poaching towards higher premium firms slows down. This is shown explicitly in Panel B of Table 5 – net employment due to poaching at high rank firms decreases, mirrored by a commensurate increase at low rank firms. Panel A shows that the average firm premium declines through two distinct channels: workers are disproportionately retained at lower premium firms, and the same workers are missing at higher premium firms relative to the counterfactual. Both effects are statistically significant, although the former channel is quantitatively larger. This pattern corresponds to a "sullying" mechanism: recessions dampen job ladder mobility and depress reallocation toward high-paying firms.

Non-employment flows. As shown in Table 4, non-employment flows also contribute negatively to the aggregate firm premium, although the magnitude is approximately half that of the poaching margin. But this does not imply that during downturns, net flows from non-employment are disproportionately recruited into low rank firms. Table 5 reveals a more nuanced pattern. In downturns, non-employment flows decline at both low- and high rank firms, and more sharply at low rank firms. At first glance, this would appear consistent with cleansing, as the relative employment share of high rank firms increases. However, the aggregate contribution depends on the interaction between employment changes and firm premia. Changes in θ_t weight each employment shift by $(\psi_{j,t-1} - \bar{\psi}_{t-1})$. Although net separations are more prevalent among low rank firms, net separations among high rank firms are concentrated in firms with particularly large premia. Consequently, reductions in employment at very high premium firms dominate the relative shift toward high ranks, generating a negative overall contribution to θ_t.

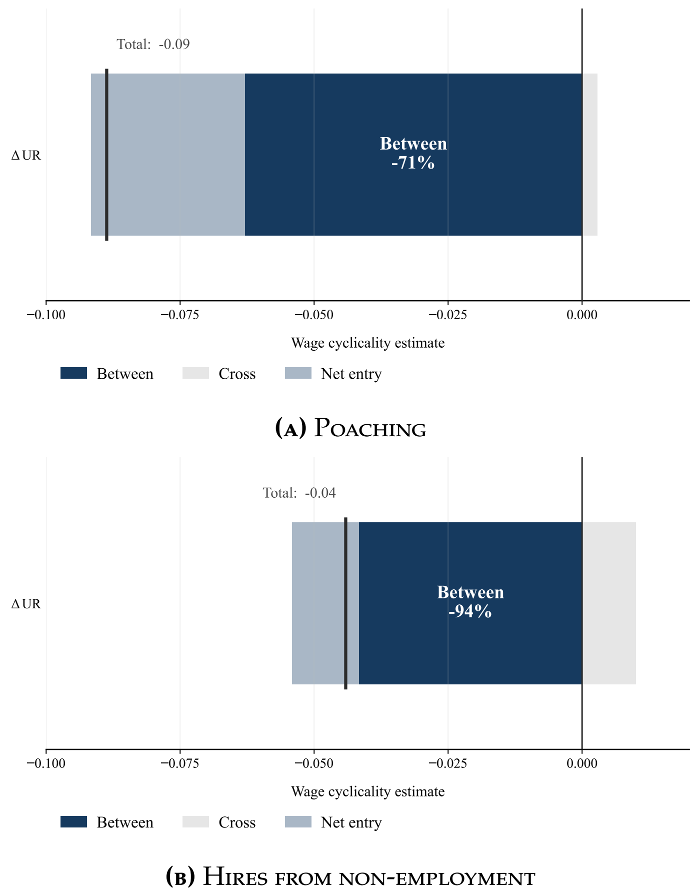
Summary. Taken together, the aggregate reallocation results show that net poaching accounts for 58 percent of the cyclical variation in the aggregate firm pay premium, flows from non-employment account for 29 percent, and recalls contribute only modestly. In downturns, the reallocation component is negative, reflecting shifts in employment shares away from higher premium firms. This pattern is most clearly visible along the poaching margin: when unemployment rises, net job-to-job reallocation toward high premium firms weakens. Non-employment flows exhibit a more nuanced pattern. Although net hires from non-employment decline more at low premium firms, separations are disproportionately concentrated among very high premium firms, so the overall contribution of non-employment flows to the aggregate firm premium is negative.

Table 4

Aggregate worker reallocation

	All	Poaching	Non-employment	Recalls
	(1)	(2)	(3)	(4)
Panel A: Change in reallocation, entry and exit effect				
$\Delta\, UR$	-0.154***	-0.0887***	-0.0441*	-0.0209
	(0.0285)	(0.0249)	(0.0226)	(0.0192)
Panel B: Change in employment				
$\Delta\, UR$	-0.0105***	—	-0.0110***	0.000490
	(0.0039)	—	(0.0022)	(0.0020)

*Notes: Panel A reports the cyclicality of changes in the aggregate firm pay premium. Panel B reports the cyclicality of changes in employment shares, as per Equation 9. Column (1) reports the total across all flow margins, while Columns (2)–(4) decompose this total into poaching, non-employment, and recall flows. Standard errors are clustered by year. *** p<0.01, ** p<0.05, * p<0.1*



(b) Hires from non-employment

Figure 4

Aggregate reallocation by flow margin

Notes: This figure shows the contribution of poaching and hires from non-employment to aggregate reallocation in the average firm pay premium. Panel A reports the poaching margin and Panel B reports the non-employment margin.

Table 5
Worker reallocation and firm rank

	All	Poaching		Non-employment	
		Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)
Panel A: Change in reallocation, entry and exit effect					
$\Delta\, UR$	-0.154***	-0.0535***	-0.0352***	0.0134	-0.0575***
	(0.0285)	(0.0136)	(0.0123)	(0.0119)	(0.0143)
Panel B: Change in employment					
$\Delta\, UR$	-0.0105***	0.00130***	-0.00130***	-0.00636***	-0.00467***
	(0.0039)	(0.0004)	(0.0004)	(0.0012)	(0.0011)

*Notes: This table reports aggregate reallocation regressions after splitting firms into low and high rank firms based on lagged pay premia. Panel A reports the cyclicality of changes in the aggregate firm pay premium. Panel B reports the cyclicality of changes in employment shares. Standard errors are clustered by year. *** p<0.01, ** p<0.05, * p<0.1*

4.2 Linking new hire wage changes to aggregate worker reallocation dynamics

In this subsection, we formally link the firm-effect components estimated in the individual-level wage difference regressions to the between component of the aggregate reallocation regression. We show that once samples are aligned and appropriate weighting is applied, the two specifications estimate the same object.

We begin with the decomposition of firm fixed effects in Equation 5. Summing across all hires on hiring margin m in period t yields:

$$\sum_{i \in m} \Delta \psi_{j(it)t} = \sum_i \underbrace{(\psi_{j(it)t-1} - \bar{\psi}_{t-1})}_{Destination} \mathbb{1}\{Hire^m(it)\} - \sum_i \underbrace{(\psi_{j(it-1)t-1} - \bar{\psi}_{t-1})}_{Origin} \mathbb{1}\{Separation^m(it)\} + \sum_i \underbrace{(\psi_{j(it)t} - \psi_{j(it)t-1})}_{Within} \mathbb{1}\{Hire^m(it)\} \tag{14}$$

Equation 14 expresses the total firm effect contribution to wage changes for hiring margin m as the difference between the premia of destination and origin firms, plus the within-firm change at the destination.

Turning to our aggregate reallocation decompositions, we start with the Between term of Equation 8 and decompose into hires and separations:

$$
\begin{aligned}
\theta_t^{Between} &= \sum_{j \in \mathcal{J}_{t-1} \wedge j \in \mathcal{J}_t} (\psi_{jt-1} - \bar{\psi}_{t-1}) \Delta \pi_{jt}^m \\
&= \sum_{j \in \mathcal{J}_{t-1} \wedge j \in \mathcal{J}_t} (\psi_{jt-1} - \bar{\psi}_{t-1}) \frac{n_{jt}^m - n_{jt-1}^m}{n_t^{DFH}} \\
&= \frac{1}{n_t^{DFH}} \Big(\sum_{i: j(it) \in \mathcal{J}_{t-1} \wedge j(it) \in \mathcal{J}_t} (\psi_{j(it)t-1} - \bar{\psi}_{t-1}) \mathbb{1}\{Hire^m(it)\} - (\psi_{j(it-1)t-1} - \bar{\psi}_{t-1}) \mathbb{1}\{Separation^m(it)\} \Big).
\end{aligned} \tag{15}
$$

Multiplying by n_t^{DFH} and normalizing by the total number of hires of hiring margin m converts into an average firm effect contribution per hire. This places the aggregate object on the same scale as the individual-level difference regression:

$$
\frac{1}{n_t^m} \Big(\sum_{i: j(it) \in \mathcal{J}_{t-1} \wedge j(it) \in \mathcal{J}_t} \underbrace{(\psi_{j(it)t-1} - \bar{\psi}_{t-1})}_{\text{Destination}} \mathbb{1}\{Hire^m(it)\} - \underbrace{(\psi_{j(it-1)t-1} - \bar{\psi}_{t-1})}_{\text{Origin}} \mathbb{1}\{Separation^m(it)\} \Big) \tag{16}
$$

The Destination and Origin components in the expression above are analogous to the Destination and Origin components of the decomposition used in the micro regressions in Equation 14. Equivalence between the regressions requires several further adjustments. First, we estimate the micro regression without the individual-level controls, as they are not observed in the aggregate regression. Second, the aggregate reallocation regressions are estimated at the period level, whereas the difference regressions are estimated at the individual level. To reconcile the two, we weight the aggregate regression by the number of hires in each period and compare with the micro regression without controls. We show equivalence between the micro and aggregate estimators formally in Appendix A. Third, we align the samples. The micro regressions condition on observing wages at both the destination and origin firms, implying that each hire must correspond to a separation. To align the timing of transitions, we restrict both samples to transitions occurring within the same period. This means that in the same period, every hire corresponds to a separation. [9].

Equivalence between the difference wage regressions and the aggregate reallocation regressions is shown in Table 6. Panel A shows cyclicality estimates of the sum of the Destination and Origin components for poaching (E–E) and hires from non-employment (N–E) in the micro wage regression (Equation 1). We start with the benchmark specification, where the poaching and non-employment estimates are equivalent to the sum of the respective E–E and N–E Destination and Origin components in Panel B, Columns (2) and (3) of Table 3. Restricting the regression to no controls and applying the sample restrictions described

[9]We also exclude transitions into entering firms as their change in firm effects is not defined in the micro regression

above make little quantitative difference to the cyclicality estimates. Full regression results for each component can be found in Table A.2 in the Appendix. Panel B shows the cyclicality estimates from the aggregate reallocation regressions on $\theta_t^{\text{Between}}$ (Equation 12). After sequentially applying scaling, weighting, and sample alignment, the aggregate reallocation estimates converge numerically to the micro wage regression coefficients. This confirms that the micro difference specification and the aggregate between regression estimate the same reallocation object under aligned samples and weights.

Table 6

Reconciling micro wage regressions with aggregate between-firm reallocation

	Poaching	Non-employment
Panel A: Micro wage regression		
Benchmark	-1.120***	-1.148***
	(0.361)	(0.238)
+ no controls	-1.130***	-1.018***
	(0.368)	(0.241)
+ sample alignment	-1.130***	-1.117***
	(0.368)	(0.276)
Panel B: Aggregate reallocation regression		
Benchmark	-0.0629***	-0.0416**
	(0.0166)	(0.0187)
+ scaled, re-weighted	-0.883***	-0.577**
	(0.2727)	(0.2259)
+ sample alignment	-1.130***	-1.117***
	(0.3727)	(0.2790)

Notes: This table compares the cyclicality estimates from the micro wage regressions and the aggregate reallocation regressions under progressively aligned specifications. Panel A reports the micro regression estimates, with standard errors clustered at the year level. Panel B reports the aggregate reallocation estimates, with heteroskedasticity-robust standard errors

5 Conclusion

This paper re-examines the cyclicality of new hire wages through the lens of worker reallocation across firms. Using matched employer–employee data for Austria over 1976–2018, we show that the high measured procyclicality of wages at hiring is driven primarily by changes in where workers are hired rather than by within-match wage adjustment. Decomposing wage changes at hiring using AKM and time-varying AKM firm pay premia, we find that the firm component accounts for essentially all of the cyclicality of job-to-job wages and for the large majority of the cyclicality of hires from non-employment.

For hires from non-employment, part of the remaining residual cyclicality also reflects composition. In particular, cyclical shifts in the origin firms from which workers separate generate persistent residual components that move systematically with the cycle. Once these origin-related components are removed, the remaining transitory cyclicality is modest. The evidence therefore points to a common conclusion across both hiring margins: measured new hire wage cyclicality is largely an outcome of cyclical worker reallocation across firms with different pay premia.

We also show that this micro decomposition has a direct aggregate counterpart. After aligning samples and weights, the firm component in the individual wage-change regressions maps directly to the between-firm reallocation term in an aggregate decomposition of changes in the average firm pay premium. This mapping clarifies that the forces driving the wage cyclicality of new hires are the same forces that govern cyclical movements in the distribution of employment across firms. In the aggregate data, downturns shift employment away from higher premium firms, with the largest contribution coming from weaker job-to-job upgrading and a smaller but still negative contribution from flows through non-employment.

Taken together, our results show that the cyclicality of new hire wages is best understood as a reallocation phenomenon. The large measured procyclicality of wages at hiring arises primarily because expansions are periods of stronger upgrading toward higher premium firms, while recessions are periods in which that upgrading weakens and employment shifts away from such firms. This links the wage cyclicality of new hires directly to cyclical worker reallocation across the firm pay distribution, and suggests that measured hiring-wage cyclicality should not be read as a direct measure of within-match wage flexibility.

References

Abowd, John M., Francis Kramarz, and David N. Margolis. 1999. "High Wage Workers and High Wage Firms." *Econometrica* 67 (2):251–334.

Baily, Martin Neil, Charles Hulten, David Campbell, Timothy Bresnahan, and Richard E Caves. 1992. "Productivity dynamics in manufacturing plants." *Brookings papers on economic activity. Microeconomics* 1992:187–267.

Bils, Mark J. 1985. "Real Wages over the Business Cycle: Evidence from Panel Data." *Journal of Political Economy* 93 (4):666–689.

Bonhomme, Stéphane, Thibaut Lamadon, and Elena Manresa. 2019. "A distributional framework for matched employer employee data." *Econometrica* 87 (3):699–739.

Card, David, Jörg Heining, and Patrick Kline. 2013a. "Workplace Heterogeneity and the Rise of West German Wage Inequality*." *The Quarterly Journal of Economics* 128 (3):967–1015.

Card, David, Jörg Heining, and Patrick Kline. 2013b. "Workplace Heterogeneity and the Rise of West German Wage Inequality." *Quarterly Journal of Economics* 128 (3):967–1015.

Davis, Steven J., John Haltiwanger, and Scott Schuh. 1996. "Small Business and Job Creation: Dissecting the Myth and Reassessing the Facts." *Small Business Economics* 8 (4):297–315.

Engbom, Niklas, Christian Moser, and Jan Sauermann. 2023. "Firm pay dynamics." *Journal of Econometrics* 233 (2):396–423.

Foster, Lucia, John C Haltiwanger, and Cornell John Krizan. 2001. "Aggregate productivity growth: Lessons from microeconomic evidence." In *New developments in productivity analysis*. University of Chicago Press, 303–372.

Gertler, Mark, Christopher Huckfeldt, and Antonella Trigari. 2020. "Unemployment Fluctuations, Match Quality, and the Wage Cyclicality of New Hires." *Review of Economic Studies* 87 (4):1876–1914.

Haefke, Christian, Marcus Sonntag, and Thijs van Rens. 2013. "Wage Rigidity and Job Creation." *Journal of Monetary Economics* 60 (8):887–899.

Haltiwanger, John, Henry Hyatt, Erika McEntarfer, and Matthew Staiger. 2025. "Cyclical worker flows: Cleansing vs. sullying." *Review of Economic Dynamics* 55:101252.

Haltiwanger, John C., Henry R. Hyatt, Lisa B. Kahn, and Erika McEntarfer. 2018. "Cyclical Job Ladders by Firm Size and Firm Wage." *American Economic Journal: Macroeconomics* 10 (2):52–85.

Lachowska, Marta, Alexandre Mas, Raffaele Saggio, and Stephen A Woodbury. 2023. "Do firm effects drift? Evidence from Washington administrative data." *Journal of Econometrics* 233 (2):375–395.

Moulton, Brent R. 1986. "Random Group Effects and the Precision of Regression Estimates." *Journal of Econometrics* 32 (3):385–397.

Pissarides, Christopher A. 2009. "The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer?" *Econometrica* 77 (5):1339–1369.

Solon, Gary, Robert Barsky, and Jonathan A Parker. 1994. "Measuring the cyclicality of real wages: how important is composition bias?" *The quarterly journal of economics* 109 (1):1–25.

Woodcock, Simon D. 2015. "Match effects." *Research in Economics* 69 (1):100–121.

Zweimüller, Josef, Rudolf Winter-Ebmer, Rafael Lalive, Andreas Kuhn, Jean-Philippe Wuellrich, Oliver Ruf, and Simon Büchi. 2009. "Austrian Social Security Database." *SSRN Electronic Journal* .

Appendix

A Equivalence between micro and aggregate estimator

For simplicity, assume no control variables and consider a particular hiring margin (we omit the index m throughout). The micro object of interest is the between component of the change in the firm effect. Define the individual contribution to the between component as

$$\Delta\psi^{BW}_{j(it)t} = (\psi_{j(it)t-1} - \bar{\psi}_{t-1})\mathbb{1}\{Hire(it)\} - (\psi_{j(it-1)t-1} - \bar{\psi}_{t-1})\mathbb{1}\{Separation(it)\} \tag{A.1}$$

Following Equation 14, let $\Delta\psi^{BW}_t = \frac{1}{n_t}\sum_i \Delta\psi^{BW}_{j(it)t}$. Note that from Equation 16, $\Delta\psi^{BW}_t = \theta^{Between} \times \frac{n^{DFH}_t}{n_t}$. Since ΔUR_t varies only at the period level, the OLS estimator from the individual-level regression can be written as:

$$\begin{aligned} \hat{\beta}_{\text{micro}} &= \frac{\sum_t \sum_i (\Delta UR_t - \overline{\Delta UR})(\Delta\psi^{BW}_{j(it)t} - \overline{\Delta\psi^{BW}})}{\sum_t \sum_i (\Delta UR_t - \overline{\Delta UR})^2} \\ &= \frac{\sum_t n_t (\Delta UR_t - \overline{\Delta UR})\Delta\psi^{BW}_t}{\sum_t n_t (\Delta UR_t - \overline{\Delta UR})^2} \end{aligned} \tag{A.2}$$

where $\overline{\Delta UR}, \overline{\Delta\psi^{BW}}$ denote grand means over all observations in the micro sample. The simplification of the estimator follows because the treatment variable ΔUR_t varies only with t. Now consider the weighted least squares estimator from the aggregate regression with weights w_t, which can be written as:

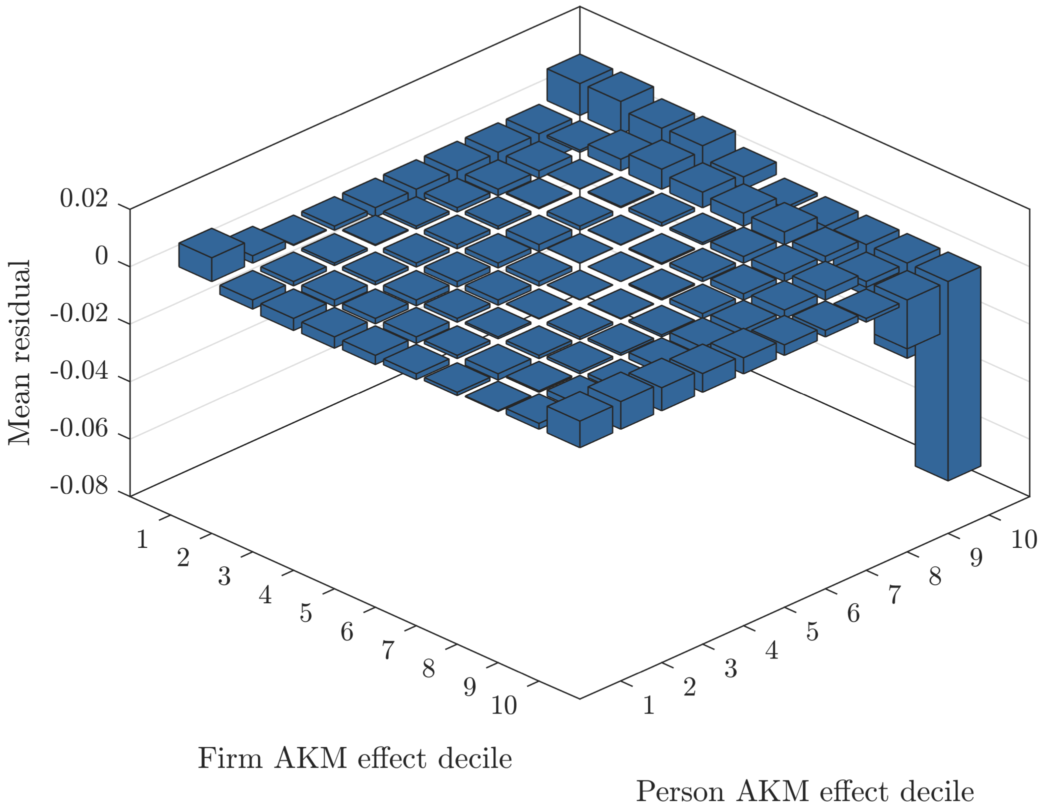
$$\hat{\beta}_{\text{agg}} = \frac{\sum_t w_t (\Delta UR_t - \overline{\Delta UR_w})\Delta\psi^{BW}_t}{\sum_t w_t (\Delta UR_t - \overline{\Delta UR_w})^2}$$

where $\overline{\Delta UR_w}$ is the weighted average of ΔUR_t. With weights $w_t = n_t$, we have $\overline{\Delta UR_w} = \overline{\Delta UR}$, and this becomes:

$$\begin{aligned} \hat{\beta}_{\text{agg}} &= \frac{\sum_t n_t (\Delta UR_t - \overline{\Delta UR})\Delta\psi^{BW}_t}{\sum_t n_t (\Delta UR_t - \overline{\Delta UR})^2} \\ &\equiv \hat{\beta}_{\text{micro}} \end{aligned} \tag{A.3}$$

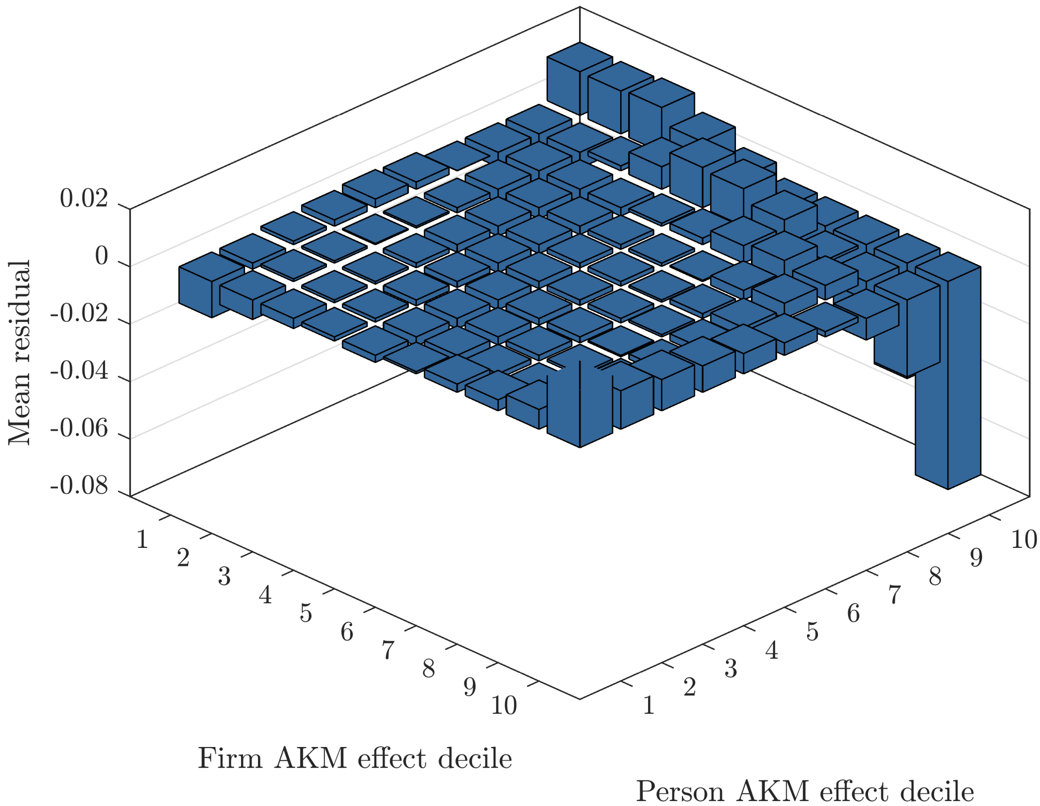
B Additional Figures

FIGURE A.1
AKM RESIDUALS



Notes: This figure plots mean residuals from the static AKM decomposition by worker and firm decile. Residuals are largest in the upper-right cells, reflecting top-coding in the ASSD contribution base.

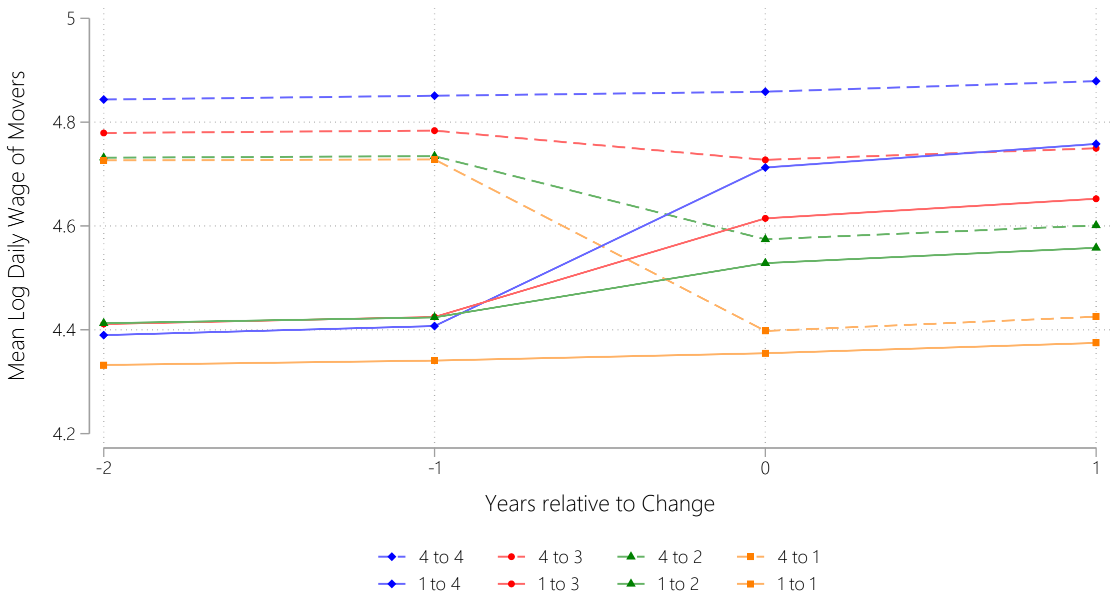
Figure A.2
TV-AKM Residuals



Notes: This figure plots mean residuals from the TV-AKM decomposition by worker and firm decile. Residuals are largest in the upper-right cells, reflecting top-coding in the ASSD contribution base.

Figure A.3
AKM Mover Event Study

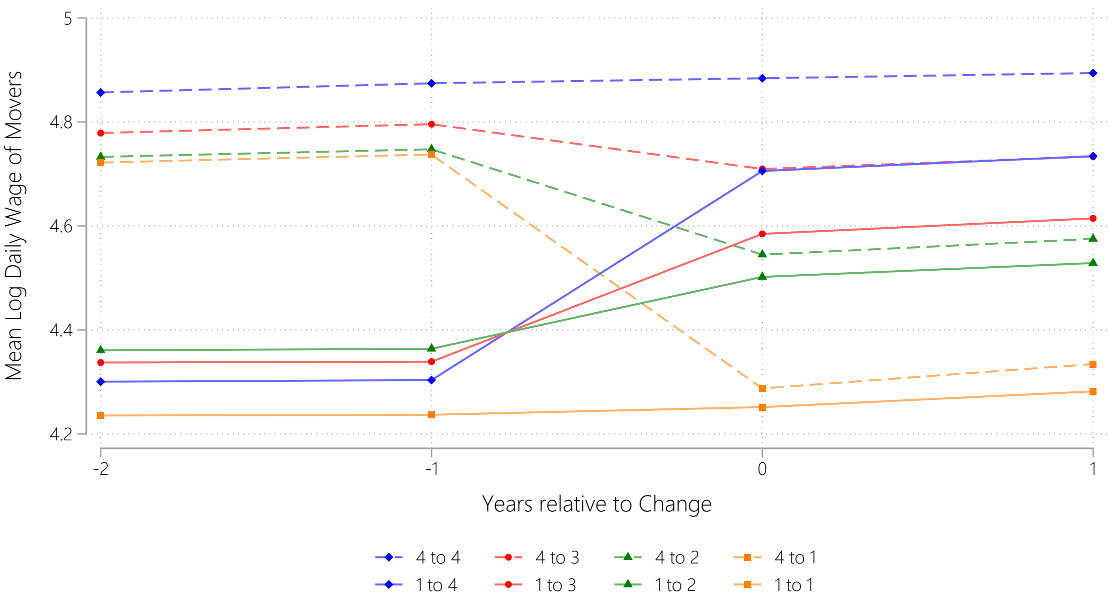
(a) 1976–2018



Notes: This figure reports the mover event study under the static AKM specification. Wage gains and losses around moves are approximately symmetric, consistent with a log-additive wage structure and limited match effects.

Figure A.4
TV-AKM Mover Event Study

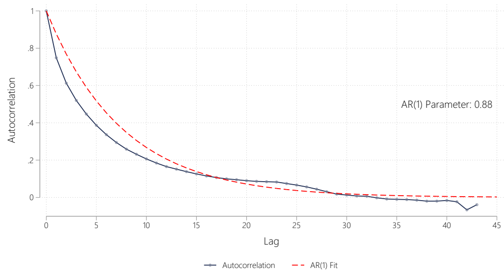
(a) 1976–2018



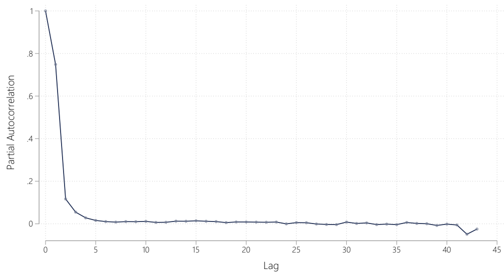
Notes: This figure reports the mover event study under the TV-AKM specification. Wage gains and losses around moves are approximately symmetric, consistent with a log-additive wage structure and limited match effects.

Figure A.5
TV-AKM Autocorrelations

(a) ACF



(b) PACF



Notes: This figure shows empirical autocorrelations and partial autocorrelations of the estimated TV-AKM firm effects. Autocorrelations β_s are computed by estimating $\psi_{jt} = \alpha_j + \beta_s \psi_{jt-s} + \varepsilon_{jts}$, where $t \geq s$. Partial autocorrelations γ are computed by estimating $\psi_{jt} = \alpha_j + \sum_{i=1}^{s} \gamma_s \psi_{jt-i} + \varepsilon_{jts}$, where $t > s$. We include a firm fixed effect α_j in every regression. Both regressions are weighted by average annual employment of firms. We fit an AR(1) parameter to the empirical ACF. Given an AR(1) process $y_t = \delta + \nu y_{t-1} + u_t$, the autocorrelation between y_t and y_{t-1} is $\rho(k) = \nu^k$. The estimate of the autoregressive parameter ν can be obtained by fitting the model $\ln \rho(k) = \beta k + \varepsilon(k)$, where k is the lag order, $\rho(k)$ is the kth-order autocorrelation, and $\varepsilon(k)$ is the regression error term. The estimate of β can be interpreted as an estimate of $\ln \nu$. Coefficients are subject to attenuation bias due to estimation error in the firm effects.

C Additional Tables

Table A.1

Number of transitions. reconciliation with aggregate regression

	Poaching		Non-employment	
	Hires	Separations	Hires	Separations
Benchmark	2,310,822	2,310,822	3,928,366	4,348,689
+ Weighted, scaled	2,310,822	2,310,822	3,928,366	4,348,689
+ Re-hired within one period	2,310,822	2,310,822	2,008,176	2,008,176
+ Balanced panel	1,446,203	1,446,203	1,445,936	1,445,936

Notes: This table reports the number of hires and separations used in the reconciliation exercise, separately for poaching and non-employment transitions. Each row applies progressively tighter sample restrictions to align the aggregate reallocation and micro wage regression samples.

Table A.2

Micro wage decomposition for reconciliation with aggregate regression

	All Workers	Movers	Destination	Origin	Between	Within	Covariates	Persistent	Transitory
Δ UR	0.148								
	(0.287)								
E-E $\times\Delta$ UR	-1.261***	-1.113**	-0.885***	0.245	-1.130***	-0.114	0.133	-0.001	-0.000
	(0.338)	(0.433)	(0.247)	(0.240)	(0.368)	(0.106)	(0.300)	(0.139)	(0.062)
N-E $\times\Delta$ UR	-1.777***	-1.629***	0.163	1.280	-1.117***	-0.174	0.157	-0.500***	0.004
	(0.433)	(0.595)	(0.885)	(0.988)	(0.276)	(0.144)	(0.296)	(0.127)	(0.068)
E-E	4.037***	6.082***	2.015***	-1.406***	3.421***	0.496***	-1.492***	3.175***	0.482***
	(0.178)	(0.203)	(0.113)	(0.148)	(0.198)	(0.061)	(0.190)	(0.073)	(0.039)
N-E	-1.031***	1.014***	-2.563***	-3.152***	0.590***	0.295***	-0.614***	0.285***	0.458***
	(0.189)	(0.251)	(0.413)	(0.476)	(0.108)	(0.072)	(0.178)	(0.059)	(0.040)
N	38,751,622	2,892,139	2,892,139	2,892,139	2,892,139	2,892,139	2,892,139	2,892,139	2,892,139

Notes: This table reports the micro wage decomposition underlying the reconciliation exercise under the TV-AKM specification. The sample is restricted to hires with a corresponding separation, re-hired within the same period, and observed in first differences. The Between effect from this decomposition is summarised in Table 6.