

The Value of Lucky Hires: Match Quality Innovations and Firm Dynamics

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Abstract

Search-and-matching models give the match-specific productivity shock a central role in job creation, job destruction, and worker turnover, but because output is rarely observed at the match level, match quality has been difficult to measure directly. I infer it from worker flows in a matched panel of workers and employers built from LinkedIn profiles (Revelio Labs), 2007 to 2025. A Hidden Markov Model classifies employment spells into seven latent match states based on spell duration, exit outcome, and the worker's employment history. For each spell, I construct a match innovation, the part of the realized outcome that could not have been predicted when the match formed, as an empirical analogue of unexpected match quality, and aggregate these innovations to the firm level. Among Compustat firms, conditional on firm controls, a 10-percentage point shift in match composition from "churning" matches prone to separation toward internal growth tracks predicts 3.9 percentage points higher employment growth, a 1.5 percentage point higher probability of survival, and 4.8 percent higher sales. These effects are comparable to prior estimates for a one standard deviation increase in TFP across U.S. manufacturing establishments, suggesting that match quality is an important source of the firm level shocks that drive growth and survival.

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1 Introduction

In search-and-matching models, match-specific productivity plays a central role in job creation, job destruction, and worker flows (Mortensen and Pissarides, 1994; Burdett and Mortensen, 1998; Moscarini and Postel-Vinay, 2016, e.g.). Often interpreted as the quality of a particular worker-firm pairing, this productivity can evolve over time and governs the value of the match: productive matches are formed and survive, while sufficiently unfavorable realizations lead to separation. Match quality therefore shapes which employment relationships are formed, how long they last, and how they end. Despite its theoretical importance, match quality is difficult to measure directly. It is inherently unobserved, match-level output is rarely recorded, and any candidate proxy is confounded by unobserved worker and firm heterogeneity. In this paper, I construct a residual-based measure of match quality at the job-spell level using a matched worker-employer panel built from LinkedIn profiles and standardized by Revelio Labs. Aggregating this measure to the firm level, I show that firms' exposure to different match quality types has quantitatively important consequences for their subsequent performance: firms with more favorable match quality experience faster employment and sales growth, and are more likely to survive.

I use the term match quality to refer to the match-specific component of a worker-firm pair that shapes how long the spell lasts and how it ends, including, for example, promotion, a move to another employer, or a transition to nonemployment. This component may evolve over time and does not transfer with the worker to a new employer. It is also distinct from firm-level technical efficiency, which raises productivity regardless of whom the firm hires. Conceptually, match quality captures forces such as complementarities between a worker and the incumbent workforce; a worker may be especially productive on a team whose members she works well with. It may also reflect labor-augmenting technology specific to the pair. For example, a salesperson may develop expertise in a particular firm's products that makes her especially effective at selling them.

Existing papers typically proxy for match quality with job duration or wages, on the premise that better matches last longer and pay more (Bowlus, 1995; Mühlbauer and Weber, 2024).¹ While these proxies are informative about underlying match quality, they have two limitations. First, no single match outcome is likely to capture all dimensions of match quality. Second, and more importantly, realized match outcomes also reflect

¹An exception is Jackson (2013), who uses student achievement to estimate the productivity of specific teacher-school pairings separately from persistent teacher and school effects. Defining match quality as the time-invariant productivity of a given pairing, he shows that a sizable share of what would otherwise be attributed to teacher quality is in fact school-specific.

unobserved worker and firm heterogeneity, making it important to distinguish these effects from the match-specific component. Using individual LinkedIn profiles compiled by Revelio Labs, I construct a new measure of match quality that addresses both limitations. The measure combines multiple dimensions of realized match outcomes and nets out the component of these outcomes that was predictable before the match formed.

The Revelio data are particularly well suited for measuring match quality because they provide detailed information on workers' employment histories at the position level. I observe not only transitions across firms, but also the positions they hold within each firm, including job titles, seniority rankings, and the timing of each transition. This allows me to distinguish promotions, lateral moves, and demotions within firms, as well as changes in job rank associated with moves across employers. These detailed career transitions provide multiple signals about how a worker-firm match evolves and ultimately ends, capturing dimensions of the employment relationship that traditional employer-employee records alone cannot provide.

I construct a residual-based measure of match innovation that captures the “surprise” in match outcomes in three steps. Throughout, I use *match quality* to refer to the structural, match-specific productivity of a worker-firm pair, while *match state* refers to the latent classification of realized match outcomes, which may also reflect worker- and firm-specific factors. *Match innovation* refers to the residual component of the match-state distribution after removing the part that is predictable before the match is formed. I interpret the effect of match innovations on firm outcomes, conditional on firm-level observables, as the effect of match quality on firms.

In the first step, I classify each spell outcome into one of seven latent match states using a multichannel Hidden Markov model. I choose the number of states based on the transition dynamics and give them economic meaning by examining the joint distribution of spell duration and transition type, which includes internal promotions, demotions, lateral transfers, movements to higher- or lower-ranking positions at other firms, relocation, transitions into education or nonemployment, and ongoing employment. Each state is characterized by its probabilities of generating these observable outcomes and by its transition probabilities, which describe how workers move between latent states across successive employment spells. Because the model does not use worker demographics, firm characteristics, or wages to define the states, it provides a fixed classification based only on the observed evolution of employment relationships.

The seven states range from short, separation-prone positions to stable jobs with long durations and opportunities for internal advancement. A definitive ranking of the seven states is not always meaningful, since their relative desirability may depend on the out-

come of interest and on the stage of a worker's career. However, separation-prone states are generally yield as less favorable outcomes than states associated with internal growth and stability. I assess the economic content of this classification using wages, which are excluded from the estimation. Entry wages generally rise as states move from temporary, separation-prone positions toward more stable positions with opportunities for internal advancement.

In the second step, I compute, for each position, a posterior probability of belonging to each of the seven states and examine which worker and firm observables predict this classification. Rather than assigning a position to a single state, I retain the full posterior distribution to account for classification uncertainty. I then estimate spell-level regressions relating these posterior probabilities to observable worker and firm characteristics, including workers' age, gender, ethnicity, and educational attainment, as well as firms' size, age, and sector. Observable characteristics predict the classification in intuitive ways. For example, younger workers are more likely to hold shorter-duration, separation-prone positions, while larger and older firms are more likely to offer positions associated with stability and internal growth. These patterns indicate that characteristics observed prior to match formation systematically predict realized match outcomes, motivating the construction of match innovations that net out this predictable component.

In the third step, I construct the match innovation by comparing a position's realized posterior distribution across match states with the distribution predicted using all information available before the current match is formed. I first re-estimate the initial-state and transition equations using a richer set of predetermined worker characteristics, including the worker's employment history and demographic characteristics. These equations generate a predicted distribution across match states for each spell. The residual between the realized and predicted distributions is my measure of match innovation, capturing the component of the match realization left unexplained by systematic differences in expected outcomes across workers. This residualization reduces persistence in match outcomes within an individual by more than 55%, with greater persistence remaining for internal transitions within a firm than for job-to-job moves across employers. This pattern is consistent with internal job transfers carrying more persistent match-specific information.

To assess the quantitative importance of match innovations for firm outcomes, I aggregate spell-level innovations among new hires to the firm level and examine how firms' exposure to different match innovations affects subsequent employment growth and survival. Controlling for firm fixed effects, lagged firm outcomes, and industry-by-time fixed effects, I interpret the remaining relationship between match innovations and subsequent

firm outcomes as reflecting firms' exposure to match quality.

I find that greater exposure to Churning matches—spells lasting less than 15 months that typically end in nonemployment, relocation, or a job-to-job move to a lower-ranking position at another firm—has the largest negative effect on employment growth. By contrast, innovations toward internal-growth states, which represent jobs that are more likely to end in lateral transfers or promotions, have the largest positive effect on employment growth. A 10 percentage point shift in the composition of a firm's new hires from Churning to Maturing Growth matches is associated with a 2.1–2.8 percentage point increase in subsequent employment growth and a 0.25 percentage point increase in the probability of survival. Among Compustat firms, the same shift is associated with a 3.3–4.7 percentage point increase in employment growth, a 0.08–1.4 percentage point increase in survival probability, and 4.7 percent higher sales. The magnitude of the employment-growth effect is comparable to prior estimates of the effect of a one-standard-deviation increase in firm-level TFP among U.S. manufacturing establishments (Blackwood et al. (2021)).

Importantly, the effects of match innovations are not confined to the year immediately following hiring. I trace their effects on employment growth, survival, and sales over the subsequent three years. For many states and outcomes, the effects remain economically meaningful two or three years later and, in some cases, become stronger over time. For example, the positive sales effect associated with shifting 10 percentage points of new hires from Churning to Early Growth matches rises from 4.7 percent in the following year to 9.1 percent three years later. This persistence suggests that the consequences of match quality extend beyond short-run worker turnover or adjustment following a hire. Taken together, the large magnitude and persistence of these effects suggest that match quality is an important source of firm-level productivity heterogeneity.

1.1 Literature

This paper contributes to the firm dynamics literature on the determinants of employment growth and survival. A large empirical literature shows that firm-level fundamentals are central to firms' growth and survival (Syverson, 2011; Sterk et al., 2021; Decker et al., 2020). For example, Blackwood et al. (2021) show that, across alternative measures of firm productivity, a one-standard-deviation increase in TFP is associated with roughly a 4.3–4.7 log-point increase in employment growth and a 1.4 percentage-point decline in the probability of exit. On the theory side, models of persistent firm heterogeneity and time-varying firm-specific shocks use these forces to generate labor adjustment as well as firms' entry and exit decisions (Hopenhayn and Rogerson, 1993; Elsby and Michaels,

2013; Cooper et al., 2007). Yet the underlying sources of the time-varying firm-level heterogeneity that drives these dynamics remain less well understood. I show that firms' exposure to unexpectedly favorable worker-firm matches is one such source: firms with greater exposure to favorable match quality subsequently experience higher employment growth and are more likely to survive.

This paper also contributes to the empirical literature on measuring worker-firm match quality. Because match quality is not directly observed, existing work typically relies on proxies such as wages and job tenure (Bowlus, 1995; van Ours and Vodopivec, 2008; Caliendo et al., 2013; Mühlbauer and Weber, 2024; Koenraadt and Timmermans, 2026), job satisfaction and employer performance evaluations (Ferreira and Taylor, 2011), or measures of skill fit (Cabral Vieira, 2005; Mavromaras et al., 2007). However, as Belot et al. (2024) emphasize, these measures may reflect factors other than match quality and do not always correlate closely with one another, suggesting that they capture different underlying objects of the employment relationship. Rather than selecting a single observed outcome as a proxy for match quality, I infer a latent match state jointly from multiple outcomes over the worker's employment history. Spell duration and the way a spell ends provide complementary signals about the underlying state of the match, allowing otherwise similar employment spells to be distinguished by their transition dynamics.

My empirical approach is related to a growing literature that uses hidden Markov and latent-state models to recover persistent unobserved labor market heterogeneity from workers' employment histories. Shibata (2019) estimates a hidden Markov model in which latent labor market states summarize workers' prior histories and predict subsequent transitions. Ahn et al. (2023) similarly use a hidden Markov model to uncover segments of the U.S. labor market that differ in employment stability, unemployment dynamics, and labor force attachment. More recently, Hong et al. (2026) allow workers' latent wage types to evolve according to a hidden Markov process that depends on the type of firm employing them. I focus on a different latent object: match states of worker-firm pairs at the spell level, rather than latent worker states. Methodologically, I develop a three-step procedure that uses the model's transition structure to separate the unexpected component of a realized match state from the predictable part using information available before the match is formed.

2 Data

The primary data sources are the Individual Profile Data and Company References from Revelio Labs. Revelio aggregates and standardizes information from LinkedIn professional profiles on a weekly basis, and has become increasingly used in academic research in recent years ((Bloom et al., 2026; Chang et al., 2026; Gulati et al., 2026; Hampole et al., 2025). The resume data provides detailed information on workers' current and historical employment positions, educational backgrounds, skills, and demographic characteristics. The data allow us to directly observe firm-to-firm transitions, internal moves and promotions within firms, as well as the timing of each position change. Employers are assigned persistent identifiers, which allow employment positions to be linked across workers and over time and enable us to construct longitudinal worker–firm employment histories as well as firm-level workforce panels.

Definition of firms. Revelio provides an employer identifier, *ultimate_parent_rcid*, which links related employer entities to their ultimate parent company. This definition more closely corresponds to the enterprise-level concept of a firm in the firm-dynamics literature and may combine multiple subsidiaries, operating units, or establishments located in different geographic areas under common ownership. We aggregate employment histories across all constituent *rcids* belonging to the same ultimate parent when constructing firm-level measures of employment, hiring, separations, growth, and survival.

Constructing worker–firm–position spells. The unit of analysis is the *worker–firm employment spell*, defined as a contiguous period during which a worker remains employed at the same firm without changing positions. Each reported employment spell is expanded into monthly observations, with a single primary position retained for each worker-month. When a worker holds multiple positions simultaneously, priority is given to a position with the same ultimate-parent employer (*ultimate_parent_rcid*) as in the preceding month to preserve employment continuity. If no such position exists, the overlapping position with the highest reported pay is retained. Finally, months that overlap with an education spell are classified as internships rather than regular employment.

Estimation Sample. The data contain a snapshot of LinkedIn profiles as of April 2026. The estimation sample spans 2007–2025, a period over which Revelio provides broad coverage of the U.S. labor market. The following restrictions are applied to construct the

estimation sample. First, I exclude positions that ended before January 2007, as Revelio’s coverage of historical employment records improves substantially thereafter. Second, I retain workers with at least one year of education history after age 16, where age is inferred from the reported education records.² Third, I keep workers with at least three employment spells, where a new spell may reflect either a change in position within the same firm or a job-to-job move. Requiring at least three spells provides sufficient within-worker employment dynamics for estimation. For computational purposes, I cap the number of employment spells per worker at 20; more than 99.5% of individuals have 20 or fewer spells during the estimation sample. After imposing these restrictions, our baseline sample contains 22,874,918 workers, 3,896,164 unique firms, and 113,560,440 worker–firm matches.

Revelio provides broad coverage of the professional labor market. Appendix Tables 8–11 report the number and share of unique workers and employers by sector at an annual frequency and compare them with the corresponding statistics from the Quarterly Census of Employment and Wages (QCEW). Coverage of individual employment positions is broad across sectors and relatively stable over time, while gradually improving over the sample period as online professional networking becomes more widespread. Because the data are constructed from online professional profiles, representation is stronger among more-educated workers and those in professional occupations, such as managers and other professional workers, while lower-wage, less-educated, and informal workers are less well represented. Across industries, information and professional services, financial services, and education are relatively overrepresented. Larger and more established firms are also better represented than younger and smaller firms, as documented in Chang et al. (2026).

Comparisons with independent data sources suggest that Revelio-based employment measures are informative about both aggregate and firm-level labor market dynamics. Hampole et al. (2025), for example, compare firm employment measured in Revelio with employment reported in Compustat and find correlations of 0.76 in employment levels and 0.56 in five-year employment growth. Appendix Table ?? provides an additional validation at the aggregate level by comparing hiring and separation rates constructed from Revelio with the corresponding series from the Job Openings and Labor Turnover Survey (JOLTS). The employment histories are also self-reported and may be updated retrospectively, so some short employment spells or periods of nonemployment may be

²I exclude all workers without education records since education is used both to infer workers’ ages and to distinguish employment gaps associated with education from periods of nonemployment. In addition, I exclude workers with a single education spell lasting more than 10 years, as such records are more likely to reflect profiles that have not been updated.

less completely recorded.

2.1 Measurement of spell transition types

A unique feature of the dataset is that it allows worker movements up and down the job ladder to be measured during both job-to-job transitions and internal transfers. A move to a higher-seniority position within a worker's employment history is interpreted as an improvement in the worker-firm match. These career movements therefore provide information about whether the match-specific component of the worker-firm relationship improves or deteriorates over time. The analysis first introduces the concept of a seniority ladder, which is central to the classification of career progression, and then describes how movements along this ladder are measured.

Seniority ladder. I use Revelio Labs' seniority variable to infer whether an individual is advancing in their career when they experience position change. Revelio Labs constructs an ordinal seniority metric for each position using three inputs: (1) job title, employer, and industry; (2) the individual's employment history, including prior positions and their associated seniority levels; and (3) the individual's age. These three measures are averaged and benchmarked against the population distribution to produce a metric comprising seven levels, ranging from 1 (entry level) to 7 (senior executive).³

This seniority ladder, defined over a worker's relative hierarchical position across all positions, is conceptually distinct from the firm-level job ladder studied in the literature. The firm job ladder describes the tendency of workers to move toward more productive and higher-paying firms (Burdett and Mortensen, 1998; Moscarini and Postel-Vinay, 2012, 2016). Under the firm-ladder definition, all positions within the same employer occupy the same rung. However, workers at the same firm can hold positions at very different seniority levels depending on their roles and responsibilities, generating meaningful within-firm variation in match quality.

Classification of spell transition types. I classify the spell transition types into one of the nine categories described below:

³The seven seniority levels are: (1) Entry Level (e.g., Accounting Intern; Software Engineer Trainee; Paralegal); (2) Junior Level (e.g., Accounts Receivable Bookkeeper; Junior Software QA Engineer; Legal Adviser); (3) Associate Level (e.g., Senior Tax Accountant; Lead Electrical Engineer; Attorney); (4) Manager Level (e.g., Account Manager; Superintendent Engineer; Lead Lawyer); (5) Director Level (e.g., Chief of Accountants; VP of Network Engineering; Head of Legal); (6) Executive Level (e.g., Managing Director, Treasury; Director of Engineering, Backend Systems; Attorney, Partner); (7) Senior Executive Level (e.g., CFO; COO; CEO). For the full methodology, see <https://www.data-dictionary.reveliolabs.com/methodology.html#seniority>.

Within-firm transitions.

1. *Downgrade*: an internal move to a lower-seniority position within the same firm.
2. *Lateral transfer*: an internal move to a position at the same seniority level within the same firm.
3. *Upgrade*: an internal move to a higher-seniority position within the same firm.

Across-firm transitions.

4. *Pull separation*: a move to a different firm at a higher seniority level.
5. *Push separation*: a move to a different firm at the same or a lower seniority level.
6. *Relocation*: a move to a different firm that also involves a move to a different geographic area.⁴ Relocations are classified separately from push and pull separations because they may reflect changes in preferences or other personal constraints that are less directly related to match quality.

Other outcomes.

7. *Transition to education*: the worker's next recorded activity is enrollment in an educational program. Note that this includes part-time employment overlapping with education.
8. *Transition to nonemployment*: the worker separates from the firm and does not record a subsequent position or educational enrollment within the observation window.⁵
9. *Ongoing*: the position has not ended as of the last data update.

Section 8.3 describes more details about the classification and 8.1 in the Appendix reports the descriptive statistics for the estimation sample.

⁴Geographic areas are defined using the BLS combined MSA classification.

⁵The spell-level share of transitions into nonemployment should not be interpreted as a layoff or discharge rate measured at a regular frequency. The former is defined over completed employment spells, with all observed job spells in the sample period serving as the denominator, whereas the latter is typically measured as the fraction of involuntary separations occurring within a given period. Transitions into nonemployment may be measured with some upward bias because workers may be less likely to report short-duration, part-time, or lower-ranking jobs on their profiles. However, such omitted transitions are also likely to reflect relatively undesirable post-separation outcomes and therefore still contain information consistent with low match quality at the previous employer. Grouping these cases with true transitions into nonemployment is thus consistent with the interpretation of this outcome as signaling a relatively poor prior match.

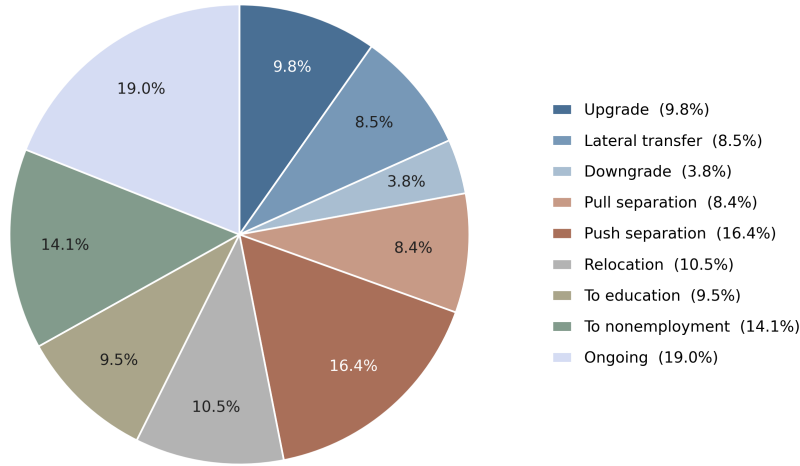


Figure 1: Distribution of Spell Transition Types

Note: The figure shows the distribution of spell transition types across the full eligible sample of workers with at least three spells. Shares are calculated over 113,560,440 spells with nonmissing exit types, including ongoing spells. Upgrade, lateral transfer, and downgrade denote transitions within the same employer.

3 Classification of Match Outcomes

In this section, I estimate a multichannel latent Markov model to recover a discrete latent match state for each position in a worker’s employment history. The model captures the idea that unobserved latent match state is persistent but can evolve over a worker’s employment history, and is only imperfectly observed through outcomes such as employment duration and exit type. This structure is analogous to a discrete state-space model, in which the latent-state transition process plays the role of the state equation and the emission process plays the role of the measurement equation. The latent state is allowed to vary within a worker–firm pair, as changes in positions within the same firm may signal changes in the underlying match state.

The primary purpose of this step is classification: selecting the number of latent states and characterizing the distinct types of worker–firm matches that they represent. I deliberately limit the covariates at this stage to construct a fixed definition of latent match states based only on employment outcomes and career dynamics, rather than worker’s demographic characteristics.

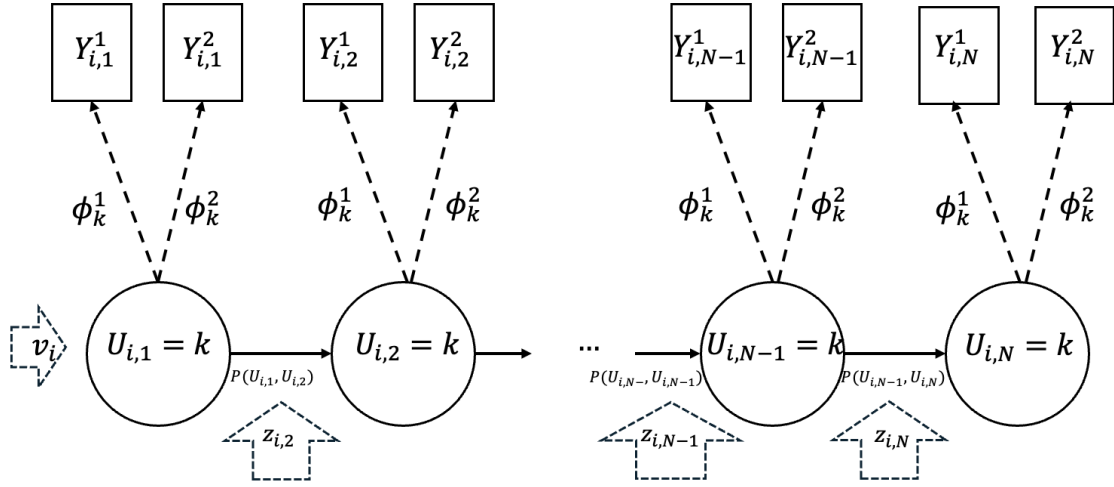


Figure 2: Latent Markov Model Structure

Note: This figure illustrates the structure of the model. $U_{i,n}$ denotes the latent match state for worker i in position n , while $Y_{i,n}^m$ denotes emission m observed for worker i in position n . The parameter ϕ_k^m denotes the emission probability for outcome m conditional on latent state k . The term $P(U_{i,n+1} | U_{i,n})$ denotes the transition probability between latent states across consecutive positions. The covariate v_i enters the initial-state distribution and corresponds to the worker's birth cohort, while $z_{i,n}$ enters the transition probabilities and captures the nonemployment gap preceding the new position.

3.1 A Multi-channel Hidden Markov Model

I model latent match outcomes at the position level as a first-order Markov process. The economic interpretation of this assumption is that, conditional on the current latent state and observed characteristics of the transition between spells, earlier match states contain no additional information about the state of the subsequent match. Thus, the current state serves as a parsimonious summary of past employment history that are relevant for future match formation. The first-order Markov structure allows the latent match states to feature persistence and history dependence while keeping the worker's employment history tractable.

Figure 2 illustrates the structure of the model. Time is discrete. Let $n = 1, 2, \dots, N$ index the worker's employment positions in chronological order, where the number of observed spells N_i may vary across workers. Let $U_n \in 1, 2, \dots, K$ denote the latent match state associated with spell n . To simplify notation, I suppress the worker index i throughout this subsection unless it is needed for clarity.

Initial State Distribution. At the first observed position for each worker, the worker is assigned to latent match state k with probability $P(U_{i,1} = k | v_i)$, where v_i denotes the

birth cohort of individual i . I allow the initial distribution of latent match states to vary by birth cohort because the first observed positions of workers in earlier cohorts typically occur in mid-career, whereas those of workers in later cohorts are more likely to represent their first jobs.⁶ I parameterize the initial-state probabilities using a multinomial logit model with birth-cohort indicators.

Transition Probabilities. After the initial spell, the latent match state evolves across successive employment spells. I allow the transition probabilities between latent match states to depend on workers' nonemployment gap preceding each spell. For each spell, a worker transitions from match state $U_{i,n}$ to $U_{i,n+1}$ with probability $P(U_{i,n} = k' \mid U_{i,n-1} = k, z_{i,n})$, where z_n represents the length and nature of the nonemployment gap.⁷ The transition probabilities are parameterized using multinomial logit models, allowing the probability of moving from each originating state to any destination state to vary by nonemployment-gap category.

Emission Probabilities. The emission model describes probability of observing outcome y^m in emission channel m when the underlying match is in latent state k . I consider two emission channels: first, spell duration Y^1 , which takes four values: 1–6 months, 7–15 months, 16–36 months, 37 or more months; second, job exit type Y^2 : takes nine values: downgrade, equal-level internal transfer, upgrade, transition to education, transition to nonemployment, pull separation, push separation, relocation, and ongoing employment. If a worker is in match state k for position n , then the probability of observing outcome y in emission channel m when the underlying match is in latent state k is $\phi_k^m(y^m) = P(Y^m = y^m \mid U_n = k)$.

The latent match states are assumed to capture all systematic dependence between spell duration and exit type, as well as the persistence in observed outcomes across positions. Importantly, the latent states capture not only match-specific characteristics but also worker- and firm-specific characteristics that contribute to explaining the dynamics of spell duration and exit type. For example, if a worker's demographic characteristics make the worker systematically more likely to remain employed in stable matches, this tendency will also be reflected in the latent states.

Conditional on the latent-state sequence $\mathbf{U}_i$, the remaining variation in observed out-

⁶ $\mathbf{v}_i$ contains indicators for eleven birth cohorts: pre-1982, for whom the first job likely occurred before the start of the sample period; 1982–1984; and subsequent three-year cohorts through 2006–2008. An additional category is included for workers with missing birth-year information.

⁷There are four categories for nonemployment gap: no gap, a short gap of one to six months, a long gap of seven or more months spent enrolled in school, or a long gap of seven or more months out of both work and school.

comes is assumed to be idiosyncratic and independent across positions. Specifically, the observed response vectors $\mathbf{Y}_{i,1}, \dots, \mathbf{Y}_{i,N}$ are assumed to be independent conditional on $\mathbf{U}_i$. Within each position, the two emission channels are further assumed to be independent conditional on the current latent state $U_{i,n}$.

Likelihood and Estimation. The model has four sets of parameters: $\Gamma = \{P(v), Q(z), \Phi^1, \Phi^2\}$. P_v is a $1 \times K$ vector giving the initial distribution over latent match states for birth cohort v , and Q_z is a $K \times K$ transition matrix associated with nonemployment gap category z . The matrices Φ^1 and Φ^2 contain the emission probabilities for spell duration and job exit type, respectively, with dimensions $4 \times K$ and $9 \times K$.

Given the model parameters Γ , the likelihood of observing individual i 's employment history ($\mathbf{Y}_i$) is

$$\begin{aligned} P(\mathbf{Y}_i \mid v_i, \mathbf{z}_i; \Gamma) &= \sum_{\mathbf{k} \in \{1, \dots, K\}^{N_i}} P(U_{i,1} = k_1 \mid v_i) \prod_{n=2}^{N_i} P(U_{i,n} = k_n \mid U_{i,n-1} = k_{n-1}, z_{i,n}) \\ &\quad \times \prod_{n=1}^{N_i} P(Y_{i,n}^1 \mid U_{i,n} = k_n) P(Y_{i,n}^2 \mid U_{i,n} = k_n) \\ &= \sum_{\mathbf{k} \in \{1, \dots, K\}^{N_i}} P_{v_i}(k_1) \prod_{n=2}^{N_i} Q_{z_{i,n}}(k_{n-1}, k_n) \prod_{n=1}^{N_i} \phi_{k_n}^1(Y_{i,n}^1) \phi_{k_n}^2(Y_{i,n}^2). \end{aligned} \quad (1)$$

where the summations integrate over all (K^N) possible sequences of latent match states. The first term gives the probability of the initial latent state, the second captures transitions between latent states across successive positions, and the third gives the probability of the observed duration and exit outcomes conditional on each latent state. The likelihood of simultaneously observing labor history of all the individuals $\{\mathbf{Y}_i\}_{i \in I}$ can be written as

$$\mathcal{L}(\Gamma) = \sum_{i=1}^I \log P(\mathbf{Y}_i \mid v_i, \mathbf{z}_i; \Gamma). \quad (2)$$

The model is estimated by maximizing the sample log-likelihood using a random sample of one million workers. I use the LMest package in R, which implements maximum likelihood estimation through the expectation-maximization (EM) algorithm. The EM algorithm alternates between computing posterior probabilities of latent states and transitions given the observed employment histories (E-step) and updating the model parameters to maximize the expected complete-data log-likelihood (M-step). I use five in-

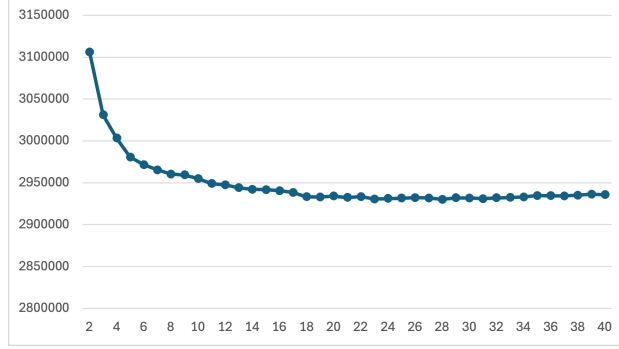


Figure 3: Bayesian Information Criterion

Notes: The figure reports the Bayesian Information Criterion (BIC) for latent Markov models estimated with $K \in [2, 40]$.

dependent random initializations and use the estimates with the highest log-likelihood. Appendix 9.0.1 provides further details on the estimation procedure.

3.2 Number of Latent States and Model Selection

I choose the number of latent states to balance statistical fit with the ability to distinguish stable and economically meaningful patterns in employment outcomes. Increasing the number of states mechanically allows the model to fit the data more closely, but additional states may capture small distinctions only available in the sample data and make the resulting classification more difficult to interpret.⁸ I select $K = 7$ based on four considerations: information criteria, out-of-sample fit, the similarity of transition patterns across states, and the stability and economic interpretation of the estimated states.

- *Information criteria.* We estimate models with $K = 2, \dots, 40$ latent states and compare the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Figure 3 reports the BIC, while Appendix Figure 12 reports the AIC. The BIC reaches its global minimum at $K = 28$, while the AIC continues to decline through $K = 40$. However, most of the improvement in fit occurs at relatively small values of K , and both criteria flatten substantially after $K = 5$. Relative to the BIC improvement attainable at its minimum, $K = 7$ already captures approximately 83% of the total reduction in BIC.

⁸Theorem 6 in Allman et al. (2009) provides a generic identifiability bound on the number of latent states as a function of the number of observable response combinations and repeated observations. In our setting, the implied upper bound exceeds four million latent states and is therefore non-binding for the values of K considered here.

- *Out-of-sample fit.* We evaluate predictive performance on a separate sample of 100,000 workers. Table 14 reports the average log-likelihood per worker in the training and validation samples for selected values of K . Out-of-sample fit improves as the number of states increases, indicating that the additional states capture some genuine structure in the data rather than over-fitting to small features in the training sample. However, the improvement as K increases is very modest.
- *Separation of the transition dynamics.* With $K = 7$, the estimated transition matrices are full rank and well behaved numerically. As K increases, the transition matrices remain formally full rank but become increasingly close to singular, with several columns becoming nearly linearly dependent. This pattern indicates that some of the additional latent states have very similar transition dynamics and therefore provide limited additional distinction in workers' employment histories.
- *Parameter stability and economic interpretation.* Finally, we compare the estimated emission and transition probabilities across independently drawn samples. With larger values of K , the estimated parameters become increasingly sensitive to the sample used for estimation: states that appear in one sample do not always have a clear counterpart with similar emission and transition patterns in another. In contrast, the $K = 7$ specification produces stable parameter estimates across samples and yields a consistent set of latent states with distinct and economically interpretable employment-outcome patterns.

Taken together, larger models provide modest improvements in statistical fit, but these gains come primarily from splitting the seven broader states into more weakly differentiated clusters. The seven-state model captures most of the improvement in fit while producing transition dynamics and emission patterns that are stable across samples and readily interpretable economically.

3.3 Classification of latent match states

In this section, I characterize the seven latent match states that capture different stages of the employment trajectory, and describe their emission profiles and transition dynamics associated with each latent state

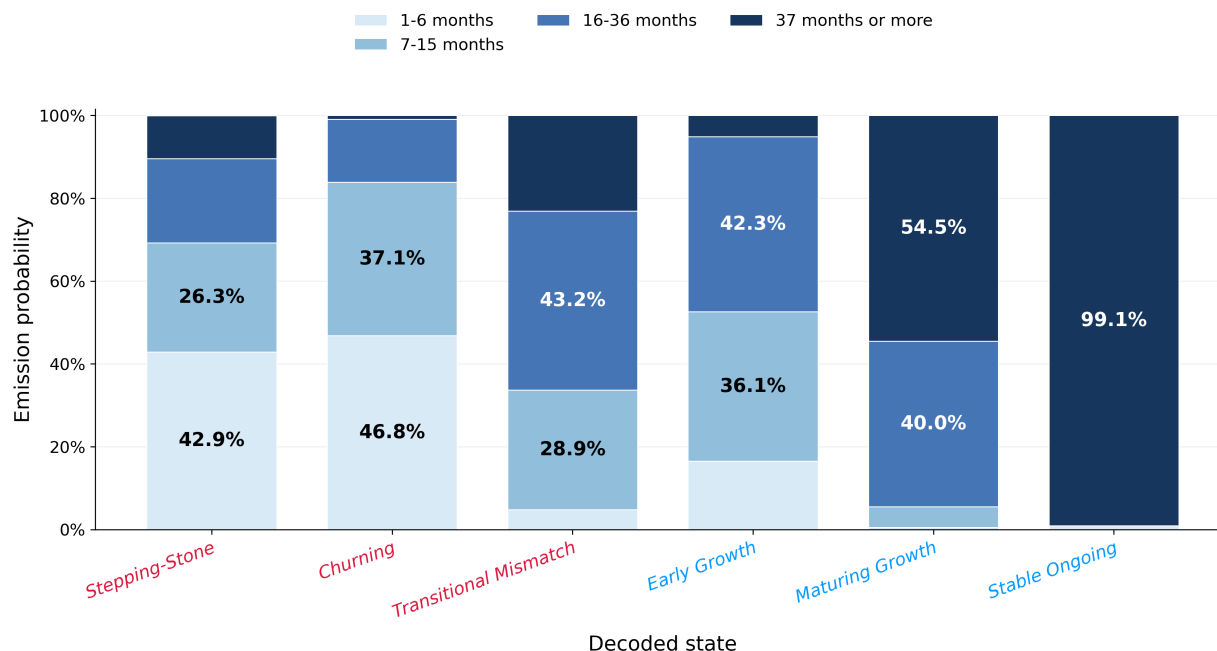
3.3.1 Characterization of the Latent States

Table 1 summarizes the employment-duration, spell transition-type, and transition profiles of the seven latent match states. The states can be broadly classified into three groups.

Table 1: Summary of the Latent Match States

Labels	Employment-relationship profile	Most likely next states
<i>Separation-Prone Matches</i>		
Stepping-Stone	Short-duration, with transition concentrated in education (37%) and nonemployment (26%).	Stepping-Stone Job (45%); Churning Job (30%).
Churning	Short-duration, with transition concentrated in push separation (26%), nonemployment (22%), and relocation (20%).	Churning Job (35%); Stable-Ongoing Match (28%); Transitional Mismatch (16%).
Transitional Mismatch	Medium-duration and separation-dominated, with frequent push separation (33%), nonemployment (24%), and pull separation (19%).	Transitional Mismatch (45%); Stable-Ongoing Match (37%).
<i>Growth-Oriented Matches</i>		
Early Growth Track	Medium-duration, advancement-oriented relationships; same-level moves and upgrades account for 64% of exits.	Early Growth Track (55%); Stable-Ongoing Match (20%); Transitional Mismatch (10%).
Maturing Growth Match	Medium-long duration, advancement-oriented relationships; same-level moves and upgrades account for 50% of exits.	Stable-Ongoing Match (54%); Maturing Growth Match (28%); Early Growth Track (12%).
Stable-Ongoing Match	Long, ongoing relationships: 99% last at least 37 months and 99.5% remain Ongoing at the end of the observation window.	Stable-Ongoing Match (79%); Early Growth Track (20%).

Notes: The table summarizes the emission and transition profiles of the seven latent states estimated by the multi-channel latent Markov model. The final column reports the most likely destination states for consecutive employment spells with no intervening nonemployment gap. Because State 7 primarily contains ongoing spells, its duration and persistence partly reflect right-censoring.



Reported probabilities; small deviations from 100% reflect rounding.

Notes: This figure reports the estimated emission probabilities for spell duration conditional on each latent match state. Spell duration is divided into four categories: 1–6 months, 7–15 months, 16–36 months, and 37 months or longer. Each bar represents the probability distribution of spell duration within a latent state.

Figure 4: Spell Duration Distribution by Latent Match State

The first consists of three separation-prone states: *Stepping-Stone Job*, *Churning Job*, and *Transitional Mismatch*, characterized by frequent separations with the current employer. The second consists of three growth-oriented states: *Early Growth Track*, *Maturing Growth Match*, and *Stable-Ongoing Match*, characterized by internal advancement or stable employment relationships with the employer. The remaining state primarily captures the first observation for older cohorts whose earlier histories are unobserved in the sample. Figures 4 and 5 show the estimated emission probabilities for spell duration and exit type for the six economically meaningful states. The underlying distribution of these latent states, and their emission and transition probabilities are reported in Appendix 9.2.

Separation-Prone Matches. *Stepping-Stone Matches* consists primarily of short-duration employment relationships, with 43 percent lasting 1–6 months and another 26 percent lasting 7–15 months. Transitions to education and nonemployment together account for over 62% of spell transitions. This state is especially prevalent in the initial match-state distributions of later birth cohorts, whose employment histories are more likely to be observed from labor-market entry. Thus, stepping stone matches often represent temporary

or early-career employment.

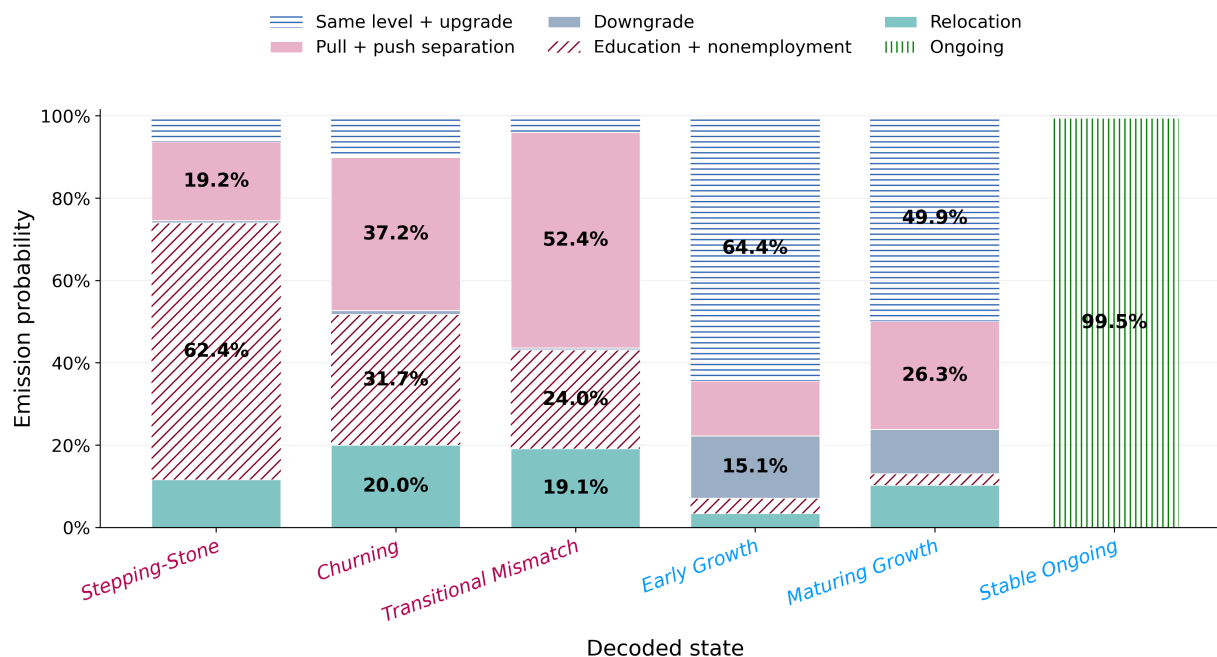
Churning Match also consists of short employment relationships, with 47 percent lasting 1–6 months and 37 percent lasting 7–15 months. However, unlike *Stepping-Stone Job*, exits from Churning matches are more concentrated in separations to other firms. These patterns suggest unstable employment relationships characterized by frequent separations rather than early-career transitions into education.

Transitional Mismatch is similarly separation-prone but has a longer duration profile. Approximately 43 percent of these relationships last 16–36 months, compared with only 17 percent for *Churning Job*. Separations to other firms account for an even larger share of exits, with push separations accounting for 33 percent, followed by transitions to nonemployment (24 percent) and pull separations (19 percent). Despite the prevalence of separations, the transition dynamics suggest that *Transitional Mismatch* is more likely than *Churning Match* and *Stepping-Stone Matches* to be followed by a *Stable-Ongoing Match*, with an estimated transition probability of 37 percent compared with 28 percent for *Churning Match* and 2 percent for *Stepping-Stone Matches*.

Growth-Oriented Matches. *Early Growth Track* is characterized by employment relationships of medium duration and frequent internal advancement. Approximately 36 percent of relationships last 7–15 months and 42 percent last 16–36 months. Same-level internal transfers and upgrades together account for over 64 percent of spell transition outcomes, the highest share among all latent states. These relationships are also likely to be followed by another *Early Growth Track* or a *Stable-Ongoing Match*, suggesting continued employment progression.

Maturing Growth Match represents longer employment relationships with continued opportunities for internal advancement. Approximately 55 percent last at least 37 months, while another 40 percent last 16–36 months. Same-level transfers and upgrades account for approximately 50 percent of spell transition outcomes. Compared with *Early Growth Track*, *Maturing Growth Match* are more likely to be followed by *Stable-Ongoing Match*, with an estimated transition probability of 54 percent. These patterns are consistent with employment relationships becoming longer and advancement less frequent as workers progress into more mature positions.

Stable-Ongoing Match consists almost entirely of long-duration employment relationships that remain active at the end of the observation window. Approximately 99 percent last at least 37 months, and 99.5 percent are still ongoing. This state is a common destination from several other states, particularly for *Maturing Growth Match*.



Reported probabilities; small deviations from 100% reflect rounding.

Notes: This figure reports the estimated emission probabilities for spell transition types conditional on each latent match state. Transition outcomes are further grouped into six categories: same-level transitions and upgrades within the firm, downgrades within the firm, pull and push separations, transitions to education or nonemployment, relocations, and ongoing employment spells. Each bar represents the probability distribution of exit outcomes within a latent state, with probabilities summing to one. Ongoing spells refer to positions that have not ended by the end of the sample period.

Figure 5: Spell Transition Distribution by Latent Match State

3.3.2 Transition Dynamics of the Seven States

Figure 6 reports the estimated transition matrices separately by the gap between consecutive employment spells. Rows denote the state of the previous spell, while columns denote the state of the subsequent spell. The first panel reports transitions with no intervening gap, the second reports transitions following a short gap of 1–6 months, and the final two panels report transitions following gaps of at least seven months associated with education and nonemployment, respectively. Approximately 65.7 percent of transitions involve no gap, 10.0 percent follow a short gap, 11.5 percent follow a long education-related gap, and 12.7 percent follow a long nonemployment gap. Shaded cells indicate transition probabilities that have large standard errors because the corresponding origin–destination transition have a small number of observations in the estimation sample. Imprecisely estimated transition probabilities are concentrated among transitions involving employment gaps, because some combinations of pre-employment gap categories and state-to-state transitions are observed only rarely in the data. I calculate standard errors using the delta method, accounting for the nonlinear mapping from the estimated multinomial-logit coefficients to transition probabilities. Appendix 9.4 describes the delta-method calculation and reports the standard errors for the transition matrices.

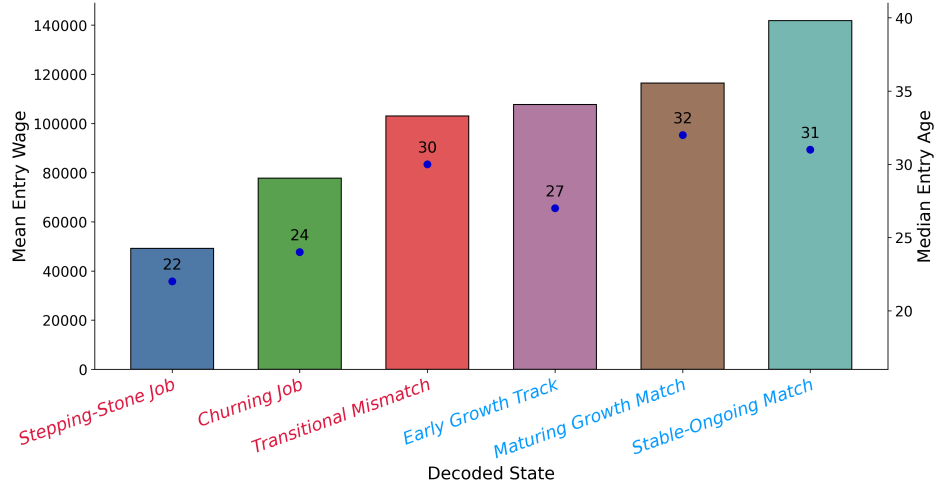
The no-gap transition matrix shows a clear concentration along the diagonal and in the upper-right portion of the matrix. The large diagonal entries indicate persistence of the latent states: workers frequently enter a subsequent employment relationship of the same latent type as their previous relationship. At the same time, transitions above the diagonal are generally more common than transitions below it, indicating that workers tend to move toward longer duration jobs with more internal advancement opportunities. The process is not monotonic, however. We also observe repeated states and movements toward moving down the career trajectory, suggesting that career progression often involves recurring or transitional steps rather than a one-directional movement up a deterministic ladder.

A short employment gap weakens the asymmetry between the upper-right and lower-left portions of the matrix. After such a gap, the two growth-oriented states transition mainly into shorter duration, separation-prone states. *Early Growth Track*) and *Maturing Growth Match* moves mainly to *Churning Match* and *Transitional Mismatch*. An employment interruption thus breaks the upward career trajectory seen in no-gap transitions. Direct transitions between growth-oriented states after a gap are often imprecisely estimated. Few workers in the data end a growth-oriented match with a nonemployment spell and then move immediately into another growth-oriented match, so these estimates rely on a small number of cases.



Notes: Each panel reports the estimated probability of transitioning from the latent match state shown on the vertical axis to the state shown on the horizontal axis, conditional on the type of gap preceding the subsequent employment relationship. Shaded cells indicate imprecisely estimated transition probabilities for which the width of the 95 percent confidence interval exceeds 0.20.

Figure 6: Transition Probabilities by Pre-employment Gap



Notes: This figure plots the mean entry wage and median starting age of workers in each latent match state. Bars show mean wages at the start of employment spells (left axis). Means are calculated across spells with nonmissing entry wages, excluding spells whose observed annualized wage-growth factor falls outside $[0.5, 2]$. Blue dots and numerical labels report median age at spell entry (right axis), calculated as entry year minus birth year. The age statistics cover spells beginning in 2007 or later, with entry ages between 15 and 100. The left-censored state is omitted. *Source: Revelio Labs and author's calculation.*

Figure 7: Wage and Age distribution by State

The transition matrix following a long education-related gap is estimated less precisely still, since this category is smaller and some origin-state-gap combinations are rare. Transitions following education are especially poorly measured for *Transitional Mismatch* and *Stable-ongoing Match*, because these two states are unlikely to be followed by education. Among the more precisely estimated cells, *Stable-ongoing Matches* remains a key destination. *Maturing Growth Mathches* moves to *Stable-ongoing Matches* with near-certain probability, consistent with workers using an education spell to move from a maturing growth relationship into a stable, ongoing one. *Early Growth Matches* is also highly persistent after education: workers return to it with probability 0.71, suggesting education reinforces an early growth trajectory. *Churning Matches* is another common destination after education, including from *Stepping-Stone Matches* — possibly reflecting a period of renewed search and experimentation as workers look for a suitable post-education match.

Following a long nonemployment gap, the transition distribution becomes more dispersed, and transitions from growth-oriented states are again frequently imprecisely estimated. Among the precisely estimated transitions, *Churning Jobs* and *Transitional Mismatch* emerge as common destinations, suggesting that workers returning to the labor market often pass through short-to-medium-duration, separation-prone matches before settling into more stable employment. Transitions from *Maturing Growth Matches* to *Stable-Ongoing Matches* are also prevalent, potentially reflecting recalls to previous employers.

3.3.3 Descriptive evidence on wages and age by states

Figure 7 compares the mean entry wages and median entry ages across states. The bars report mean wages and the markers report the median age of workers for that group. Note that neither wages nor worker age is used to define the latent states, so systematic differences along these dimensions provide an independent check that the estimated states capture economically meaningful differences across matches.

The patterns broadly align with a life-cycle interpretation of the latent match states. States associated with workers' initial labor-market experiences tend to have lower mean wages, whereas more mature matches are associated with higher wages. *Stepping-Stone Jobs*, *Churning Jobs*, and *Early Growth Matches* are disproportionately held by younger workers. This pattern is particularly pronounced for *Stepping-Stone Jobs*, which has a median age of 22. Its strong concentration among very young workers supports the interpretation of *Stepping-Stone Jobs* as an entry-stage employment state rather than one that is prevalent throughout workers' careers. In contrast, *Maturing Growth Matches*, *Transitional Mismatches*, and *Stable-Ongoing Positions* have median ages of 30 or above.

In the next section, I examine these relationships more systematically using spell-level multinomial regressions that relate latent-state membership to a broader set of worker and firm characteristics.

4 Characteristics of Latent Match States

In the second step, I recover the posterior distribution over latent states for each employment spell and provide descriptive evidence on how worker and firm characteristics are associated with the types of matches formed. This analysis helps identify predetermined factors that should be controlled for in the third step.

4.1 Posterior State Distribution

Taking the model parameters estimated in the first step as given, the second step recovers the posterior distribution over latent match states for each observed position. Rather than assigning each position to its most likely state, the full vector of posterior probabilities across the K latent states is retained. This soft classification preserves uncertainty in latent-state assignments.

Two posterior distributions are considered, differing in the information used to infer the latent state. First, *local decoding* conditions on the worker's full observed employment

history. For position n of worker i , the locally decoded posterior probability of latent state k is

$$\pi_{i,n,k}^{Local} \equiv P \left(U_{i,n} = k \mid \mathbf{Y}_{i,1:N_i}, \mathbf{z}_{i,1:N_i}, v_i; \hat{\Gamma} \right), \quad (3)$$

where $\mathbf{Y}_{i,1:N_i} = (\mathbf{Y}_{i,1}, \dots, \mathbf{Y}_{i,N_i})$ denotes the full sequence of observed employment outcomes for worker i , and $\mathbf{z}_{i,1:N_i} = (\mathbf{z}_{i,1}, \dots, \mathbf{z}_{i,N_i})$ denotes the corresponding sequence of employment gaps.

Second, *filtered decoding* assigns the posterior probabilities conditioning only on information observed through the current position.

$$\pi_{i,n,k}^{Filtered} \equiv P \left(U_{i,n} = k \mid \mathbf{Y}_{i,1:n}, \mathbf{z}_{i,1:n}, v_i; \hat{\Gamma} \right). \quad (4)$$

Unlike local decoding, filtered decoding does not use outcomes from positions occurring after n . It therefore represents the posterior distribution over the current latent state based only on the worker's employment history observed up to that point.

Both procedures produce a K -dimensional probability vector for each spell, $\hat{\pi}_{i,n}^d = (\hat{\pi}_{i,n,1}^d, \dots, \hat{\pi}_{i,n,K}^d)$, where $\sum_{k=1}^K \hat{\pi}_{i,n,k}^d = 1$, where $d \in \{Local, Filtered\}$ denotes local or filtered decoding.

For the spell-level analysis in this section, I use the locally decoded posterior probabilities because the objective is to characterize the latent states as accurately as possible using the worker's complete observed employment history. In Section 5, where I construct match-state innovations, I instead use filtered posterior probabilities so that the inferred state at position n does not incorporate information from subsequent employment outcomes.

4.2 Worker and Firm Characteristics of Latent Match States

Next, a spell-level multinomial logit model is estimated to characterize how worker and firm attributes are associated with decoded match quality. The estimates are interpreted as descriptive associations between observable characteristics and match-type membership rather than causal effects of these characteristics on match quality.

Let U_{ij}^t denote the decoded match-quality state between worker i and firm j at quarter t . I model the log-odds of being in state k relative to the baseline state, Transitional

Mismatch (S4), as a linear function of worker and firm characteristics:

$$\log \frac{P(U_{ij}^t = k \mid X_{ijt})}{P(U_{ij}^t = \text{Transitional Mismatch} \mid X_{ijt})} = \gamma_0^k + X_{ijt}' \gamma^k, \quad k \neq \text{Transitional Mismatch}, \quad (5)$$

where X_{ijt} includes bins for worker age, worker's highest educational attainment at the start of the match, worker ethnicity, firm industry, firm size, firm age, and year-quarter fixed effects. Each element of γ^k gives the change in the log-odds of state k (relative to Transitional Mismatch) associated with moving from the reference category to the corresponding covariate bin, holding all other covariates fixed. $\exp(\gamma^k)$ is the odds ratio associated with that covariate bin. Tables 17–23 in Appendix 9.5 report the estimated coefficients and odds ratios for each state–characteristic combination.

Figures 8 and 9 report the estimated odds ratios from the multinomial logit regressions, organized by covariate and latent match state. I focus on four economically interpretable, non-censored states—Stepping-Stone Jobs (S1), Churning Jobs (S3), Early Growth Track (S5), and Maturing Growth Track (S6)—and omit the two states that are strongly affected by censoring. The baseline outcome category in the multinomial logit is Transitional Mismatch (S4). Appendix Tables 17–23 report the corresponding coefficient estimates and standard errors.

The first row of Figure 8 reports odds ratios by worker age, using workers between ages 30 and 35 as the reference group. Age is strongly associated with the type of match formed. Younger workers are substantially more likely to be observed in Stepping-Stone Jobs, Churning Jobs, and Early Growth Track positions relative to Transitional Mismatch. The age gradient is particularly pronounced for *Stepping-Stone Matches*: workers under age 20 have much higher odds of belonging to this state, and the odds decline sharply with age. This pattern is consistent with Stepping-Stone Jobs disproportionately capturing positions held early in workers' careers. *Churning Matches* display a similar, though less pronounced, age gradient. *Early Growth Track* positions are also more common among younger workers, while workers above age 35 are progressively less likely to be observed in this state. In contrast, the *Maturing Growth Track* is concentrated more heavily among prime-age workers: workers below age 30 and workers above age 45 are less likely to be observed in this state than workers ages 30–35.

The second row reports odds ratios by workers' highest degree at the time of hire, with a bachelor's degree as the reference category. Educational attainment is also strongly related to the distribution of workers across latent match states. Workers with only a high-school or associate degree are substantially less likely to be observed in the two growth-

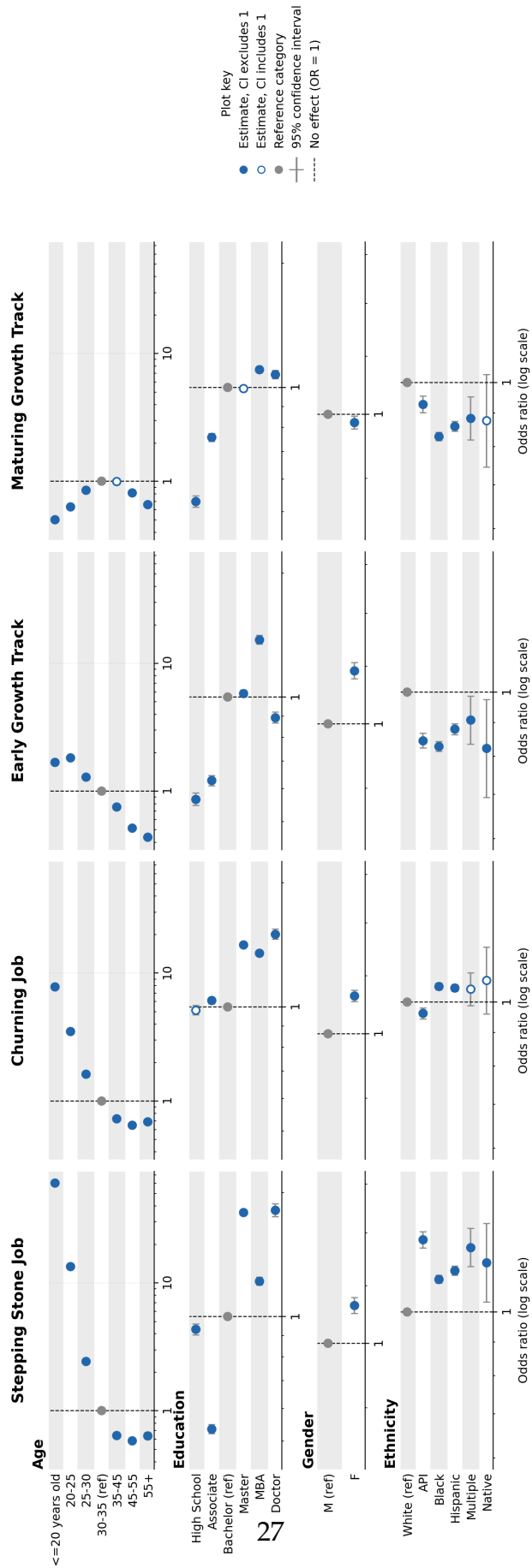


Figure 8: Demographic Characteristics

track states, particularly the *Maturing Growth Track*. By contrast, workers with graduate degrees are generally more likely to appear in several of the non-censored states. Master's, MBA, and doctoral degree holders have particularly high odds of being observed in *Stepping-Stone* and *Churning Jobs* relative to workers with a bachelor's degree. MBA holders are also substantially more likely to be observed in the *Early Growth Track*, while the differences between bachelor's and graduate-degree holders are smaller for the *Maturing Growth Track*.

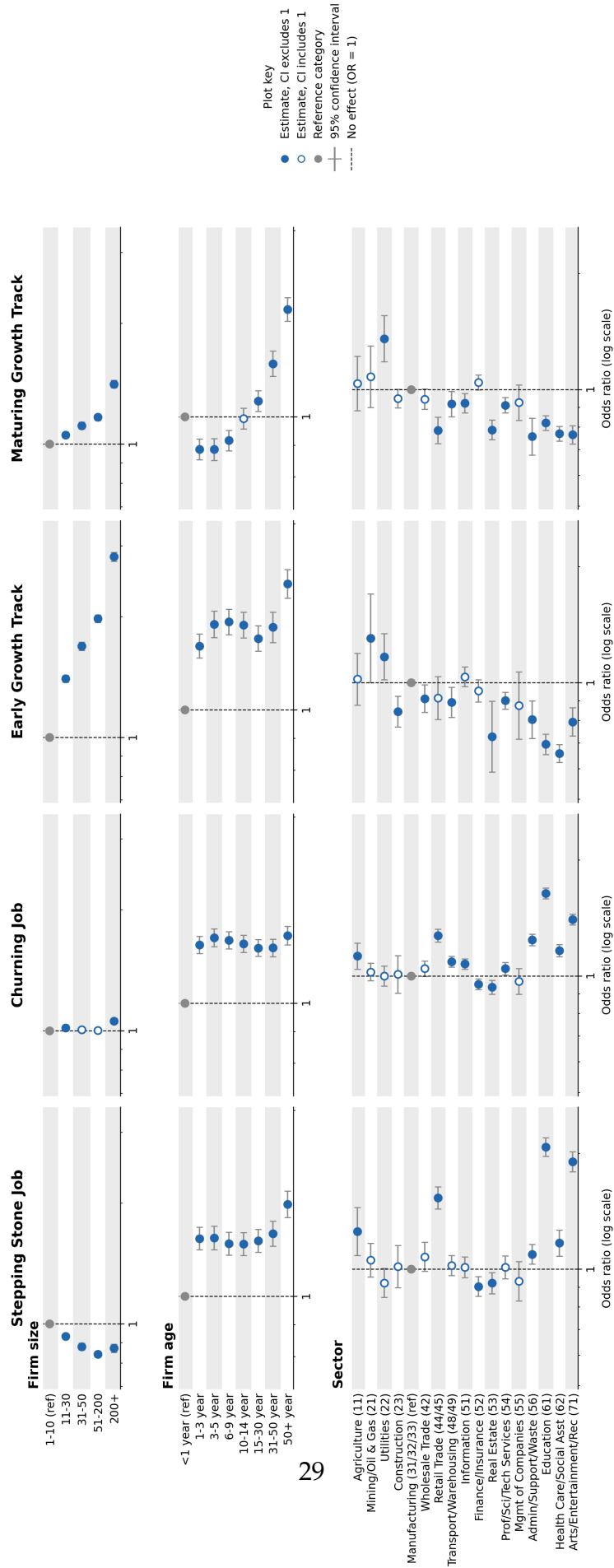
The third row reports odds ratios by gender, with male workers as the reference group. Female workers are more likely than male workers to be observed in *Stepping-Stone Matches*, *Churning Jobs*, and *Early Growth Track* positions relative to *Transitional Mismatch*. The difference is largest for *Stepping-Stone Matches* and *Early Growth Track* positions. In contrast, female workers are slightly less likely to be observed in the *Maturing Growth Track*.

The final row reports odds ratios by ethnicity, with White workers as the reference group. The associations differ considerably across latent states. API, Black, and Hispanic workers are more likely than White workers to be observed in *Stepping-Stone Matches*, with particularly large differences for API workers. Black and Hispanic workers are also somewhat more likely to be observed in *Churning Jobs*. In contrast, these groups are less likely than White workers to be observed in either the *Early Growth Track* or the *Maturing Growth Track*. The estimates for workers classified as Multiple or Native ethnicity are less precise in several specifications, as reflected in their wider confidence intervals.

Figure 9 reports the estimated odds ratios for firm characteristics, including firm size, firm age, and sector, using *Transitional Mismatch* as the omitted match-state category. Thus, the coefficients describe how firm characteristics are associated with the odds of belonging to each reported state relative to *Transitional Mismatch*.

The first row reports odds ratios by firm size, with firms employing 1–10 workers as the reference group. Firm size is strongly associated with the distribution of latent match states, particularly for the two growth-oriented states. The odds of being observed in the *Early Growth Track* increase monotonically with firm size. The relationship is even more pronounced for the *Maturing Growth Track*, where the odds rise more distinctly across firm-size categories, with the largest firms substantially more likely to form these matches than firms with 1–10 employees. In contrast, larger firms are less likely to form *Stepping-Stone Matches*, while the relationship between firm size and *Churning Matches* is comparatively weak. These patterns suggest that larger firms are disproportionately associated with matches characterized by internal advancement and longer-term career progression.

The second row reports odds ratios by firm age, with firms younger than one year



serving as the reference group. Firm age is positively associated with several match states, but the pattern differs across states. Older firms are more likely to form *Stepping-Stone* and *Churning Jobs* relative to very young firms, with the association remaining fairly stable across much of the firm-age distribution. The *Early Growth Track* also becomes more likely as firms age, particularly among the oldest firms. The strongest age gradient appears for the *Maturing Growth Track*. Firms in the intermediate age categories are initially less likely than newly established firms to be associated with this state, but the relationship reverses among more established firms: firms aged 31–50 years and especially firms older than 50 years are substantially more likely to form *Maturing Growth Tracks*. Importantly, these associations are estimated conditional on firm size, indicating that the relationship between firm maturity and growth-oriented matches is not driven solely by older firms being larger.

The final row reports odds ratios across sectors, with Manufacturing as the reference category. There is substantial heterogeneity in the distribution of latent match states across industries. Educational Services and Arts, Entertainment, and Recreation are relatively more likely to be associated with *Stepping-Stone* and *Churning Jobs*, while being less likely to form either *Early* or *Maturing Growth Track Matches*. Retail Trade shows a similar, though less pronounced pattern, with relatively greater representation in the shorter-duration states and lower odds of appearing in the growth-oriented states.

By contrast, Utilities stands out for its relatively high representation in the growth-oriented states, particularly the *Maturing Growth Track*. Mining, Quarrying, and Oil and Gas Extraction is also more likely to be associated with the *Early Growth Track*, although its association with the *Maturing Growth Track* is less precisely estimated. Several service sectors, including Real Estate, Administrative and Support Services, and Health Care and Social Assistance, also have relatively low odds of appearing in the growth-oriented states. These sector-level estimates should be interpreted with some caution because Revelio have relatively poor coverage in these sectors compared to their representations in the economy.

LinkedIn coverage is particularly high in Professional, Scientific, and Technical Services and Information, reflecting the platform's strong representation of knowledge-intensive and highly skilled labor markets. These sectors exhibit less pronounced differences across latent match states than sectors such as Education, Arts and Entertainment, or Retail Trade, although their state distributions are still not uniform. Information sector is relatively more concentrated in *Churning Jobs* and less represented in the *Maturing Growth Track*, while Professional, Scientific, and Technical Services is somewhat less likely to be associated with either growth-oriented state. These patterns are consistent

with the relatively high employment turnover commonly observed in these sectors.

5 Match Innovations

In the third step, I construct a spell-level innovation to isolate the match-specific component of a worker–firm relationship. The latent Markov model’s initial-state and transition equations are re-estimated using a richer set of predetermined worker characteristics. These estimates generate a predicted distribution over latent match states for each spell, conditional on the worker’s observable characteristics and prior employment history. The match-state innovation is then constructed as the difference between the realized posterior state distribution and the predicted distribution. It therefore measures the extent to which the realized match outcome differs from what could have been predicted based on information available to the firm at the time the match was formed. Relative to the residual from a two-way fixed-effects model, this measure also allows for time-varying worker heterogeneity summarized by the worker’s most recent employment spell.

The term *match innovation* refers to the empirical object recovered from the data, while *match quality* is reserved for its structural interpretation. Even if workers are equally likely to meet all firms, the distribution of realized matches need not be independent across employment spells because hiring is selective. As emphasized by Borovičková and Shimer (2024), while the distribution of potential match quality may be independent across jobs for a given worker, the quality of realized matches can remain correlated across spells through selection. To assess the extent to which the innovation measure removes persistent worker heterogeneity, the persistence of match innovations across consecutive employment spells within workers is compared with that of the underlying latent-state distributions. Match innovations exhibit substantially lower persistence, providing suggestive evidence that the innovation measure removes much of the persistent worker heterogeneity embedded in the raw match-state probabilities.

5.1 Construction of Spell-level Match Innovations

Re-estimating State Distributions with Expanded Worker Covariates. We construct the match-state innovation as the difference between the realized posterior distribution over latent match states and the distribution that would have been predicted using information available prior to the current match. We fix the latent-state definitions and emission probabilities estimated in Step 1 and estimate richer covariate-dependent models for the initial-state and transition distributions.

For the first observed position, we estimate a weighted multinomial logit for the initial-state distribution. Let $\mathbf{X}_{i,1}$ denote the predetermined worker characteristics observed at the first position, including gender, ethnicity, education, and year-quarter of hire, while v_i denotes the worker's birth cohort. The model yields initial distribution

$$P(U_{i,1} = k \mid \mathbf{X}_{i,1}, v_i), \quad k = 1, \dots, K. \quad (6)$$

The initial-state model is estimated by weighted multinomial logit, using the locally decoded posterior probability $\pi_{i,1,k}^{Local}$ from step 2 as the weight associated with state k . Thus, each first position contributes to each candidate state in proportion to its posterior probability, rather than being assigned deterministically to a single state.

For subsequent positions, we estimate a separate multinomial logit for each possible origin state. $\mathbf{X}_{i,n>1}$ additionally contains worker age instead of birth cohort, worker ethnicity, gender, education attainments, and the quarter of the hire, and let $z_{i,n+1}$ denote the pre-employment gap preceding position $n + 1$. The transition model is

$$P(U_{i,n+1} = k' \mid U_{i,n} = k, \mathbf{X}_{i,n+1}, z_{i,n+1}), \quad n = 1, \dots, N_i - 1. \quad (7)$$

For each origin state k , the model is estimated using the joint soft-assignment local decoding weight

$$w_{i,n+1,kk'} = \pi_{i,n,k}^{Local} \pi_{i,n+1,k'}^{Local}, \quad (8)$$

so that each observed transition contributes to all possible origin–destination state pairs in proportion to their posterior probabilities. We use the locally decoded posterior probabilities as weights since they provide the most informative ex-post measure of the probability that each position belongs to a given latent state.

Constructing Match Innovations with Filtered State Probabilities. Then, we use the filtered decoded posterior probabilities to construct the match-state innovation at the spell-level. This ensures that both the predicted and realized state distributions do not incorporate information from employment positions happening after the current match.

For the first observed position, the predicted state distribution is given directly by the estimated initial-state model:

$$\hat{p}_{i,1,k} = \hat{P}(U_{i,1} = k \mid v_i, \mathbf{X}_{i,1}^I). \quad (9)$$

For positions $n \geq 2$, we combine the filtered posterior distribution over the previous latent state with the estimated covariate-dependent transition probabilities. Specifically,

the predicted probability that worker i enters state k in position n is

$$\hat{p}_{i,n+1,k'} = \sum_{k=1}^K \pi_{i,n,k}^{Filtered} \hat{P}(U_{i,n+1} = k' \mid U_{i,n} = k, \mathbf{X}_{i,n+1}, z_{i,n+1}), \quad n = 1, \dots, N_i - 1. \quad (10)$$

Let $\hat{\mathbf{p}}_{i,n} = (\hat{p}_{i,n,1}, \dots, \hat{p}_{i,n,K})$ denote the vector of the one-step-ahead predicted distribution over latent match states, and let $\boldsymbol{\pi}_{i,n}^{Filtered} = (\pi_{i,n,1}^{Filtered}, \dots, \pi_{i,n,K}^{Filtered})$ denote the vector of filtered posterior probabilities over the realized matches. We define the match-state innovation for state k as

$$\varepsilon_{i,n} = \boldsymbol{\pi}_{i,n}^{Filtered} - \hat{\mathbf{p}}_{i,n}. \quad (11)$$

Because both $\boldsymbol{\pi}_{i,n}^{Filtered}$ and $\hat{\mathbf{p}}_{i,n}$ are probability distributions,

$$\sum_{k=1}^K \varepsilon_{i,n,k} = 0. \quad (12)$$

The distinction between local and filtered decoding is important for the construction. Local posterior probabilities are used when re-estimating the richer initial and transition models because they provide the most informative ex-post classification of each position. On the other hand, filtered probabilities are used when constructing the predicted and realized state distributions so that the innovation does not incorporate information from future employment outcomes. The resulting innovation measures the component of the current match-state distribution that cannot be predicted from the worker's observable characteristics and employment history available before the current match outcomes are formed.

Table ?? reports summary statistics for the seven components of the spell-level match innovation. The mean innovation is close to zero for every state, indicating that the predicted state distributions are well aligned with the realized filtered distributions on average. At the same time, the innovations exhibit substantial dispersion at the spell level. The standard deviation ranges from 0.094 for Stable-Stagnant Matches (S2) to 0.317 for Stable-Ongoing Matches (S7), while the mean absolute innovation ranges from 0.046 to 0.203 across states.

Part of this difference in dispersion reflects the way the two censored states are identified in the data. Stable-Stagnant Matches (S2) is associated with left-censored employment histories and is concentrated among the first observed positions of workers whose earlier employment histories are not observed. Because this censoring status is almost entirely defined by worker's demographic characteristics, assignment to this state is com-

Table 2: Summary Statistics of Spell-Level Match Innovations

	Mean	Std. Dev.	Mean Absolute Value
inn ₁ (Stepping-stone)	0.002	0.141	0.083
inn ₂ (Stable-Stagnant)	0.001	0.094	0.046
inn ₃ (Churning)	-0.001	0.176	0.120
inn ₄ (Transitional)	-0.002	0.211	0.169
inn ₅ (Early Growth)	0.000	0.224	0.161
inn ₆ (Maturing Growth)	-0.002	0.130	0.079
inn ₇ (Stable Ongoing)	0.002	0.317	0.203

Notes: The table reports summary statistics for the seven components of the spell-level match innovation, $\epsilon_{i,n} = \pi_{i,n}^{Filtered} - \hat{\mathbf{p}}_{i,n}$. Statistics are calculated over 86,108,301 employment spells in the sample.

paratively easier to predict from information available prior to the current match. Stable-Ongoing Matches (S7), by contrast, captures matches that remain ongoing at the end of the sample. Whether a currently observed match will ultimately remain ongoing through the sample endpoint is inherently more difficult to predict in advance. As a result, realized posterior probabilities for S7 may differ more from their predicted probabilities, contributing to the larger dispersion of its match innovation.

5.2 Innovation Persistence within an Individual

The match innovation is designed to remove the component of the realized match state that is predictable from worker characteristics and prior employment history. Now, we evaluate how well the innovation achieves this goal and how much of the persistence in latent match states is removed by the prediction procedure.

I compare the cosine similarity between the seven-dimensional vectors associated with consecutive job spells of the same worker, using a random sample of one million workers.⁹ We run the exercise separately for transitions across firms and transitions between positions within the same firm. We compare the observed similarity with a firm-random baseline, constructed in the following way: for each actual transition, we replace the subsequent-spell vector with a vector belonging to a different worker, drawn from the same hire-quarter and pre-employment-gap cell. Note that the random baseline may differ for transition across firms and within firms, because the distribution across hire-quarter and gap cells may differ between transitions within the same firm and across

⁹For two seven-dimensional vectors $\mathbf{x}$ and $\mathbf{y}$, cosine similarity is defined as $\cos(\mathbf{x}, \mathbf{y}) = \mathbf{x}'\mathbf{y} / (\|\mathbf{x}\| \|\mathbf{y}\|)$. We calculate this measure directly from the raw state-probability or innovation vectors without standardization.

firms. If cosine similarity of the actual transition relative to this random baseline equals zero, then it indicates that consecutive spells of the same worker are no more similar than observably comparable spells drawn from unrelated workers and firms, suggesting that the innovation fully eliminate worker persistence effect in the latent-state distribution.

Table 3 shows that the prediction procedure removes a major fraction of the persistence in latent match states. For workers moving across firms, mean cosine similarity falls from 0.552 for state probabilities to 0.148 for match innovations. For workers changing positions within the same firm, it falls from 0.631 to 0.119. Relative to the common-pool firm-random baseline, excess similarity falls from 0.225 to 0.102 across firms and from 0.315 to 0.136 within firms, reductions of approximately 55 and 57 percent, respectively. Thus, the innovation construction substantially reduces the persistence present in the latent-state distributions, although the remaining across-firm similarity is still statistically different from the firm-random baseline.

Next, we compare job-to-job moves across firms with position changes within firms. Since our construction of match innovations is not abstract of firm-specific effect, we expect greater persistence when a worker remains at the same firm. The results support this prediction. Relative to the common-pool firm-random baseline, cosine similarity of match innovations is 0.119 for position changes within the same firm and 0.148 for job-to-job moves across firms.

Finally, we repeat these comparisons separately by pre-employment-gap category and the results are reported in Appendix Table 13. The innovation construction substantially reduces persistence across most gap categories, especially among job transitions with no gap in between.

In the Appendix, I also evaluate persistence using an unrestricted vector autoregression that allows each cell of the previous spell's state distribution to predict each cell of the subsequent spell's distribution. Appendix Tables 25 and 24 report the coefficient matrices for state probabilities and match innovations. Consistent with the cosine-similarity results, the predictive relationships are substantially weaker for match innovations than for the underlying state probabilities. In particular, the innovation coefficients are generally small in magnitude, indicating that much of the state-specific dependence across consecutive spells is removed by the prediction procedure. The remaining dependence is not eliminated completely, however, consistent with the positive excess cosine similarity documented above.

Table 3: Cosine Similarity of State Probabilities and Match Innovations

	Consecutive Spells	Random Baseline	Consecutive minus Random	Number of Pairs
<i>Match innovations</i>				
Different firm	0.148	0.046	0.102	1,651,815
Same firm (no gap)	0.119	-0.017	0.136	815,155
<i>State probabilities</i>				
Different firm	0.552	0.326	0.225	1,651,815
Same firm (no gap)	0.631	0.316	0.315	815,155

Notes: This table reports the cosine similarity of state-probability vectors across consecutive job spells within the same worker, using a random sample of one million workers. Each entry reports the mean cosine similarity between two seven-dimensional vectors. Actual consecutive spells compare adjacent spells belonging to the same worker. For different-firm transitions, the worker changes firms; for same-firm transitions, the worker changes positions within the same firm. The common-pool firm-random baseline keeps the source worker’s previous-spell vector fixed and pairs it with a next-spell vector belonging to a different worker and firm in the same hire-quarter and pre-employment-gap cell. Randomized next-spell vectors are drawn from all eligible transitions before separating the same-firm and different-firm source samples. The comparisons use 1,651,563 valid different-firm randomized pairs and 988,622 valid same-firm randomized pairs. Results use the filtered one-million-worker sample.

6 Firm Growth and Survival

Having constructed spell-level measures of match-state innovations, we next aggregate these innovations to the firm level and examine whether changes in firms’ exposure to favorable and unfavorable match innovations predict subsequent firm activity. The main analysis focuses on innovations associated with newly formed positions. We first examine employment growth and survival in the full Revelio sample. We then link firms to Compustat and test whether the same match innovations predict employment growth, survival, and sales among publicly listed firms.

6.1 Firm-level Exposure to Match Innovations

I construct firms’ exposure to match innovations at the annual frequency using all new positions formed during the year. Although the underlying data allows measuring changes in firms’ exposure to match innovations at the monthly frequency, I aggregate these measures to the annual level. This reduces the influence of short-run fluctuations in hiring and worker turnover and allows the firm-level measures to capture more persistent changes in the composition and quality of a firm’s worker matches.

For each firm j in year t , its match innovation for state k is

$$\bar{\varepsilon}_{j,t,k}^m = \frac{1}{N_{jt}^m} \sum_{(i,n) \in \mathcal{S}_{jt}^m} \varepsilon_{i,n,k}, \quad m \in \{New\ spells, Stock\} \quad (13)$$

For the new-position measure, $\mathcal{S}_{jt}^{New}$ consists of spells beginning at firm j during year t , so $\bar{\varepsilon}_{j,t,k}^{New}$ captures the average match innovation among new positions over the year. For the stock measure, $\mathcal{S}_{jt}^{Stock}$ consists of employment spells active at firm j in the fourth quarter of year t ; $\bar{\varepsilon}_{j,t,k}^{Stock}$ therefore summarizes the average unexpected component of match quality among the firm's year-end workforce. Since the spell-level innovation vector sums to zero across states, the firm-level averages satisfy the same adding-up restriction:

$$\sum_{k=1}^K \bar{\varepsilon}_{j,t,k}^m = 0. \quad (14)$$

Because the seven innovation components sum to zero, they cannot all be included in a regression simultaneously. We therefore omit Transitional Match (S4) throughout, so each included coefficient is interpreted relative to S4: an increase in the innovation toward state k , holding the other included innovations fixed, corresponds to an equal reduction in the innovation toward Transitional Match. Coefficients thus capture reallocations of unexpected match-state probability rather than independent increases in individual components. For the same reason, we focus our discussion on the four states with the clearest economic interpretation—Stepping-Stone (S1), Churning (S3), Early Growth (S5), and Maturing Growth (S6)—and set aside Stable-Stagnant (S2) and Stable Ongoing (S7), both of which are disproportionately shaped by the censored endpoints of workers' observed employment histories.

Table 4 reports summary statistics for the firm-year innovations. The first two columns use the full Revelio sample, and the last two restrict to firms matched to Compustat. Standard deviations vary substantially across states—from 0.093 for Early Growth in the full sample to 0.112 for Churning. The dispersion is generally, though not uniformly, smaller among Compustat firms.

6.2 Empirical Methods

I estimate the following regression at the firm level:

$$O_{jt} = \sum_{k \in \{1,2,3,5,6,7\}} \delta_k \bar{\varepsilon}_{j,t-1,k} + C_{j,t-1} + u_{jt}, \quad (15)$$

Table 4: Summary Statistics of Firm-Year Exposure to Match Innovations

	Full Sample		Compustat Firms	
	Stock	New Positions	Stock	New Positions
inn ₁ (Stepping-stone)	−0.041 (0.101)	0.007 (0.127)	−0.037 (0.045)	−0.004 (0.059)
inn ₂ (Stable-Stagnant)	0.023 (0.102)	0.004 (0.086)	0.093 (0.192)	−0.016 (0.140)
inn ₃ (Churning)	−0.087 (0.112)	−0.002 (0.154)	−0.064 (0.053)	−0.004 (0.075)
inn ₄ (Transitional)	−0.027 (0.215)	0.014 (0.184)	−0.004 (0.113)	0.014 (0.102)
inn ₅ (Early Gr)	−0.079 (0.093)	−0.048 (0.113)	−0.048 (0.066)	0.002 (0.085)
inn ₆ (Maturing Gr)	−0.009 (0.101)	−0.015 (0.082)	0.032 (0.068)	0.004 (0.058)
inn ₇ (Stable Ongoing)	0.220 (0.375)	0.042 (0.295)	0.028 (0.055)	0.004 (0.048)
N (firm-years)	17,053,441	10,083,811	87,745	81,513

Notes: The table reports summary statistics for the seven match innovations aggregated to the firm-year level. Each cell reports the mean, with the standard deviation in parentheses. The stock measure averages spell-level innovations across employment spells active at the firm in the fourth quarter of each year. The new-hire measure averages spell-level innovations across employment spells beginning at the firm during the year. Columns (1)–(2) report statistics for the full Revelio sample, while columns (3)–(4) restrict the sample to firm-years matched to Compustat. *Source:* Revelio Labs and Compustat.

where O_{jt} measures the activity of firm j in year t and $\bar{e}_{j,t-1,k}$ is the firm’s realized match innovation for outcome k in year $t - 1$. In the full Revelio sample, we consider four outcomes: (1) firm’s annual separation rate, (2) firm’s annual hiring rate, (3) the firm’s annual employment growth rate, following Davis et al. (2013), and (4) an indicator for whether the firm survives from $t - 1$ to t .¹⁰ $C_{j,t-1}$ contains lagged firm-level controls that vary across specifications. We estimate the survival regression as a linear probability model, and we cluster standard errors at the firm level throughout.

The identification rests on two assumptions. First, the predicted probability distribution of employment outcomes captures all unobserved worker heterogeneity, including, for example, persistent differences in ability and the accumulation of human capital over time. Because the hidden Markov model conditions on workers’ employment histories and a rich set of worker covariates, including worker’s birth cohorts, education attainments, gender, ethnicity, employment gap before the current position, and the time of the hire, the realized match innovations are plausibly exogenous with respect to worker-

¹⁰The separation and hiring rates are defined as the number of separations and new hires during the year, respectively, divided by employment at the beginning of the year. Employment growth is measured using the DHS growth rate, $g_{jt} = \frac{N_{jt} - N_{j,t-1}}{\frac{1}{2}(N_{jt} + N_{j,t-1})}$. The survival indicator equals one if the firm has positive employment in year t . Because employment is measured using LinkedIn profiles, the disappearance of a firm’s observed workforce may indicate a substantial contraction or cessation of activity, but does not necessarily imply firm exit.

specific effects. The persistence exercise in section 5.2 also provides supporting evidence that the procedure substantially reduces worker-specific persistence.

Even if the assumption that match innovations are independent of unobserved worker heterogeneity does not fully hold, the results provide new evidence on how unexpected match outcomes relate to subsequent firm performance. At the time of hiring, firms may infer workers' otherwise unobserved characteristics from their observable attributes and employment histories. To the extent that these characteristics are captured by the information used to construct the predicted match-state distribution, their influence is removed from the match innovation. The resulting measure therefore captures deviations from expected match outcomes conditional on this information. The findings thus shed light on the economic value of unexpectedly favorable or unfavorable matches to firms.

Second, the identification assumes that conditional on $C_{j,t-1}$, realized match innovations are orthogonal to other time-varying firm-level determinants of subsequent outcomes. We need suitable firm-level controls because the distribution of exposure to match innovations across industries and business characteristics is not random, as shown in section 4. For example, employment in retail is typically much less stable than in manufacturing, and large firms are more likely than small startups to offer internal job ladders. Because the predicted probabilities contain no information about the destination firm, controlling for firm characteristics is important when estimating effects on firm outcomes.

I consider the following set of controls. I include firm fixed effects to absorb persistent differences in firm-level demand and productivity, which prior work identifies as important determinants of firms' growth paths (Sterk et al., 2021). I also include industry-by-year fixed effects, with industries defined at the six-digit NAICS level, incorporating more than 1,000 industry cells per year. These fixed effects capture time-varying industry-level demand and technology shocks that may jointly affect match outcomes and firm performance. In addition, I control for lagged firm outcomes to account for transitory firm-level shocks that may influence subsequent firm activity. In a second set of regressions, I additionally control for workers' predicted match-state distributions aggregated to the firm level. These controls capture the observable composition of a firm's new matches, which may be correlated with realized match innovations through sorting and may independently affect subsequent firm outcomes. Reassuringly, all specifications yield similar magnitudes and identical rankings of the effects across match-outcome states.

The empirical specification relies on the assumption that realized match innovations are unrelated to other time-varying firm-level shocks that independently predict subsequent firm outcomes. This would fail if, for example, a positive firm-specific technology shock in year t both generated better match outcomes and raised subsequent employ-

ment growth, biasing our estimates upward. The firm-level controls capture an important part of demand and productivity heterogeneity. To further assess the role of match innovations, I estimate the effects over longer horizons. If the estimates were driven only by transitory demand or productivity shocks, the effects may attenuate as the horizon lengthens. Instead, they remain statistically significant and, for some match states, the effect become stronger. I therefore interpret the estimates as economically informative about the effect of match-quality innovations on subsequent firm outcomes.

6.3 Match Innovations and Firm Outcomes

Table 5 reports the effect of match innovations on firm separation rates, hiring rate, growth rate and survival. Columns (1)-(4) controls for industry-by-year fixed effects, firm fixed effects and lagged firm outcomes; columns (5)-(8) additionally control for lagged predicted state probabilities, aggregated to the firm-level in the same way as match innovations. Columns (5)-(8) are my preferred estimates. Table 6 reports the corresponding results restricted to Compustat firms.

Effects in the following year using the full sample. The clearest contrast is between Churning and the two growth-track states. In the full Revelio sample, a 10 percentage point shift toward Churning matches is associated with a 0.87 percentage point higher separation rate, while the same shift toward Early Growth and Maturing Growth matches is associated with declines in the separation rate of 0.80 and 2.13 percentage points, respectively. It is perhaps unsurprising that greater exposure to shorter-duration, separation-prone matches predicts higher subsequent separation rates than exposure to growth-oriented matches. However, the differences in estimates across states with similar spell-duration distributions are particularly interesting. Although Stepping-stone and Churning matches have similar spell-duration distributions, a shift from Transitional Mismatch toward these two states has opposite effects on firms' subsequent separation rates: greater exposure to Stepping-stone matches predicts lower separations, while greater exposure to Churning matches predicts higher separations. Furthermore, Early Growth matches have substantially longer durations than Stepping-stone matches, and their transition outcomes are characterized primarily by internal advancement rather than separation. Nevertheless, greater exposure to Stepping-stone matches predicts a larger decline in subsequent separation rates than greater exposure to Early Growth matches. Taken together, these findings suggest that the estimated effects on subsequent separations are not simply a mechanical reflection of the spell durations and exit

outcomes used to infer the latent match states. Instead, differences in firms' exposure to these states contain additional information about subsequent workforce dynamics beyond the observed characteristics used to classify individual matches.

In terms of hiring rates, Stepping-stone and Early Growth matches have the largest positive associations with subsequent hiring. A 10 percentage point shift from Transitional Mismatch toward Stepping-stone matches is associated with a 0.24 percentage point higher hiring rate, while an equivalent shift toward Early Growth matches is associated with a 0.22 percentage point higher hiring rate. By contrast, the same shift toward Maturing Growth matches is associated with a 0.33 percentage point lower hiring rate.

Together, these results suggest that match innovations are important predictors of subsequent net employment growth and firm survival. A 10 percentage point shift toward Churning matches is associated with 1.0 percentage point lower employment growth and a 0.14 percentage point lower probability of firm survival. In contrast, shifts of the same magnitude toward Early Growth and Maturing Growth matches are associated with 1.0 and 1.7 percentage points higher employment growth, respectively, and 0.09 and 0.11 percentage points higher survival probabilities. Taken together, a 10 percentage point shift in match composition from Churning toward either of the two growth-track states predicts 2.0–2.7 percentage points higher employment growth and a 0.23–0.25 percentage point higher probability of firm survival.

Effects in the following year using Compustat firms. When restricting the sample to Compustat firms, the effect on subsequent firm performances is even stronger. Table 6 reports the corresponding results, where separation, hires, growth and survival are all measured using Revelio data. A 10 percentage point shift from Transitional Mismatch toward Churning matches is associated with a 0.88 percentage point higher separation rate, while shifts of the same magnitude toward Early Growth and Maturing Growth matches are associated with 0.78 and 2.27 percentage point lower separation rates, respectively. In terms of hiring, Stepping-stone and Early Growth matches have the largest positive associations, with a 10 percentage point shift toward these states predicting 0.25 and 0.24 percentage point higher hiring rates, respectively. By contrast, the same shift toward Maturing Growth matches predicts a 0.33 percentage point lower hiring rate.

Together, these differences translate into substantial variation in subsequent employment growth and firm survival. A 10 percentage point shift toward Churning matches is associated with 1.03 percentage points lower employment growth and a 0.14 percentage point lower probability of firm survival. In contrast, shifts of the same magnitude toward Early Growth and Maturing Growth matches predict 1.01 and 1.82 percentage points

higher employment growth, respectively, and 0.09 and 0.11 percentage point higher survival probabilities. Taken together, a 10 percentage point shift in match composition from Churning toward either of the two growth-track states predicts 2.04–2.85 percentage points higher employment growth and a 0.23–0.25 percentage point higher probability of firm survival.

Table 7 reports the effects on employment growth, firm survival, and log sales using Compustat annual data (SP Global Market Intelligence, 2026). The Compustat data provide an independent check on the effects estimated above, as the employment and sales measures come from a separate data source. A 10-percentage-point shift in exposure from Churning toward either of the two growth-track states predicts 3.31–3.91 percentage points higher employment growth, a 1.45–1.49 percentage point higher probability of firm survival, and a 2.34–4.76% increase in sales.

Effects over the next three years using Compustat firms. Next, I trace the effects of match innovations on firm outcomes over the subsequent three years. For many states and outcomes, the effects remain economically meaningful two or three years later and, in some cases, become stronger over time. Figure 10 reports the effects of a 10-percentage-point shift in new-hire match innovations from Transitional Mismatch toward each of the indicated states on annual employment growth, firm survival (left axis), and log sales (right axis), using Compustat annual data. All specifications control for the aggregated predicted state probabilities. The figures also report 90% confidence intervals.

The most striking result is the strengthening positive association between Early Growth matches and firm sales. A 10-percentage-point shift in new positions from Transitional Mismatch toward Early Growth predicts approximately 2% higher sales in the first year. The difference increases to over 5% in year $t + 2$ and becomes even larger in year $t + 3$, suggesting that favorable matches are associated with persistent and growing positive effects on firm sales levels several years after hiring. In contrast, the negative association between Churning matches and sales remains relatively stable over time, potentially because these unfavorable matches have limited lasting effects on firm sales as the workers involved leave the firm.

Turning to employment growth, a shift toward Stepping-Stone, Early Growth, or Maturing Growth matches predicts higher annual employment growth even in the third year after hiring. For Maturing Growth matches, the effect on employment growth during the second year is even stronger than during the first year. Interestingly, while Churning matches initially predict lower employment growth, they predict higher annual employment growth in the second year, with an even stronger positive association in the third

Table 5: New-Hire Match Innovations and Firm Outcomes

	Sep. (1)	Hires (2)	Growth (3)	Surv. (4)	Sep. (5)	Hires (6)	Growth (7)	Surv. (8)
inn_1 (Stepping-st)	−0.1002* (0.0010)	0.0240* (0.0010)	0.1154* (0.0013)	0.0153* (0.0004)	−0.1057* (0.0010)	0.0246* (0.0010)	0.1208* (0.0013)	0.0154* (0.0004)
inn_3 (Churning)	0.0874* (0.0010)	0.0116* (0.0009)	−0.1039* (0.0012)	−0.0136* (0.0003)	0.0877* (0.0010)	0.0108* (0.0009)	−0.1029* (0.0012)	−0.0135* (0.0003)
inn_5 (Early Gr)	−0.0803* (0.0008)	0.0217* (0.0009)	0.1058* (0.0011)	0.0093* (0.0003)	−0.0777* (0.0008)	0.0235* (0.0009)	0.1010* (0.0011)	0.0094* (0.0002)
inn_6 (Maturing Gr)	−0.2128* (0.0012)	−0.0327* (0.0013)	0.1665* (0.0016)	0.0106* (0.0003)	−0.2265* (0.0011)	−0.0329* (0.0013)	0.1819* (0.0016)	0.0113* (0.0003)
inn_7 (Stable Ongoing)	−0.1015* (0.0005)	−0.0039* (0.0006)	0.0897* (0.0007)	0.0041* (0.0002)	−0.1049* (0.0005)	−0.0037* (0.0006)	0.0933* (0.0007)	0.0044* (0.0002)
pred_1 (Stepping-st)					0.0033* (0.0013)	0.0307* (0.0014)	−0.0215* (0.0017)	−0.0037* (0.0004)
pred_3 (Churning)					0.0324* (0.0016)	0.0391* (0.0018)	−0.0611* (0.0022)	−0.0156* (0.0006)
pred_5 (Early Gr)					0.0486* (0.0017)	0.0348* (0.0019)	−0.0832* (0.0023)	−0.0004 (0.0006)
pred_6 (Maturing Gr)					−0.0827* (0.0036)	0.0843* (0.0040)	0.0409* (0.0049)	−0.0139* (0.0012)
pred_7 (Stable Ongoing)					−0.0806* (0.0014)	0.0390* (0.0016)	0.0600* (0.0019)	−0.0006 (0.0004)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predicted	No	No	No	No	Yes	Yes	Yes	Yes
Within R ²	0.0346	0.0117	0.0168	0.0092	0.0381	0.0118	0.0191	0.0097
N	7,476,741	7,476,741	7,509,821	7,576,673	7,476,741	7,476,741	7,509,821	7,576,673

Notes: This table reports estimates of lagged match-state innovations of new positions to firm outcomes using the full sample. Outcomes are annual separation and hiring rates, employment growth following Davis et al. (2013), and firm survival. All models include firm and 6-digit NAICS industry-by-year fixed effects, firm fixed effects, and lagged firm outcomes. Separation and hiring regressions control for their lagged outcome; growth and survival models control for lagged employment growth. All lags are one year. Columns (5)–(8) also include lagged predicted state probabilities. State 4 (Transitional Mismatch) is the reference for innovations and probabilities. I report the within R-square and standard errors are clustered at the firm level. * $p < 0.10$ *Source: Revelio Labs.*

Table 6: New-Hire Match Innovations and Firm Outcomes I (Compustat Firms)

	Sep. (1)	Hires (2)	Growth (3)	Surv. (4)	Sep. (5)	Hires (6)	Growth (7)	Surv. (8)
inn_1 (Stepping-st)	−0.1646* (0.0157)	0.0268 (0.0171)	0.1861* (0.0232)	−0.0079* (0.0038)	−0.1718* (0.0160)	0.0348* (0.0173)	0.2029* (0.0236)	−0.0076* (0.0038)
inn_3 (Churning)	0.1248* (0.0152)	−0.0931* (0.0150)	−0.2348* (0.0232)	−0.0079* (0.0035)	0.1238* (0.0152)	−0.0917* (0.0150)	−0.2340* (0.0231)	−0.0081* (0.0036)
inn_5 (Early Gr)	−0.1376* (0.0107)	0.0969* (0.0122)	0.2295* (0.0168)	−0.0014 (0.0020)	−0.1383* (0.0107)	0.0973* (0.0122)	0.2308* (0.0168)	−0.0013 (0.0019)
inn_6 (Maturing Gr)	−0.3043* (0.0150)	−0.0474* (0.0170)	0.2393* (0.0239)	0.0003 (0.0030)	−0.3060* (0.0149)	−0.0484* (0.0170)	0.2394* (0.0236)	0.0004 (0.0029)
inn_7 (Stable Ongoing)	−0.1569* (0.0080)	0.0161* (0.0090)	0.1648* (0.0125)	−0.0027* (0.0016)	−0.1592* (0.0081)	0.0180* (0.0090)	0.1692* (0.0125)	−0.0026 (0.0016)
pred_1 (Stepping-st)					−0.0029 (0.0174)	−0.0466* (0.0204)	−0.0545* (0.0275)	0.0023 (0.0049)
pred_3 (Churning)					−0.0191 (0.0254)	−0.0392 (0.0298)	−0.0443 (0.0400)	0.0048 (0.0047)
pred_5 (Early Gr)					0.0869* (0.0214)	−0.0592* (0.0233)	−0.1518* (0.0322)	0.0065 (0.0049)
pred_6 (Maturing Gr)					−0.0948* (0.0471)	−0.1472* (0.0524)	−0.1095 (0.0741)	0.0097 (0.0098)
pred_7 (Stable Ongoing)					−0.0976* (0.0221)	0.0059 (0.0251)	0.0918* (0.0346)	0.0084* (0.0047)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predicted	No	No	No	No	Yes	Yes	Yes	Yes
Within R^2	0.0771	0.0729	0.0978	0.0031	0.0800	0.0740	0.1005	0.0036
N	72,815	72,815	72,831	72,869	72,815	72,815	72,831	72,869

Notes: This table reports estimates of lagged match-state innovations of new positions to firm outcomes using Compustat firms. Outcomes are annual separation and hiring rates, employment growth following Davis et al. (2013), and firm survival, all measured using Revelio Labs data. All models include firm and 6-digit NAICS industry-by-year fixed effects, firm fixed effects, and lagged firm outcomes. Separation and hiring regressions control for their lagged outcome; growth and survival models control for lagged employment growth. All lags are one year. Columns (5)–(8) also include lagged predicted state probabilities. State 4 (Transitional Mismatch) is the reference for innovations and probabilities. I report the within R -square and standard errors are clustered at the firm level. * $p < 0.10$ *Source:* Revelio Labs, Compustat.

Table 7: Match Innovations and Firm Outcomes II (Compustat Firms)

	Emp. growth (1)	Survival (2)	Log sales (3)	Emp. growth (4)	Survival (5)	Log sales (6)
inn_1 (Stepping-st)	0.1172* (0.0365)	0.0514* (0.0180)	0.0400 (0.0691)	0.1341* (0.0367)	0.0536* (0.0181)	0.0684 (0.0709)
inn_3 (Churning)	-0.1675* (0.0327)	-0.0988* (0.0195)	-0.2407* (0.0771)	-0.1586* (0.0328)	-0.0973* (0.0195)	-0.2341* (0.0779)
inn_5 (Early Gr)	0.2324* (0.0266)	0.0513* (0.0137)	0.2360* (0.0695)	0.2327* (0.0268)	0.0517* (0.0138)	0.2420* (0.0705)
inn_6 (Maturing Gr)	0.1719* (0.0332)	0.0475* (0.0165)	0.0002 (0.0844)	0.1721* (0.0334)	0.0473* (0.0164)	0.0030 (0.0843)
inn_7 (Stable Ongoing)	0.1376* (0.0189)	0.0554* (0.0105)	0.0468 (0.0447)	0.1419* (0.0190)	0.0560* (0.0105)	0.0565 (0.0448)
pred_1 (Stepping-st)				-0.1054* (0.0379)	-0.0179 (0.0239)	-0.2162* (0.0924)
pred_3 (Churning)				-0.1552* (0.0545)	-0.0290 (0.0350)	-0.3214* (0.1336)
pred_5 (Early Gr)				-0.2934* (0.0478)	-0.0429 (0.0287)	-0.1850 (0.1289)
pred_6 (Maturing Gr)				-0.3072* (0.1025)	-0.0489 (0.0641)	-0.6028* (0.2429)
pred_7 (Stable Ongoing)				-0.0666 (0.0505)	-0.0296 (0.0316)	-0.1058 (0.1391)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Predicted	No	No	No	Yes	Yes	Yes
Within R ²	0.0117	0.0114	0.4673	0.0136	0.0116	0.4677
N	59,908	61,691	53,831	59,908	61,691	53,831

Notes: This table reports estimates of lagged match-state innovations of new positions to firm outcomes using Compustat firms. Outcomes are employment growth following Davis et al. (2013), firm survival and log of sales, all measured using Revelio Labs data. All models include firm and 6-digit NAICS industry-by-year fixed effects, firm fixed effects, and lagged firm outcomes. Separation and hiring regressions control for their lagged outcome; growth and survival models control for lagged employment growth. All lags are one year. Columns (4)–(6) also include lagged predicted state probabilities. Transitional Mismatch is the reference for innovations and probabilities. I report the within R-square and standard errors are clustered at the firm level. * $p < 0.10$ Source: Revelio Labs, Compustat.

year. One possible explanation is that firms gradually replace these unfavorable matches with new workers in subsequent years, leading to increased hiring and a recovery in employment growth as firms rebuild their workforce.

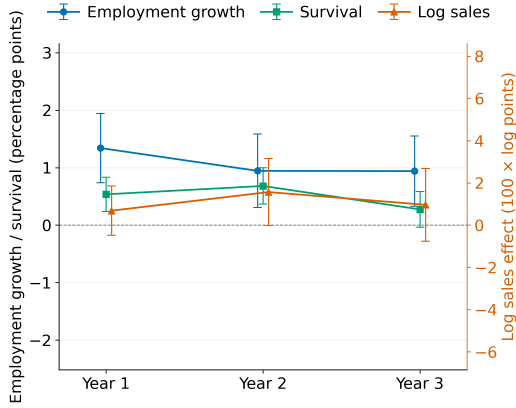
I report the remaining results on hiring and separation rates, employment growth, and firm survival using the full sample, as well as results for Compustat firms based on Revelio data, in Appendices [9.7](#) and [9.8](#).

7 Conclusion

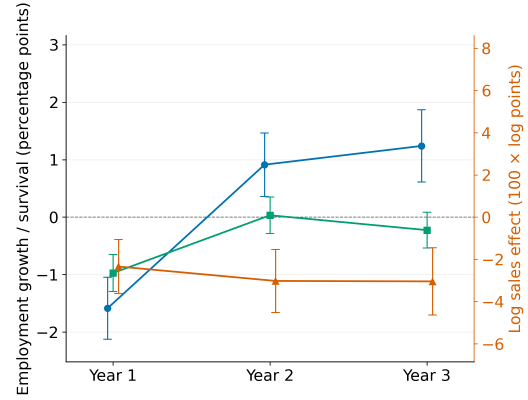
This paper develops a new measure of worker-firm match quality and studies whether unexpected changes in match quality predict subsequent firm performance. Using a matched employer-employee panel from Revelio Labs, I classify employment spells into seven latent match states using a multichannel Hidden Markov model and construct match innovations as the difference between realized and predicted state probabilities.

Aggregating these innovations to the firm level, I find that changes in match quality predict subsequent employment growth, survival, and sales, even after controlling for firm fixed effects and the ex ante predicted distribution of match states. Because Transitional Match (S4) is the omitted reference state, the coefficients measure outcomes associated with reallocating unexpected match probability from S4 toward the indicated state. Relative to Transitional Match, greater exposure to Churning predicts weaker firm performance, while greater exposure to Early Growth predicts faster growth, higher survival, and higher sales. Maturing Growth also predicts stronger employment outcomes. These patterns are present in the full Revelio sample and remain visible among firms matched to Compustat.

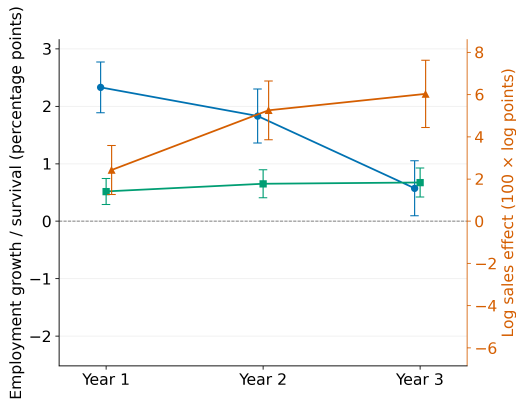
The results suggest that variation in the realized quality of worker-firm matches is an important dimension of firm dynamics that is distinct from persistent firm heterogeneity. Models of firm growth that focus only on technology or demand shocks may therefore miss an additional channel operating through the quality of firms' employment relationships. Future work could further investigate the mechanisms linking match quality to firm performance and how these innovations interact with hiring, separations, and internal worker mobility.



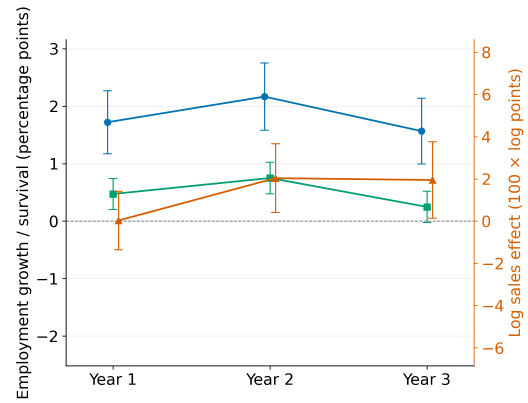
(a) Stepping-Stone



(b) Churning



(c) Early Growth



(d) Maturing Growth

Notes: Each panel plots the estimated effects of a 10-percentage-point increase in new-hire match innovations for the indicated state, relative to Transitional Mismatch, on firm outcomes one, two, and three years after hiring. Estimates are obtained from separate regressions for each horizon and do not represent cumulative effects. Error bars indicate approximate 90% confidence intervals. All specifications include firm and six-digit NAICS industry-by-year fixed effects and lagged predicted state probabilities. Employment growth and survival regressions control for lagged employment growth, while log-sales regressions control for lagged log sales. Lagged outcome controls are measured at the same lag as the match innovations. Employment growth and survival effects are expressed in percentage points on the left axis, while log-sales effects are interpreted as percentage changes and displayed on the right axis. The corresponding regression estimates are reported in Appendix 9.8.

Source: Revelio Labs and Compustat.

Figure 10: Effects of Match Innovations on Firm Outcomes Over Three Years

References

- Hie Joo Ahn, Bart Hobijn, and Ayşegül Şahin. The dual us labor market uncovered. Technical report, National Bureau of Economic Research, 2023.
- Elizabeth S Allman, Catherine Matias, and John A Rhodes. Identifiability of parameters in latent structure models with many observed variables. 2009.
- Michèle Belot, Xiaoying Liu, and Vaios Triantafyllou. Measuring the quality of a match. *Labour Economics*, 89:102568, 2024.
- G. Jacob Blackwood, Lucia S. Foster, Cheryl A. Grim, John Haltiwanger, and Zoltan Wolf. Macro and micro dynamics of productivity: From devilish details to insights. *American Economic Journal: Macroeconomics*, 13(3):142–172, 2021. doi: 10.1257/mac.20170282.
- Nicholas Bloom, Gideon Moore, Lisa K Simon, and Caelan Wilkie-Rogers. Time travel on professional profiles. Technical report, National Bureau of Economic Research, 2026.
- Katarína Borovičková and Robert Shimer. Assortative matching and wages: The role of selection. Technical report, National Bureau of Economic Research, 2024.
- Audra J Bowlus. Matching workers and jobs: Cyclical fluctuations in match quality. *Journal of Labor Economics*, 13(2):335–350, 1995.
- Kenneth Burdett and Dale T Mortensen. Wage differentials, employer size, and unemployment. *International economic review*, pages 257–273, 1998.
- José A. Cabral Vieira. Skill mismatches and job satisfaction. *Economics Letters*, 89(1):39–47, 2005.
- Marco Caliendo, Konstantinos Tatsiramos, and Arne Uhlendorff. Benefit duration, unemployment duration, and job match quality: A regression-discontinuity approach. *Journal of Applied Econometrics*, 28(4):604–627, 2013.
- Samuel Chang, Hans B Christensen, and Ziang Zhang. From linkedin to labor statistics: Using revelio microdata for labor market research in developing economies. *Journal of Development Economics*, page 103922, 2026.
- Russell Cooper, John Haltiwanger, and Jonathan L Willis. Search frictions: Matching aggregate and establishment observations. *Journal of Monetary Economics*, 54:56–78, 2007.

- Steven J Davis, R Jason Faberman, and John C Haltiwanger. The establishment-level behavior of vacancies and hiring. *The Quarterly Journal of Economics*, 128(2):581–622, 2013.
- Ryan A. Decker, John Haltiwanger, Ron S. Jarmin, and Javier Miranda. Changing business dynamism and productivity: Shocks versus responsiveness. *American Economic Review*, 110(12):3952–3990, 2020. doi: 10.1257/aer.20190680.
- Michael W L Elsby and Ryan Michaels. Marginal jobs, heterogeneous firms, and unemployment flows. *American Economic Journal: Macroeconomics*, 5(1):1–48, 2013.
- Pedro Ferreira and Mark Taylor. Measuring match quality using subjective data. *Economics Letters*, 113(3), 2011.
- Eliza Forsythe. Occupational job ladders within and between firms. Technical report, IZA Discussion Papers, 2023.
- Victoria Gregory, Guido Menzio, and David Wiczer. The alpha beta gamma of the labor market. *Journal of Monetary Economics*, 150:103695, 2025.
- Piyush Gulati, Arianna Marchetti, and Phanish Puranam. Collaborative work management technologies and managerial intensity in us corporations: An examination. *Management Science*, 2026.
- Menaka Hampole, Dimitris Papanikolaou, Lawrence DW Schmidt, and Bryan Seegmiller. Artificial intelligence and the labor market. Technical report, National Bureau of Economic Research, 2025.
- Long Hong, Rasmus Lentz, and Jean-Marc Robin. A hidden markov model of wages and employment mobility with worker and firm heterogeneity: Evidence from italian register data. 2026.
- Hugo Hopenhayn and Richard Rogerson. Job turnover and policy evaluation: A general equilibrium analysis. *Journal of political Economy*, 101(5):915–938, 1993.
- C Kirabo Jackson. Match quality, worker productivity, and worker mobility: Direct evidence from teachers. *Review of Economics and Statistics*, 95(4):1096–1116, 2013.
- Jeroen Koenraadt and Oscar Timmermans. Employee-generated disclosures and labor markets. *Available at SSRN 5350469*, 2026.

- Kostas Mavromaras, Séamus McGuinness, and Mark Wooden. Overskilling in the Australian labour market. *Australian Economic Review*, 40(3):307–312, 2007.
- Dale T Mortensen and Christopher A Pissarides. Job creation and job destruction in the theory of unemployment. *The review of economic studies*, 61(3):397–415, 1994.
- Giuseppe Moscarini and Fabien Postel-Vinay. The contribution of large and small employers to job creation in times of high and low unemployment. *American Economic Review*, 102(6):2509–2539, 2012.
- Giuseppe Moscarini and Fabien Postel-Vinay. Did the job ladder fail after the great recession? *Journal of Labor Economics*, 34(S1):S55–S93, 2016.
- Sabrina Mühlbauer and Enzo Weber. Predicting job match quality: A machine learning approach. Technical report, IAB-Discussion Paper, 2024.
- Mr Ippei Shibata. *Labor market dynamics: A hidden Markov approach*. International Monetary Fund, 2019.
- SP Global Market Intelligence. Compustat North America Fundamentals Annual. Wharton Research Data Services (WRDS), 2026. URL <https://wrds-www.wharton.upenn.edu/>.
- Vincent Sterk, Petr Sedláček, and Benjamin Pugsley. The nature of firm growth. *American Economic Review*, 111(2):547–579, 2021. doi: 10.1257/aer.20190748.
- Chad Syverson. What determines productivity? *Journal of Economic literature*, 49(2):326–365, 2011.
- Jan C. van Ours and Milan Vodopivec. Does reducing unemployment insurance generosity reduce job match quality? *Journal of Public Economics*, 92:684–695, 2008.

8 Data Appendix

8.1 Descriptive Statistics

PLACEHOLDER Table ?? reports descriptive statistics for the main analysis sample. The sample comprises [X] million workers, [Y] million worker–firm employment spells, and [Z] thousand unique employer firms, with workers observed in an average of [A] spells each. Spell sequences range in length from 1 to [B] spells per worker, with a median of [C] spells.

Duration distribution. Spells are distributed across the four duration categories as follows: [X]% are classified as very short (1–6 months), [Y]% as short (7–15 months), [Z]% as medium (16–36 months), and [W]% as long (37 months or more). The concentration of spells in the shorter categories reflects both the reality of high labor market turnover and the tendency of workers to omit short-lived positions from their profiles, potentially understating the true incidence of very short spells.

Exit-type distribution. Among concluded spells, the most common exit type is upgrade ([X]%), followed by pull separation ([Y]%), stay or equal-level transfer ([Z]%), and push separation ([W]%). Downgrades account for [V]% of exits, transitions to education for [U]%, and transitions to nonemployment for [T]%. Ongoing or right-censored spells represent approximately 23% of all spells in the sample.

Pre-spell gap categories. [**PLACEHOLDER**: frequencies of the pre-spell gap categories, capturing the elapsed time between the end of a worker’s previous spell and the start of the current one.]

Worker characteristics. The sample skews toward college-educated workers: [X]% hold at least a bachelor’s degree, compared with [Y]% in the Current Population Survey for employed individuals over the sample period. Male workers account for [Z]% of the sample; [W]% are predicted non-Hispanic White, [V]% Asian, [U]% Hispanic, and [T]% Black. Occupation categories are dominated by professional and technical roles, consistent with the stronger coverage of Revelio Labs in knowledge-intensive sectors.

Firm characteristics. The median firm in our sample employs [X] workers (as observed in the Revelio Labs data), has been in operation for [Y] years, and is located in one of the top-25 U.S. metropolitan areas. Approximately [Z]% of firms are in professional services

or information technology. Employment growth rates average [W]% per quarter, with substantial cross-sectional and time-series dispersion.

Firm growth and survival. Over the sample period, [X]% of firms survive through the end of the observation window. Average employment growth is [Y]% per year, with considerable heterogeneity: [Z]% of firm-years record employment declines. These outcomes are examined in the second-stage analysis in relation to the match-quality distributions recovered from the HMM.

8.2 Distribution of Firms and Employment Across Sectors by Year

8.3 Classification of job exit types

Internal transfers. We first check whether a subsequent position at the same employer begins within 31 days of the end date of the current position. If so, we classify the transition as one of three internal transfer types based on the seniority level of the next position relative to the current one. A *downgrade* captures a move to a lower-seniority position within the same firm, signaling a deterioration in match quality that nonetheless remains above the worker's reservation threshold. A *lateral transfer* denotes a move to a different position at the same seniority level and carries no direct signal about the direction of match quality change. An *upgrade* captures a move to a higher-seniority position and signals an improvement in match quality. We then advance to the next position in the employment spell and repeat this classification until no subsequent qualifying position exists, at which point we treat the final position in the spell as a separation and apply the classification procedure described below.

Job-to-job moves within the same area. A transition is classified as a job-to-job move if a position at a different employer begins within 31 days of the end date of the current position, provided the new position extends beyond that end date. Among same-area job-to-job moves, we distinguish between two types. A *pull separation* is a move to a different employer within the same area at a strictly higher seniority level, indicating that the new match offers higher quality than the previous one. A *push separation* is a move to a different employer within the same area at an equal or lower seniority level. Although a downward move along the seniority ladder does not necessarily mean the previous match quality fell below the reservation threshold, it suggests the new match offers substantially higher utility for the worker to accept a lower rank.

Relocation. We classify a job-to-job move as a relocation if the new position is in a different geographic area and begins within two months of the end date of the current

Table 8: Number of Establishments by Year and Sector

Year	Source	11	21	22	23	31-33	42	44-45	48-49	51	52	53	54	55	56	61	62	71	72	81	92	99
		Agric.	Mining	Utilities	Const.	Mfg.	Wholesale	Retail	Transp.	Info.	Finance	Real Est.	Prof. Svcs	Mgmt	Admin	Educ.	Health	Arts	Hosp.	Other	Pub. Admin	Unclass. Missing
2007	Revello	15,030	5,508	7,465	85,388	192,742	74,713	159,934	37,749	99,446	96,365	63,689	285,276	8,275	74,985	96,749	132,930	46,107	69,958	88,752	169,698	3,537
	QCEW	95,203	29,418	15,848	887,529	360,737	626,672	1,047,530	246,527	140,824	489,927	368,875	965,658	48,761	453,194	120,995	713,125	112,900	597,319	1,147,925	71,343	191,725
2008	Revello	17,215	6,128	8,480	93,212	208,135	81,111	179,669	41,363	113,158	105,447	70,594	325,050	9,052	84,514	108,410	147,142	52,339	79,119	99,216	186,249	43,899
	QCEW	94,750	30,702	15,974	878,331	359,103	628,682	1,048,989	247,011	141,685	488,495	364,528	992,124	51,049	462,150	123,594	732,925	113,870	606,756	1,186,086	71,894	198,588
2009	Revello	19,258	6,547	9,542	99,373	221,766	87,032	199,818	44,414	128,291	113,954	76,931	367,964	9,709	94,013	120,068	160,943	58,734	88,327	109,822	203,631	4,356
	QCEW	94,436	31,118	16,173	828,247	350,493	617,849	1,030,743	242,310	141,235	475,406	350,994	998,010	51,571	458,640	124,386	749,426	113,259	609,263	1,220,570	72,398	175,743
2010	Revello	22,079	7,216	10,779	107,729	240,525	94,873	226,008	48,803	145,453	123,751	84,592	416,288	10,777	105,303	133,636	176,923	66,078	100,160	122,308	223,869	4,797
	QCEW	94,484	31,487	16,307	788,985	341,833	613,877	1,022,957	239,563	139,197	464,732	342,002	1,008,602	52,069	462,115	127,924	767,846	112,685	616,964	1,249,369	72,494	171,006
2011	Revello	24,177	7,775	11,514	114,079	254,305	100,488	246,681	52,342	158,519	130,391	90,097	448,913	11,544	113,355	144,418	190,429	71,589	111,138	131,913	239,100	5,251
	QCEW	95,181	32,529	16,329	759,549	336,372	613,845	1,020,233	242,355	138,125	461,203	336,500	1,025,810	53,676	466,221	130,582	783,212	113,116	627,410	1,309,746	72,130	180,628
2012	Revello	26,485	8,353	12,138	121,595	269,866	106,479	269,947	56,740	172,647	137,760	96,382	483,718	12,371	122,042	156,348	204,809	77,809	123,769	142,806	254,962	5,743
	QCEW	96,361	33,965	16,557	743,466	334,039	615,836	1,024,770	245,916	138,532	463,013	337,644	1,049,214	56,146	475,330	133,940	800,069	114,942	639,461	1,285,436	71,539	188,918
2013	Revello	27,810	8,816	12,694	129,166	284,575	112,023	292,092	60,966	186,202	145,234	102,990	518,127	13,307	130,974	167,923	218,705	83,614	136,114	153,141	270,577	6,227
	QCEW	97,810	34,942	16,760	739,923	334,005	619,147	1,031,955	248,826	139,283	463,993	344,225	1,074,459	58,506	484,061	137,104	1,273,293	117,330	647,580	788,031	70,576	183,608
2014	Revello	31,133	9,372	13,467	138,023	301,992	118,438	316,999	66,016	201,759	154,098	120,019	558,386	14,183	141,076	181,662	233,829	89,992	150,111	164,673	289,363	6,756
	QCEW	99,711	35,896	16,892	749,251	337,039	620,881	1,036,609	253,038	144,933	470,209	352,619	1,105,203	60,115	493,419	139,671	1,302,469	120,949	656,934	805,422	70,728	188,060
2015	Revello	30,046	9,794	14,317	147,075	319,945	125,018	344,514	71,194	218,072	164,051	120,019	601,897	15,280	151,855	196,482	250,555	96,875	165,316	177,531	309,187	7,312
	QCEW	101,480	35,826	17,031	758,455	339,872	619,387	1,037,343	258,683	146,282	474,306	360,022	1,138,169	61,688	507,961	144,867	1,341,973	123,942	666,585	817,922	71,077	194,230
2016	Revello	36,546	10,124	15,107	155,558	335,842	130,920	371,022	75,844	233,876	173,380	128,556	644,636	16,152	162,477	211,044	266,209	103,219	179,542	190,439	328,345	7,879
	QCEW	102,973	34,169	17,148	771,310	342,909	615,539	1,039,759	263,038	150,725	478,353	369,245	1,155,618	63,231	521,117	147,728	1,401,074	126,611	678,164	827,358	71,016	230,401
2017	Revello	39,352	10,586	15,926	164,149	351,875	136,782	399,641	81,010	250,279	184,491	138,040	690,373	17,004	173,759	227,053	283,068	109,608	193,228	204,216	348,129	8,351
	QCEW	104,003	32,464	17,321	782,720	345,930	612,334	1,038,669	265,752	156,444	482,572	378,585	1,173,332	64,772	528,655	150,376	1,452,487	129,814	694,573	834,706	70,580	208,895
2018	Revello	42,651	11,116	16,997	173,324	370,490	143,201	430,620	87,320	268,904	196,643	148,053	744,462	18,108	187,253	246,416	301,095	116,543	207,715	219,403	371,118	8,782
	QCEW	105,520	32,464	17,694	806,981	350,659	615,153	1,040,887	274,460	166,607	489,787	396,285	1,217,498	66,941	545,611	154,720	1,508,053	136,543	709,233	850,946	71,169	146,218
2019	Revello	45,664	11,493	18,114	181,235	387,077	148,853	458,602	92,986	286,241	209,039	157,900	796,903	19,152	200,060	265,911	319,543	122,692	220,522	233,723	395,128	9,165
	QCEW	106,500	32,610	17,948	828,425	354,230	615,309	1,040,219	285,012	177,863	495,938	409,866	1,255,858	69,668	562,787	138,392	1,565,040	142,652	722,367	855,660	71,776	155,111
2020	Revello	48,308	11,791	19,227	188,233	401,540	153,439	484,981	98,184	307,778	222,635	167,536	854,408	20,107	212,912	286,048	337,410	127,449	225,083	247,670	417,916	9,397
	QCEW	108,262	31,866	18,408	844,774	357,417	614,286	1,039,293	294,031	192,020	510,396	425,033	1,308,176	73,047	578,811	162,830	1,667,037	146,977	724,289	817,827	72,232	179,495
2021	Revello	50,288	12,066	20,411	194,354	412,945	156,393	504,182	103,501	326,168	235,158	175,990	899,130	20,973	223,262	302,636	352,321	132,429	232,374	258,163	434,997	9,586
	QCEW	109,728	31,093	19,168	869,257	365,513	618,141	1,047,926	312,263	218,801	534,342	443,343	1,413,855	79,750	608,788	169,458	1,716,099	151,608	735,639	835,005	72,295	234,337
2022	Revello	52,145	12,370	21,366	199,484	422,262	158,818	521,146	108,050	343,081	245,021	183,247	942,179	21,696	234,468	318,717	365,355	136,867	239,215	266,771	448,443	9,752
	QCEW	111,707	30,978	20,292	900,420	379,839	634,699	1,055,007	333,813	257,553	559,303	466,119	1,558,055	87,478	650,577	178,702	1,773,095	160,705	757,863	861,187	72,391	345,682
2023	Revello	53,984	12,584	22,398	203,226	430,286	161,187	538,559	111,418	359,895	253,308	189,483	989,574	22,543	246,120	335,085	377,470	140,278	241,083	273,763	457,287	9,778
	QCEW	113,506	30,933	21,415	925,221	391,322	638,779	1,068,227	345,839	279,935	572,931	481,593	1,658,686	94,657	676,793	185,983	1,820,164	168,116	776,697	875,283	72,837	336,977
2024	Revello	55,626	12,772	23,015	205,174	436,655	163,324	554,932	113,183	373,634	259,682	193,604	1,028,960	23,426	254,960	347,378	387,237	142,094	238,522	279,099	460,072	9,703
	QCEW	113,723	30,738	22,077	936,179	396,248	637,175	1,066,813	343,787	288,795	579,030	485,770	1,715,086	100,043	683,561	190,194	1,943,893	173,163	788,069	878,983	72,907	274,636
2025	Revello	56,854	12,909	23,125	204,545	437,701	164,332	549,022	113,559	383,688	262,810	195,218	1,055,559	24,414	260,606	355,713	388,908	141,674	230,506	278,841	460,343	9,508
	QCEW	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
All	Revello	36,814	9,859	15,583	152,891	330,554	127,233	370,967	77,086	239,847	179,654	131,269	665,884	16,214	167,052	221,142	268,152	100,842	170,095	191,697	329,917	7,338
	QCEW	102,519	32,400	17,741	822,168	354,309	620,977	1,040,996	274,568	175,491	497,441	389,625	1,211,856	66,287	534,433	148,969	1,295,071	132,177	680,843	969,303	71,743	210,237

Notes: Each cell reports the percentage of unique workers in a given year employed in each sector. Rows sum to 100 percent. Sources: *Individual positions* files with valid end date from Revello.

Table 9: Number of Workers by Year and Sector

Year	Source	11	21	22	23	31-33	42	Wholesale	42	Retail	44-45	Transp.	48-49	51	Finance	52	Real Est.	53	Prof. Svcs	54	Mgmt	55	Admin	56	Educ.	61	Health	62	Arts	71	Hosp.	72	Other	81	92	Pub. Admin	99	Missing			
2007	Revelo	59,269	213,618	185,995	542,960	4,369,894	693,058	2,021,785	616,087	2,514,070	3,098,836	638,436	3,355,802	30,926	791,443	2,254,378	1,907,212	459,646	876,697	902,890	2,790,705	19,877	8,077,434	216,721	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
	QCEW	1,165,065	660,278	564,101	7,470,978	13,801,244	5,987,142	15,446,908	5,038,523	3,018,755	5,965,017	2,111,695	7,536,567	1,839,616	8,315,439	8,870,932	13,945,929	1,787,026	11,310,142	4,389,416	1,102,132	1,012,239	1,055,595	3,104,190	23,223	8,988,557	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2008	Revelo	68,266	244,345	213,229	587,838	4,857,038	758,735	2,249,640	667,299	2,729,526	3,280,733	692,982	3,693,505	35,101	890,212	2,662,457	2,223,476	539,364	1,012,239	1,055,595	3,104,190	23,223	8,988,557	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
	QCEW	1,166,399	713,399	574,974	7,035,736	13,349,786	5,954,822	15,423,640	5,000,400	2,973,997	5,829,985	2,070,279	7,720,772	1,895,417	9,923,164	8,979,959	14,354,052	1,811,185	1,349,733	4,434,791	4,515,167	206,318	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2009	Revelo	76,320	253,715	228,462	601,884	4,684,464	789,935	2,461,639	680,870	2,820,297	3,328,150	726,304	3,840,229	38,168	953,312	3,063,072	2,501,425	607,817	1,113,294	1,178,280	3,392,089	25,959	9,772,801	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
	QCEW	1,140,124	641,021	578,042	5,866,074	11,778,517	5,561,625	14,479,860	4,668,250	2,793,101	5,590,122	1,929,876	7,739,469	1,855,139	9,084,602	8,986,657	14,645,784	1,761,776	1,100,713	4,321,928	4,522,592	173,694	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2010	Revelo	88,967	284,799	252,317	649,073	5,007,680	868,268	2,826,663	740,724	3,104,376	3,577,662	798,188	4,223,680	43,797	1,091,889	3,575,839	2,890,049	709,204	1,294,931	1,358,067	3,744,645	30,982	10,845,514	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
	QCEW	1,144,585	651,364	569,343	5,409,062	11,455,600	5,466,213	14,417,382	4,575,633	2,683,163	5,455,488	1,874,874	7,355,400	1,854,778	7,331,721	8,933,733	14,908,395	1,748,010	1,102,398	4,299,245	4,529,882	152,464	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2011	Revelo	101,428	329,882	275,530	715,074	5,447,677	964,507	3,231,500	822,988	3,401,769	3,859,873	872,853	4,636,575	48,730	1,245,273	4,055,756	3,293,838	810,549	1,500,339	1,527,005	3,984,903	36,282	11,790,746	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
	QCEW	1,158,995	729,776	565,878	5,393,207	11,668,416	5,545,553	14,602,592	4,656,840	2,648,137	5,475,771	1,869,031	7,368,658	1,914,343	7,645,388	8,814,066	15,189,532	1,765,456	1,297,213	4,361,236	4,407,927	173,576	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2012	Revelo	115,080	372,953	296,406	799,763	5,862,604	1,065,399	3,642,960	911,306	3,714,665	4,160,095	962,988	5,058,217	54,402	1,410,432	4,518,111	3,720,844	927,338	1,731,137	1,718,061	4,255,088	41,898	12,816,599	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
	QCEW	1,188,505	797,846	565,263	5,506,227	11,872,709	5,656,442	14,801,178	4,741,656	2,643,737	5,533,414	1,902,838	7,795,401	2,003,075	7,920,502	8,751,331	15,486,986	1,814,723	1,168,508	4,513,473	4,375,428	171,660	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2013	Revelo	127,582	404,689	312,141	895,348	6,231,601	1,154,599	4,008,676	996,273	4,016,806	4,437,999	1,074,168	5,448,302	59,225	1,554,109	4,909,798	4,117,106	1,040,070	1,939,683	1,872,174	4,490,368	47,330	13,617,283	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	QCEW	1,208,781	813,087	563,840	5,739,777	11,963,258	5,738,845	15,012,242	4,813,868	2,660,089	5,594,825	1,951,372	8,020,732	2,087,081	8,202,508	8,778,877	16,242,082	1,863,739	12,081,654	4,114,555	4,347,157	165,000	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2014	Revelo	141,832	437,657	332,806	1,004,890	6,651,997	1,253,248	4,360,468	1,110,159	4,270,818	4,729,553	1,205,418	5,888,677	64,771	1,711,422	5,295,319	4,532,786	1,156,574	2,139,282	2,043,770	4,754,959	52,999	14,367,799	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	QCEW	1,286,195	841,689	565,436	6,053,318	12,124,876	5,815,746	15,283,710	4,955,722	2,686,625	5,604,138	2,001,580	8,248,497	2,154,136	8,303,186	8,806,861	16,367,260	1,924,513	1,247,720	4,199,876	4,345,431	214,677	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2015	Revelo	156,021	422,876	355,994	1,113,324	7,063,592	1,343,504	4,678,951	1,229,305	4,762,433	5,055,875	1,342,892	6,338,888	71,507	1,862,839	5,665,731	5,014,707	1,275,645	2,339,710	2,215,352	5,030,875	59,141	15,043,331	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	QCEW	1,246,155	751,894	571,723	6,340,070	12,259,494	5,874,045	15,582,161	5,167,352	2,701,773	5,703,281	2,053,504	8,322,590	2,197,652	8,718,059	8,692,883	17,004,593	1,987,762	1,285,204	4,273,143	4,352,479	239,962	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2016	Revelo	171,296	383,092	372,633	1,210,381	7,360,802	1,410,452	4,939,558	1,337,787	5,100,116	5,339,190	1,471,388	6,770,094	78,456	1,993,221	6,001,887	5,461,811	1,392,963	2,541,489	2,392,092	5,305,539	66,044	15,701,215	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	QCEW	1,257,935	613,374	571,180	6,600,554	12,264,621	5,859,324	15,765,252	5,342,733	2,740,898	5,793,444	2,088,864	8,739,889	2,230,131	8,883,037	8,936,930	17,488,144	2,061,946	13,232,468	4,350,424	4,401,656	271,704	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2017	Revelo	188,686	387,907	393,109	1,328,130	7,726,585	1,487,235	5,223,653	1,466,082	5,455,051	5,640,626	1,618,613	7,122,049	87,009	2,137,763	6,438,302	5,908,325	1,511,314	2,750,283	2,554,870	5,580,748	73,143	16,427,799	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	QCEW	1,260,212	623,706	570,695	6,860,090	12,574,561	5,896,327	15,796,495	5,528,229	2,733,504	5,875,237	2,141,670	8,893,889	2,278,042	8,993,570	8,975,323	17,902,264	2,117,797	13,522,526	4,397,567	4,406,228	219,504	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2018	Revelo	210,655	413,924	415,715	1,463,330	8,199,255	1,575,555	5,500,539	1,619,017	5,867,863	5,970,763	1,779,174	7,637,117	100,222	2,308,964	6,925,113	6,391,789	1,637,857	2,963,632	2,756,826	5,896,416	80,659	17,153,701	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	QCEW	1,262,394	673,302	569,231	7,137,234	12,615,096	5,855,321	15,731,946	5,781,483	2,749,662	5,921,583	2,201,212	9,185,159	2,347,219	9,162,003	9,039,554	18,323,260	2,181,036	13,732,954	4,464,268	4,454,650	127,754	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2019	Revelo	233,764	423,578	436,450	1,579,312	8,548,534	1,637,742	5,699,833	1,745,847	6,288,512	6,273,804	1,926,494	8,129,512	108,395	2,456,349	7,369,161	6,855,883	1,734,522	3,097,761	2,930,148	6,208,643	86,779	17,657,232	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	QCEW	1,262,034	674,835	565,841	7,390,264	12,742,690	5,883,667	15,545,740	6,063,396	2,779,183	5,995,755	2,259,847	9,437,601	2,407,183	9,208,977	9,101,102	18,742,396	2,241,807	13,922,308	4,516,136	4,492,186	130,762	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2020	Revelo	245,392	396,679	442,245	1,635,066	8,534,843	1,630,972	5,833,403	1,812,188	6,452,933	6,409,856	2,001,329	8,301,923	106,651	2,507,628	7,261,078	7,076,971	1,610,314	2,938,781	2,984,815	6,328,966	85,166	17,998,189	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	QCEW	1,240,048	540,312	560,717	7,142,252	12,050,345	5,620,210	14,701,633	6,157,336	2,638,060	5,353,457	2,130,057	9,353,431	2,318,008	8,677,798	8,597,856	18,121,463	1,594,692	10,984,979	3,907,965	4,460,959	137,503	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	
2021	Revelo	265,477	374,468	468,950	1,734,196	8,949,861	1,687,395	6,095,727	1,911,169	7,096,956	6,846,418	2,131,156	8,983,746	106,615	2,677,798	7,739,262	7,576,139	1,692,784	3,053,235																						

Table 10: Distribution of Establishments by Year and Sector

Year	Source	11	21	22	23	31-33	42	44-45	48-49	51	52	53	54	55	56	61	62	71	72	81	92	99	Missing
		Agric.	Mining	Utilities	Const.	Mfg.	Wholesale	Retail	Transp.	Info.	Finance	Real Est.	Prof. Svcs	Mgmt	Admin	Educ.	Health	Arts	Hosp.	Other	Pub. Admin	Unclss.	Missing
2007	Revelio	0.8%	0.3%	0.4%	4.6%	10.4%	4.0%	8.6%	2.0%	5.4%	5.2%	3.4%	15.4%	0.4%	4.0%	5.2%	7.2%	2.5%	3.8%	4.8%	9.2%	0.2%	2.1%
	QCEW	1.1%	0.3%	0.2%	10.2%	4.1%	7.2%	12.0%	2.8%	1.6%	5.6%	4.2%	11.1%	0.6%	5.2%	1.4%	8.2%	1.3%	6.8%	13.1%	0.8%	2.2%	–
2008	Revelio	0.8%	0.3%	0.4%	4.5%	10.1%	3.9%	8.7%	2.0%	5.5%	5.1%	3.4%	15.8%	0.4%	4.1%	5.3%	7.1%	2.5%	3.8%	4.8%	9.0%	0.2%	2.1%
	QCEW	1.1%	0.3%	0.2%	9.9%	4.1%	7.1%	11.9%	2.8%	1.6%	5.5%	4.1%	11.2%	0.6%	5.2%	1.4%	8.3%	1.3%	6.9%	13.4%	0.8%	2.2%	–
2009	Revelio	0.8%	0.3%	0.4%	4.4%	9.8%	3.8%	8.8%	2.0%	5.6%	5.0%	3.4%	16.2%	0.4%	4.1%	5.3%	7.1%	2.6%	3.9%	4.8%	9.0%	0.2%	2.1%
	QCEW	1.1%	0.4%	0.2%	9.5%	4.0%	7.1%	11.8%	2.8%	1.6%	5.4%	4.0%	11.4%	0.6%	5.2%	1.4%	8.6%	1.3%	7.0%	13.9%	0.8%	2.0%	–
2010	Revelio	0.9%	0.3%	0.4%	4.3%	9.5%	3.8%	8.9%	1.9%	5.8%	4.9%	3.3%	16.5%	0.4%	4.2%	5.3%	7.0%	2.6%	4.0%	4.8%	8.9%	0.2%	2.1%
	QCEW	1.1%	0.4%	0.2%	9.0%	3.9%	7.0%	11.7%	2.7%	1.6%	5.3%	3.9%	11.5%	0.6%	5.3%	1.5%	8.8%	1.3%	7.1%	14.3%	0.8%	2.0%	–
2011	Revelio	0.9%	0.3%	0.4%	4.2%	9.4%	3.7%	9.1%	1.9%	5.8%	4.8%	3.3%	16.5%	0.4%	4.2%	5.3%	7.0%	2.6%	4.1%	4.9%	8.8%	0.2%	2.1%
	QCEW	1.1%	0.4%	0.2%	8.6%	3.8%	7.0%	11.6%	2.7%	1.6%	5.2%	3.8%	11.6%	0.6%	5.3%	1.5%	8.9%	1.3%	7.1%	14.9%	0.8%	2.0%	–
2012	Revelio	0.9%	0.3%	0.4%	4.2%	9.2%	3.6%	9.2%	1.9%	5.9%	4.7%	3.3%	16.5%	0.4%	4.2%	5.3%	7.0%	2.7%	4.2%	4.9%	8.7%	0.2%	2.1%
	QCEW	1.1%	0.4%	0.2%	8.4%	3.8%	6.9%	11.6%	2.8%	1.6%	5.2%	3.8%	11.8%	0.6%	5.4%	1.5%	9.0%	1.3%	7.2%	14.5%	0.8%	2.1%	–
2013	Revelio	0.9%	0.3%	0.4%	4.1%	9.1%	3.6%	9.3%	1.9%	5.9%	4.6%	3.3%	16.6%	0.4%	4.2%	5.4%	7.0%	2.7%	4.3%	4.9%	8.6%	0.2%	2.2%
	QCEW	1.1%	0.4%	0.2%	8.3%	3.8%	7.0%	11.6%	2.8%	1.6%	5.2%	3.9%	12.1%	0.7%	5.4%	1.5%	14.3%	1.3%	7.3%	8.8%	0.8%	2.1%	–
2014	Revelio	0.9%	0.3%	0.4%	4.1%	9.0%	3.5%	9.4%	2.0%	6.0%	4.6%	3.3%	16.6%	0.4%	4.2%	5.4%	6.9%	2.7%	4.5%	4.9%	8.6%	0.2%	2.2%
	QCEW	1.1%	0.4%	0.2%	8.3%	3.7%	6.9%	11.4%	2.8%	1.6%	5.2%	3.9%	12.2%	0.7%	5.4%	1.5%	14.4%	1.3%	7.3%	8.9%	0.8%	2.1%	–
2015	Revelio	0.9%	0.3%	0.4%	4.1%	8.8%	3.5%	9.5%	2.0%	6.0%	4.5%	3.3%	16.6%	0.4%	4.2%	5.4%	6.9%	2.7%	4.6%	4.9%	8.5%	0.2%	2.2%
	QCEW	1.1%	0.4%	0.2%	8.2%	3.7%	6.7%	11.3%	2.8%	1.6%	5.1%	3.9%	12.3%	0.7%	5.5%	1.6%	14.6%	1.3%	7.2%	8.9%	0.8%	2.1%	–
2016	Revelio	0.9%	0.3%	0.4%	4.0%	8.7%	3.4%	9.6%	2.0%	6.1%	4.5%	3.3%	16.7%	0.4%	4.2%	5.5%	6.9%	2.7%	4.6%	4.9%	8.5%	0.2%	2.2%
	QCEW	1.1%	0.4%	0.2%	8.2%	3.6%	6.5%	11.1%	2.8%	1.6%	5.1%	3.9%	12.3%	0.7%	5.5%	1.6%	14.9%	1.3%	7.2%	8.8%	0.8%	2.4%	–
2017	Revelio	1.0%	0.3%	0.4%	4.0%	8.5%	3.3%	9.7%	2.0%	6.1%	4.5%	3.4%	16.8%	0.4%	4.3%	5.5%	6.9%	2.7%	4.7%	5.0%	8.5%	0.2%	2.2%
	QCEW	1.1%	0.3%	0.2%	8.2%	3.6%	6.4%	10.9%	2.8%	1.6%	5.1%	4.0%	12.3%	0.7%	5.6%	1.6%	15.2%	1.4%	7.3%	8.8%	0.7%	2.2%	–
2018	Revelio	1.0%	0.3%	0.4%	3.9%	8.4%	3.2%	9.8%	2.0%	6.1%	4.5%	3.4%	16.9%	0.4%	4.2%	5.6%	6.8%	2.6%	4.7%	5.0%	8.4%	0.2%	2.3%
	QCEW	1.1%	0.3%	0.2%	8.3%	3.6%	6.3%	10.7%	2.8%	1.7%	5.0%	4.1%	12.5%	0.7%	5.6%	1.6%	15.5%	1.4%	7.3%	8.8%	0.7%	1.5%	–
2019	Revelio	1.0%	0.2%	0.4%	3.9%	8.3%	3.2%	9.8%	2.0%	6.1%	4.5%	3.4%	17.0%	0.4%	4.3%	5.7%	6.8%	2.6%	4.7%	5.0%	8.4%	0.2%	2.3%
	QCEW	1.1%	0.3%	0.2%	8.3%	3.6%	6.2%	10.5%	2.9%	1.8%	5.0%	4.1%	12.7%	0.7%	5.7%	1.6%	15.8%	1.4%	7.3%	8.6%	0.7%	1.6%	–
2020	Revelio	1.0%	0.2%	0.4%	3.8%	8.1%	3.1%	9.8%	2.0%	6.2%	4.5%	3.4%	17.2%	0.4%	4.3%	5.8%	6.8%	2.6%	4.5%	5.0%	8.4%	0.2%	2.3%
	QCEW	1.1%	0.3%	0.2%	8.3%	3.5%	6.0%	10.2%	2.9%	1.9%	5.0%	4.2%	12.9%	0.7%	5.7%	1.6%	16.4%	1.4%	7.1%	8.0%	0.7%	1.8%	–
2021	Revelio	1.0%	0.2%	0.4%	3.7%	8.0%	3.0%	9.7%	2.0%	6.3%	4.5%	3.4%	17.3%	0.4%	4.3%	5.8%	6.8%	2.6%	4.5%	5.0%	8.4%	0.2%	2.4%
	QCEW	1.0%	0.3%	0.2%	8.2%	3.5%	5.8%	9.9%	2.9%	2.1%	5.0%	4.2%	13.4%	0.8%	5.8%	1.6%	16.2%	1.4%	6.9%	7.9%	0.7%	2.2%	–
2022	Revelio	1.0%	0.2%	0.4%	3.7%	7.8%	2.9%	9.7%	2.0%	6.4%	4.5%	3.4%	17.5%	0.4%	4.4%	5.9%	6.8%	2.5%	4.4%	5.0%	8.3%	0.2%	2.5%
	QCEW	1.0%	0.3%	0.2%	8.0%	3.4%	5.7%	9.4%	3.0%	2.3%	5.0%	4.2%	13.9%	0.8%	5.8%	1.6%	15.8%	1.4%	6.8%	7.7%	0.6%	3.1%	–
2023	Revelio	1.0%	0.2%	0.4%	3.6%	7.7%	2.9%	9.7%	2.0%	6.5%	4.5%	3.4%	17.7%	0.4%	4.4%	6.0%	6.8%	2.5%	4.3%	4.9%	8.2%	0.2%	2.6%
	QCEW	1.0%	0.3%	0.2%	8.0%	3.4%	5.5%	9.3%	3.0%	2.4%	5.0%	4.2%	14.4%	0.8%	5.9%	1.6%	15.8%	1.5%	6.7%	7.6%	0.6%	2.9%	–
2024	Revelio	1.0%	0.2%	0.4%	3.6%	7.6%	2.9%	9.7%	2.0%	6.5%	4.5%	3.4%	18.0%	0.4%	4.5%	6.1%	6.8%	2.5%	4.2%	4.9%	8.1%	0.2%	2.7%
	QCEW	1.0%	0.3%	0.2%	8.0%	3.4%	5.4%	9.1%	2.9%	2.5%	4.9%	4.1%	14.6%	0.9%	5.8%	1.6%	16.6%	1.5%	6.7%	7.5%	0.6%	2.3%	–
2025	Revelio	1.0%	0.2%	0.4%	3.6%	7.6%	2.9%	9.5%	2.0%	6.7%	4.6%	3.4%	18.4%	0.4%	4.5%	6.2%	6.8%	2.5%	4.0%	4.8%	8.0%	0.2%	2.4%
	QCEW	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
All	Revelio	0.9%	0.3%	0.4%	4.0%	8.7%	3.4%	9.4%	2.0%	6.0%	4.7%	3.4%	16.9%	0.4%	4.2%	5.6%	6.9%	2.6%	4.3%	4.9%	8.6%	0.2%	2.3%
	QCEW	1.1%	0.3%	0.2%	8.6%	3.7%	6.5%	10.9%	2.8%	1.8%	5.2%	4.0%	12.5%	0.7%	5.5%	1.5%	13.2%	1.4%	7.1%	10.2%	0.8%	2.2%	–

Notes: Each cell reports the percentage of unique workers in a given year employed in each sector. Rows sum to 100 percent. Sources: *Individual positions* files with valid end date from Revelio.

Table 11: Distribution of Workers by Year and Sector

Year	Source	11	21	22	23	31-33	42	44-45	48-49	51	52	53	54	55	56	61	62	71	72	81	92	99	Missing
		Agric.	Mining	Utilities	Const.	Mfg.	Wholesale	Retail	Transp.	Info.	Finance	Real Est.	Prof. Svcs	Mgmt	Admin	Educ.	Health	Arts	Hosp.	Other	Pub. Admin	Unclss.	Missing
2007	Revelio	0.2%	0.6%	0.5%	1.5%	12.0%	1.9%	5.6%	1.7%	6.9%	8.5%	1.8%	9.2%	0.1%	2.2%	6.2%	5.2%	1.3%	2.4%	2.5%	7.7%	0.1%	22.2%
	QCEW	0.9%	0.5%	0.5%	6.0%	11.1%	4.8%	12.5%	4.1%	2.4%	4.8%	1.7%	6.1%	1.5%	6.7%	7.2%	11.3%	1.4%	9.1%	3.5%	3.6%	0.2%	-
2008	Revelio	0.2%	0.6%	0.5%	1.5%	11.5%	1.9%	5.6%	1.7%	6.8%	8.1%	1.7%	9.1%	0.1%	2.2%	6.6%	5.5%	1.3%	2.5%	2.6%	7.7%	0.1%	22.3%
	QCEW	0.9%	0.6%	0.5%	5.7%	10.8%	4.8%	12.4%	4.1%	2.4%	4.7%	1.7%	6.3%	1.5%	6.4%	7.3%	11.7%	1.5%	9.2%	3.6%	3.7%	0.2%	-
2009	Revelio	0.2%	0.6%	0.5%	1.4%	10.9%	1.8%	5.7%	1.6%	6.5%	7.7%	1.7%	8.9%	0.1%	2.2%	7.1%	5.8%	1.4%	2.6%	2.7%	7.9%	0.1%	22.7%
	QCEW	1.0%	0.5%	0.5%	5.0%	10.1%	4.8%	12.4%	4.0%	2.4%	4.8%	1.7%	6.3%	1.6%	6.1%	7.7%	12.5%	1.5%	9.4%	3.7%	3.9%	0.1%	-
2010	Revelio	0.2%	0.6%	0.5%	1.4%	10.4%	1.8%	5.9%	1.5%	6.5%	7.5%	1.7%	8.8%	0.1%	2.3%	7.4%	6.0%	1.5%	2.7%	2.8%	7.8%	0.1%	22.6%
	QCEW	1.0%	0.6%	0.5%	4.7%	9.9%	4.7%	12.4%	3.9%	2.3%	4.7%	1.6%	6.3%	1.6%	6.3%	7.7%	12.9%	1.5%	9.5%	3.7%	3.9%	0.1%	-
2011	Revelio	0.2%	0.6%	0.5%	1.4%	10.3%	1.8%	6.1%	1.6%	6.4%	7.3%	1.6%	8.8%	0.1%	2.4%	7.7%	6.2%	1.5%	2.8%	2.9%	7.5%	0.1%	22.3%
	QCEW	1.0%	0.6%	0.5%	4.6%	9.9%	4.7%	12.4%	4.0%	2.3%	4.7%	1.6%	6.4%	1.6%	6.5%	7.5%	12.9%	1.5%	9.6%	3.7%	3.8%	0.1%	-
2012	Revelio	0.2%	0.6%	0.5%	1.4%	10.1%	1.8%	6.3%	1.6%	6.4%	7.2%	1.7%	8.7%	0.1%	2.4%	7.8%	6.4%	1.6%	3.0%	3.0%	7.3%	0.1%	22.0%
	QCEW	1.0%	0.7%	0.5%	4.6%	9.9%	4.7%	12.4%	4.0%	2.2%	4.6%	1.6%	6.5%	1.7%	6.6%	7.3%	12.9%	1.5%	9.8%	3.8%	3.7%	0.1%	-
2013	Revelio	0.2%	0.6%	0.5%	1.4%	9.9%	1.8%	6.4%	1.6%	6.4%	7.1%	1.7%	8.7%	0.1%	2.5%	7.8%	6.6%	1.7%	3.1%	3.0%	7.2%	0.1%	21.7%
	QCEW	1.0%	0.7%	0.5%	4.7%	9.8%	4.7%	12.3%	3.9%	2.2%	4.6%	1.6%	6.6%	1.7%	6.7%	7.2%	13.3%	1.5%	9.9%	3.4%	3.6%	0.1%	-
2014	Revelio	0.2%	0.6%	0.5%	1.5%	9.8%	1.9%	6.4%	1.6%	6.5%	7.0%	1.8%	8.7%	0.1%	2.5%	7.8%	6.7%	1.7%	3.2%	3.0%	7.0%	0.1%	21.3%
	QCEW	1.0%	0.7%	0.5%	4.9%	9.7%	4.7%	12.3%	4.0%	2.2%	4.5%	1.6%	6.6%	1.7%	6.8%	7.1%	13.3%	1.5%	10.0%	3.4%	3.5%	0.2%	-
2015	Revelio	0.2%	0.6%	0.5%	1.5%	9.8%	1.9%	6.5%	1.7%	6.6%	7.0%	1.9%	8.8%	0.1%	2.6%	7.8%	6.9%	1.8%	3.2%	3.1%	6.9%	0.1%	20.8%
	QCEW	1.0%	0.6%	0.4%	5.0%	9.6%	4.6%	12.2%	4.1%	2.1%	4.5%	1.6%	6.7%	1.7%	6.8%	7.0%	13.4%	1.6%	10.1%	3.4%	3.4%	0.2%	-
2016	Revelio	0.2%	0.5%	0.5%	1.6%	9.6%	1.8%	6.4%	1.7%	6.6%	7.0%	1.9%	8.7%	0.1%	2.6%	7.8%	7.1%	1.8%	3.3%	3.1%	6.9%	0.1%	20.5%
	QCEW	1.0%	0.5%	0.4%	5.1%	9.5%	4.5%	12.2%	4.1%	2.1%	4.5%	1.6%	6.7%	1.7%	6.9%	6.9%	13.5%	1.6%	10.2%	3.4%	3.4%	0.2%	-
2017	Revelio	0.2%	0.5%	0.5%	1.6%	9.5%	1.8%	6.4%	1.8%	6.7%	6.9%	2.0%	8.7%	0.1%	2.6%	7.9%	7.2%	1.9%	3.4%	3.1%	6.8%	0.1%	20.2%
	QCEW	1.0%	0.5%	0.4%	5.2%	9.4%	4.5%	12.0%	4.2%	2.1%	4.5%	1.6%	6.8%	1.7%	6.8%	6.8%	13.6%	1.6%	10.3%	3.3%	3.4%	0.2%	-
2018	Revelio	0.2%	0.5%	0.5%	1.7%	9.4%	1.8%	6.3%	1.9%	6.8%	6.9%	2.0%	8.8%	0.1%	2.7%	8.0%	7.4%	1.9%	3.4%	3.2%	6.8%	0.1%	19.7%
	QCEW	0.9%	0.5%	0.4%	5.3%	9.4%	4.4%	11.8%	4.3%	2.1%	4.4%	1.6%	6.9%	1.8%	6.9%	6.8%	13.7%	1.6%	10.3%	3.3%	3.3%	0.1%	-
2019	Revelio	0.3%	0.5%	0.5%	1.7%	9.3%	1.8%	6.2%	1.9%	6.9%	6.9%	2.1%	8.9%	0.1%	2.7%	8.1%	7.5%	1.9%	3.4%	3.2%	6.8%	0.1%	19.3%
	QCEW	0.9%	0.5%	0.4%	5.5%	9.4%	4.3%	11.5%	4.5%	2.1%	4.4%	1.7%	7.0%	1.8%	6.8%	6.7%	13.8%	1.7%	10.3%	3.3%	3.3%	0.1%	-
2020	Revelio	0.3%	0.4%	0.5%	1.8%	9.2%	1.8%	6.3%	2.0%	7.0%	6.9%	2.2%	9.0%	0.1%	2.7%	7.9%	7.6%	1.7%	3.2%	3.2%	6.8%	0.1%	19.4%
	QCEW	1.0%	0.4%	0.4%	5.6%	9.5%	4.4%	11.6%	4.8%	2.1%	4.7%	1.7%	7.4%	1.8%	6.7%	6.8%	14.3%	1.3%	8.7%	3.1%	3.5%	0.1%	-
2021	Revelio	0.3%	0.4%	0.5%	1.8%	9.2%	1.7%	6.2%	2.0%	7.3%	7.0%	2.2%	9.2%	0.1%	2.7%	7.9%	7.8%	1.7%	3.1%	3.2%	6.8%	0.1%	18.9%
	QCEW	0.9%	0.4%	0.4%	5.6%	9.3%	4.3%	11.6%	5.0%	2.1%	4.7%	1.7%	7.5%	1.8%	6.8%	6.6%	14.0%	1.4%	9.2%	3.1%	3.4%	0.1%	-
2022	Revelio	0.3%	0.4%	0.5%	1.8%	9.1%	1.7%	6.0%	2.0%	7.4%	7.0%	2.2%	9.3%	0.1%	2.8%	8.1%	7.8%	1.8%	3.1%	3.2%	6.7%	0.1%	18.6%
	QCEW	0.9%	0.4%	0.4%	5.5%	9.3%	4.3%	11.2%	5.1%	2.2%	4.5%	1.7%	7.6%	1.8%	6.9%	6.5%	13.8%	1.6%	9.7%	3.2%	3.2%	0.2%	-
2023	Revelio	0.3%	0.4%	0.5%	1.8%	9.1%	1.7%	5.7%	2.0%	7.2%	6.9%	2.3%	9.4%	0.1%	2.8%	8.3%	7.9%	1.8%	3.0%	3.3%	6.8%	0.1%	18.7%
	QCEW	0.9%	0.4%	0.4%	5.6%	9.2%	4.4%	11.0%	5.0%	2.1%	4.5%	1.7%	7.6%	1.8%	6.6%	6.5%	14.1%	1.6%	9.9%	3.2%	3.2%	0.2%	-
2024	Revelio	0.3%	0.4%	0.5%	1.9%	9.0%	1.7%	5.5%	1.9%	7.1%	7.0%	2.3%	9.4%	0.1%	2.8%	8.4%	7.9%	1.8%	2.9%	3.3%	6.9%	0.1%	18.8%
	QCEW	0.9%	0.4%	0.4%	5.7%	9.0%	4.3%	10.9%	5.0%	2.0%	4.4%	1.7%	7.5%	1.8%	6.4%	6.6%	14.6%	1.7%	9.9%	3.3%	3.3%	0.2%	-
2025	Revelio	0.3%	0.4%	0.5%	1.9%	9.0%	1.7%	5.3%	1.9%	7.2%	7.1%	2.3%	9.6%	0.1%	2.8%	8.3%	8.0%	1.8%	2.7%	3.3%	6.9%	0.1%	18.9%
	QCEW	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
All	Revelio	0.2%	0.5%	0.5%	1.6%	9.9%	1.8%	6.0%	1.8%	6.8%	7.2%	1.9%	9.0%	0.1%	2.5%	7.7%	6.9%	1.7%	3.0%	3.0%	7.1%	0.1%	20.6%
	QCEW	1.0%	0.5%	0.4%	5.2%	9.7%	4.6%	12.0%	4.3%	2.2%	4.6%	1.6%	6.8%	1.7%	6.7%	7.0%	13.3%	1.5%	9.7%	3.4%	3.5%	0.2%	-

Notes: Each cell reports the percentage of unique workers in a given year employed in each sector. Rows sum to 100 percent. Sources: *Individual positions* files with valid end date from Revelio.

position. Geographic area is defined at the MSA or CSA level.¹¹ Internal transfers across regions are not classified as relocation, since they reflect changes in match quality with the same employer rather than a geographic reallocation decision. We interpret relocation as primarily driven by shifts in personal or household preferences rather than a deterioration in the prior employment match.

Transition into education. A position is classified as transitioning into education if an education record begins within three months of the position’s end date. Because enrollment decisions are typically planned in advance, this transition does not necessarily reflect declining match quality with the previous employer and is therefore treated as a separate category.

Transition into nonemployment. A position is classified as transitioning into nonemployment if none of the above conditions are met: there is no same-area position beginning within one month, no different-area position beginning within two months, and no education record beginning within three months. A transition into nonemployment signals that match quality with the previous employer has fallen below the quality threshold.

Figure 11a shows the distribution of transition types for all completed primary positions. Overall, 27.6% of separations end in nonemployment. This share is higher than expected, partly because users tend to omit jobs that could signal poor performance or low ability. We do not view this as a major concern for our estimates, since these missing transitions likely also reflect very low match quality with the previous employer, similar to true transitions into nonemployment.

We observe push separations (21.2%) at nearly twice the rate of pull separations (10.7%). This pattern may seem counterintuitive. Why would more job-to-job transitions ended in equal or lower seniority roles? There are two potential explanations for this: First, workers may rationally accept a lower-seniority position at a more productive firm, tolerating short-term wage losses in exchange for better long-run career prospects.¹² Second, push separations likely over represent secondary-sector workers, who experi-

¹¹We do not classify moves across MSAs within the same CSA as relocation, since CSAs represent regions with overlapping labor and commuting markets. The BLS defines CSAs as groups of metropolitan or micropolitan statistical areas with an employment interchange of at least 15%.

¹²A recent case illustrates this dynamic well. Andrej Karpathy — former AI director at Tesla and founding research scientist at OpenAI — joined Anthropic as a senior research leader after founding the AI education startup Eureka Labs. His transition from CEO of Eureka Labs to a research role at Anthropic would be classified as a push separation (though this specific move falls outside my sample, which ends in December 2025; see <https://www.reuters.com/business/autos-transportation/former-tesla-ai-executive-openai-founding-member-andrej-karpathy-joins-anthropic-2026-05-19/>). Karpathy’s decision suggests that his match quality at Anthropic is likely higher than it was at Eureka Labs at the time of the change, making the transition productively rational despite the nominal demotion in title.

ence high churn and rarely climb the job ladder in a linear fashion. For these workers, match quality is highly dispersed across employers, so most matches are short-lived, and early-career workers in particular tend to move laterally across jobs while searching for a good fit (Ahn et al. (2023), Gregory et al. (2025)). In both cases, a push separation either indicates the previous match have substantially fallen in quality, or the new match have much higher match quality.

Internal transfers across the seniority ladder are associated with larger salary changes than job-to-job moves across firms. As shown in Figure 11a, 19.3% of position changes are classified as internal transfers, with promotions (8.7%) and lateral transfers (7.3%) occurring more frequently than downgrades (3.3%). This distribution is consistent with the finding of Forsythe (2023) using CPS and SIPP data, who find that over 40% of moves are to lower ranked occupations. Although downgrades are relatively rare, they are associated with substantial salary losses, averaging \$17,400 in annual salary — more than double the average decline of \$8,125 observed for push separations. Promotions, by contrast, are associated with an average annual salary gain of \$26,720, meaningfully larger than the \$23,349 average gain for pull separations ?? . Table 12 shows these patterns are robust to controlling for year-month (Column 2) and sector fixed effects (Column 3), indicating that the pattern is not driven by aggregate macroeconomic conditions or by the concentration of different transition types in particular industries.

Turning to cyclical patterns, salary changes across all transition types decline during recessions, but internal promotions and push separations are most affected. Relative to normal times, salary growth associated with promotions falls by \$1,789 during recessions, and push separations experience an additional decline of \$1,766. Notably, during recessions the salary gains from promotions and pull separations become statistically indistinguishable, suggesting that the advantage of internal advancement over cross-firm mobility compresses during downturns.

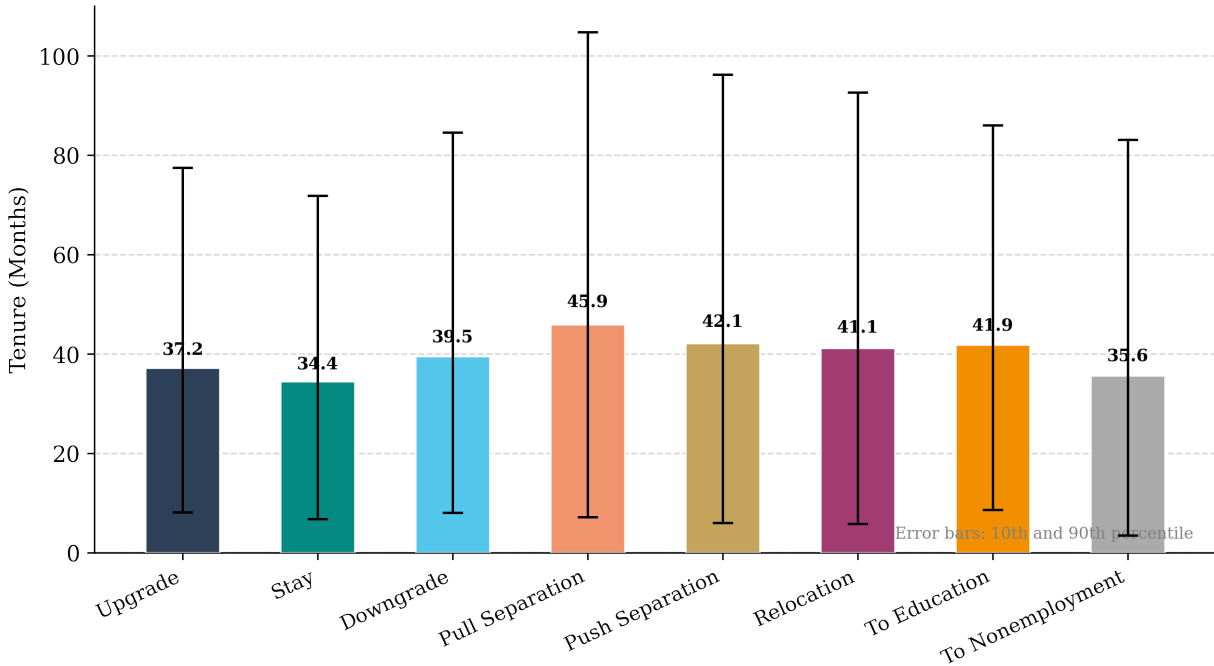
8.4 Worker and Firm Covariates

The Revelio Labs data provide a rich set of observable worker and firm characteristics, which we use in the descriptive second-stage analysis to examine the determinants of the latent match-quality states recovered by the LMM. These variables are not included in the baseline LMM, which is estimated on the two emission channels alone to preserve the model’s interpretive parsimony.

Table 12: Salary Change and Tenure by Separation Type

	(1) pct	(2) pct	(3) pct	(4) pct	(5) USD	(6) pct
<i>Main effects</i>						
Upgrade	0.345*** (0.003)	0.346*** (0.003)	0.352*** (0.003)	0.350*** (0.003)	21821.9*** (110.1)	0.314*** (0.006)
Downgrade	−0.238*** (0.003)	−0.239*** (0.003)	−0.232*** (0.002)	−0.232*** (0.003)	−20299.8*** (93.2)	−0.207*** (0.004)
Pull sep.	0.448*** (0.004)	0.443*** (0.004)	0.417*** (0.003)	0.416*** (0.004)	19501.9*** (82.3)	0.367*** (0.007)
Push sep.	−0.085*** (0.003)	−0.089*** (0.003)	−0.096*** (0.003)	−0.098*** (0.003)	−9857.1*** (106.9)	−0.098*** (0.004)
Relocation	0.120*** (0.004)	0.116*** (0.004)	0.102*** (0.005)	0.102*** (0.005)	473.7*** (101.8)	0.078*** (0.012)
<i>× USREC</i>						
Upgrade × Rec.				0.030*** (0.010)	−458.9 (350.0)	
Downgrade × Rec.				−0.006 (0.005)	601.8* (310.5)	
Pull sep. × Rec.				0.017** (0.008)	58.7 (315.4)	
Push sep. × Rec.				0.031 (0.026)	−184.8 (352.0)	
Relocation × Rec.				0.006 (0.009)	720.0 (459.0)	
<i>× UNRATE</i>						
Upgrade × UR						0.007*** (0.001)
Downgrade × UR						−0.004*** (0.001)
Pull sep. × UR						0.009*** (0.001)
Push sep. × UR						0.000 (0.001)
Relocation × UR						0.004** (0.002)
Year-month FE	No	Yes	Yes	Yes	Yes	Yes
Sector FE	No	No	Yes	Yes	Yes	Yes
Observations	80,005,113	80,005,113	71,065,892	71,065,892	71,065,892	71,060,757
R ²	0.001	0.001	0.001	0.001	0.109	0.001

Notes: The dependent variable in columns (1)–(3) is the salary change in USD, defined as the start salary of the next position minus the end salary of the current position. Column (4) uses a random sample. The baseline group is *Stay* (same employer, same seniority level). All specifications include a constant (not reported). Standard errors (in parentheses) are two-way clustered by worker and year-month. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.



(a) Job duration by separation types

Note: This figure shows the mean, 10th percentile, and 90th percentile of job duration for primary jobs, grouped by the type of subsequent separation. Source: Revelio Labs

Worker characteristics. For each worker we observe highest level of educational attainment (high school or below, some college, bachelor’s degree, master’s degree, professional or doctoral degree), which is drawn from the Revelio Labs education file. Age at the time of hire is inferred from the year of the worker’s earliest recorded educational enrollment. Gender is predicted from the worker’s name using a classification algorithm, and predicted ethnicity (White, Black, Hispanic, Asian, or other) is similarly inferred from name and, where available, location signals. We also observe each worker’s occupation category (mapped to the Revelio Labs jobs taxonomy), the geographic location of the position (state and metropolitan area), and the worker’s prior employment history—including the number and types of prior spells, prior seniority progression, and prior separations—which we summarize in a set of pre-spell history variables. All worker characteristics are measured as of the start of each spell.

Firm characteristics. For each employer we observe total employment (headcount), firm age (years since the earliest position recorded in the data), industry sector, and primary metropolitan area of operations. Where financial data are available from Compustat (for publicly listed firms), we supplement these with balance-sheet and income-statement characteristics. We also observe time-varying organizational characteristics such as the

Table 13: Cosine Similarity by Pre-Employment-Gap Category

	Consecutive Spells	Random Baseline	Actual Minus Firm Random	Number of Pairs
<i>Panel A: No gap transition</i>				
Match innovations, different firm	0.1552	0.0375	0.1178	1,018,697
Match innovations, same firm	0.1190	-0.0170	0.1360	815,155
State probabilities, different firm	0.6004	0.3130	0.2874	1,018,697
State probabilities, same firm	0.6308	0.3162	0.3146	815,155
<i>Panel B: Pre-employment gap of 1–6 months</i>				
Match innovations, different firm	0.1654	0.0676	0.0977	250,588
Match innovations, same firm	0.0788	0.0625	0.0163	16,492
State probabilities, different firm	0.5589	0.3824	0.1764	250,588
State probabilities, same firm	0.5049	0.3704	0.1346	16,492
<i>Panel C: Pre-employment gap of 7 or more months due to education</i>				
Match innovations, different firm	0.0823	0.0654	0.0169	130,472
Match innovations, same firm	0.1138	0.0649	0.0488	136,483
State probabilities, different firm	0.2977	0.2953	0.0024	130,472
State probabilities, same firm	0.4063	0.2955	0.1108	136,483
<i>Panel D: Other pre-employment gaps of 7 or more months</i>				
Match innovations, different firm	0.1360	0.0518	0.0842	252,058
Match innovations, same firm	0.0261	0.0565	-0.0304	20,857
State probabilities, different firm	0.4782	0.3410	0.1371	252,058
State probabilities, same firm	0.4231	0.3427	0.0804	20,857

Notes: Each entry reports the mean cosine similarity between two seven-dimensional vectors. Actual consecutive spells compare adjacent spells belonging to the same worker. For different-firm transitions, the worker changes firms; for same-firm transitions, the worker changes positions within the same firm. The common-pool firm-random baseline keeps the source worker's previous-spell vector fixed and pairs it with a next-spell vector belonging to a different worker and firm in the same hire-quarter and pre-employment-gap cell. The donor pool is constructed from all eligible transitions before separating the same-firm and different-firm source samples. The final column reports the number of actual consecutive-spell pairs. Results use the filtered one-million-worker sample.

firm's recent employment growth rate and its recent hiring and separation rates, which serve as proxies for firm-level labor demand conditions.

8.5 Testing persistence by employment gap

8.5.1 Cosine similarity

8.5.2 Vector autoregression

The rows of each matrix correspond to lagged components in states $1, \dots, 7$, while the columns correspond to next-spell components in states $1, \dots, 7$. The matrices $\hat{A}_D^{\text{inn}}$ and $\hat{A}_S^{\text{inn}}$ describe innovation persistence across and within firms, respectively. The matrices $\hat{A}_D^p$ and $\hat{A}_S^p$ provide the corresponding results for the latent-state probability vectors.

$$\widetilde{\text{inn}}_{i,n+1,k} = \sum_{j=1}^7 A_{D,jk} \widetilde{\text{inn}}_{in,j} + \varepsilon_{i,n+1,k}, \quad k = 1, \dots, 7. \quad (16)$$

$$\widehat{A}_D^{inn} = \begin{bmatrix} 0.1475 & -0.0523 & 0.0349 & 0.0572 & -0.1408 & 0.0079 & -0.0544 \\ -0.0680 & 0.0190 & -0.0107 & 0.0037 & 0.1468 & -0.0591 & -0.0318 \\ 0.0436 & -0.0051 & 0.0554 & -0.0172 & -0.1716 & 0.1017 & -0.0068 \\ 0.0148 & 0.0671 & -0.0539 & -0.0232 & 0.0257 & -0.0348 & 0.0043 \\ -0.0629 & 0.0783 & 0.0037 & -0.0107 & 0.0692 & -0.0749 & -0.0027 \\ 0.0296 & -0.0588 & 0.0296 & 0.0421 & -0.1613 & 0.1640 & -0.0454 \\ -0.1047 & -0.0483 & -0.0589 & -0.0520 & 0.2320 & -0.1047 & 0.1367 \end{bmatrix}. \quad (17)$$

$$\widehat{A}_S^{inn} = \begin{bmatrix} -0.0245 & -0.0011 & 0.0267 & -0.0626 & 0.1147 & -0.0475 & -0.0056 \\ -0.0380 & -0.0221 & -0.0039 & -0.0192 & 0.0901 & 0.0313 & -0.0383 \\ 0.0613 & 0.0011 & 0.1008 & -0.0667 & -0.0886 & 0.0236 & -0.0315 \\ 0.0955 & -0.0059 & -0.0386 & 0.0216 & -0.0228 & 0.0061 & -0.0558 \\ 0.0241 & 0.0415 & -0.0305 & 0.1138 & -0.1387 & 0.0040 & -0.0142 \\ -0.0185 & 0.0156 & -0.0297 & 0.0796 & -0.1195 & 0.0882 & -0.0158 \\ -0.0999 & -0.0291 & -0.0247 & -0.0666 & 0.1648 & -0.1057 & 0.1611 \end{bmatrix}. \quad (18)$$

$$\widehat{A}_D^p = \begin{bmatrix} 3.6595 & 0.0834 & 8.6382 & -4.7580 & -6.4308 & -0.5466 & -0.6458 \\ 3.1977 & 0.5441 & 8.6277 & -4.6041 & -6.9447 & -0.1754 & -0.6454 \\ 2.5744 & 0.1206 & 9.0315 & -4.6568 & -5.6923 & -0.7137 & -0.6638 \\ 3.0725 & 0.0525 & 8.7802 & -3.5147 & -7.1097 & -0.6310 & -0.6499 \\ -19.3296 & -0.9756 & -52.6047 & 26.7694 & 39.6381 & 2.9162 & 3.5863 \\ 3.2377 & 0.1136 & 8.6760 & -4.6148 & -6.5269 & -0.2470 & -0.6387 \\ 3.5877 & 0.0614 & 8.8511 & -4.6210 & -6.9338 & -0.6026 & -0.3429 \end{bmatrix}. \quad (19)$$

$$\hat{A}_S^p = \begin{bmatrix} 0.7910 & -0.0644 & -0.0787 & -0.6979 & 0.0302 & 0.0697 & -0.0499 \\ -0.0970 & 0.3711 & 0.0135 & -0.0756 & -0.5060 & 0.3520 & -0.0581 \\ -0.3148 & -0.0794 & 0.4291 & -0.0598 & 0.3088 & -0.2133 & -0.0705 \\ -0.1827 & -0.0809 & 0.1272 & 0.6756 & -0.3306 & -0.1494 & -0.0592 \\ -0.2995 & -0.0598 & -0.9240 & 0.3795 & 1.0890 & -0.1706 & -0.0147 \\ -0.0041 & -0.0236 & 0.0865 & -0.2341 & -0.0686 & 0.2903 & -0.0465 \\ 0.1070 & -0.0630 & 0.3464 & 0.0123 & -0.5229 & -0.1788 & 0.2989 \end{bmatrix}. \quad (20)$$

8.6 Firm-Level Outcomes

To examine how match quality relates to firm performance, we construct a panel of firm-quarter observations tracking firm-level employment and survival outcomes. *Firm employment* in a given quarter is defined as the number of workers with an active spell at the firm during that quarter. *Employment growth* is the quarter-on-quarter log change in employment. *Firm survival* is an indicator equal to one if the firm has at least one active position recorded in the data in each quarter through the end of the observation window.

Because Revelio Labs data are derived from online profiles, coverage of firms is inherently incomplete and unequal. Large firms with a strong online presence are well represented, whereas small or private firms with few workers on professional networking platforms may have only a handful of observed positions—or none at all. Observed employment therefore understates true employment, and the degree of understatement varies across firms and over time. We account for this by including firm fixed effects in all firm-level regressions and by focusing on within-firm variation in employment growth and survival rather than cross-sectional levels.

Where relevant, we supplement the employment panel with information from Revelio Labs job postings. *Expected hires* is a forward-looking measure constructed from the stock of active job postings, scaled by historical offer-acceptance rates, and serves as a proxy for the firm's intended employment growth. This variable allows us to distinguish between realized employment changes and planned hiring activity.

9 Multi-channel Latent Markov Model Appendix

9.0.1 Estimation

We maximize the log-likelihood (??) using the *EM algorithm*. Direct maximization of (??) is computationally demanding because equation (1) sums over K^T latent-state histories. The EM algorithm alleviates this difficulty by alternating between two steps:

- *E-step*: Compute the posterior distribution of the latent-state history given the current parameter estimates, leveraging the Markovian structure through the Baum–Welch (forward–backward) algorithm. This reduces the computational complexity from $O(K^T)$ to $O(K^2T)$.
- *M-step*: Update all parameters by maximizing the expected complete-data log-likelihood given the posterior state probabilities from the E-step.

The algorithm iterates until the relative change in log-likelihood falls below 10^{-5} . Because the EM algorithm can converge to local optima, we estimate each model from five independent random restarts and retain the solution with the highest log-likelihood. Each restart is run as an independent task on a high-performance computing cluster and assigned a distinct seed to ensure reproducibility.

The model is estimated on a training sample of one million workers drawn from the Revelio Labs data. The remaining workers are used for out-of-sample validation, as described in Section ??.

9.1 Model Selection

Table 14: Out-of-Sample Log-Likelihood per Worker

k	Training mean	Test mean	Train–test gap	Training workers	Test workers
7	–14.65269	–14.64467	–0.00802	100,000	900,000
9	–14.62349	–14.68503	0.06154	100,000	100,000
15	–14.54983	–14.61068	0.06085	100,000	100,000
28	–14.51930	–14.58378	0.06448	100,000	100,000

Notes: Log-likelihoods are reported as means per worker. A less negative test log-likelihood indicates better out-of-sample fit.

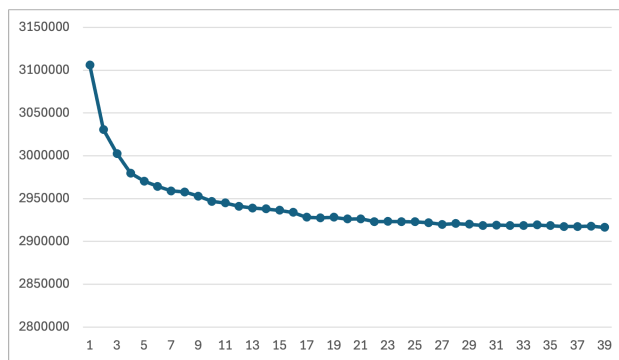


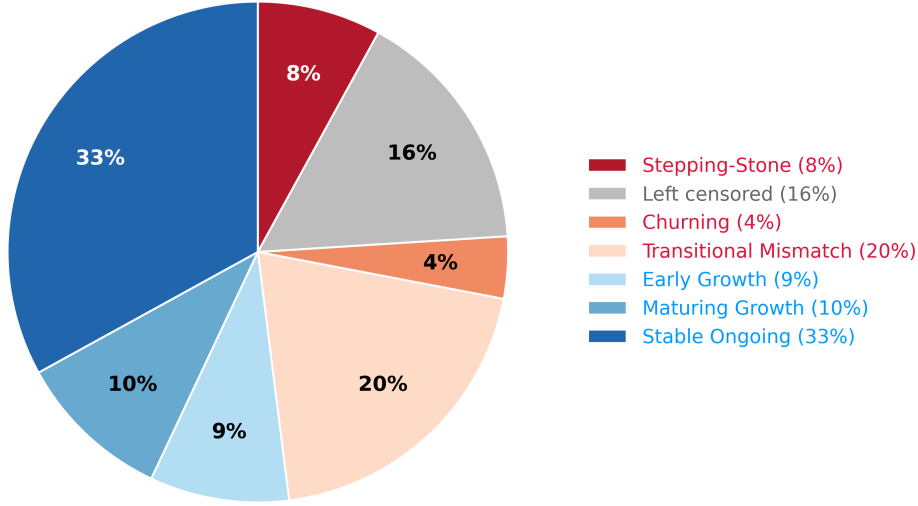
Figure 12: Akaike Information Criterion

Notes: The figure reports the Akaike Information Criterion (AIC) for latent Markov models estimated with different numbers of latent states K .

Table 15: Estimated Emission Probabilities

Initial distribution	1	2	3	4	5	6	7
	0.582	0.309	0.013	0.036	0.044	0.004	0.012
Emission 1: Employment duration	1	2	3	4	5	6	7
1–6 months	0.429	0.043	0.468	0.048	0.165	0.005	0.009
7–15 months	0.263	0.138	0.371	0.289	0.361	0.050	0.000
16–36 months	0.204	0.298	0.152	0.432	0.423	0.400	0.000
37 months or more	0.103	0.521	0.009	0.231	0.051	0.545	0.991
Emission 2: Job-exit type	1	2	3	4	5	6	7
Education	0.367	0.105	0.094	0.000	0.034	0.017	0.000
Nonemployment	0.257	0.205	0.223	0.240	0.003	0.010	0.000
Downgrade	0.005	0.050	0.010	0.005	0.151	0.108	0.002
Same level	0.044	0.096	0.053	0.010	0.306	0.193	0.002
Upgrade	0.019	0.112	0.048	0.031	0.338	0.306	0.002
Pull separation	0.042	0.120	0.117	0.190	0.047	0.109	0.000
Push separation	0.150	0.203	0.255	0.334	0.087	0.154	0.000
Relocation	0.116	0.109	0.200	0.191	0.034	0.103	0.000
Ongoing	0.000	0.000	0.000	0.000	0.000	0.000	0.995

Notes: This table reports the estimated initial and emission probabilities from the seven-state multi-channel latent Markov model. The reported initial distribution is the weighted average of the cohort-specific initial distributions, where the weights are the cohort shares in the estimation sample. The complete set of cohort-specific initial distributions is reported in Appendix Table 16. The first emission is employment duration, and the second is job-exit type. Within each emission panel, a column reports the conditional distribution of the corresponding emission given the latent state. Entries may not sum exactly to one because of rounding. *Sources:* Revelio Labs and authors' calculations.



Notes: This figure shows the reported frequency distribution across the seven latent employment states. Each slice represents a state's share of the total, including the left-censored category. Percentages sum to 100%. *Sources:* Revelio Labs and author's calculations.

Figure 13: Distribution of Latent States

9.2 Emission Probabilities

9.3 Estimated Initial Distribution by Cohorts

9.4 Standard Errors for Transition Probabilities.

We compute standard errors for the estimated transition probabilities using the delta method. The latent Markov model parameterizes each row of the transition matrix as a multinomial logit, so the transition probabilities are nonlinear functions of the estimated logit coefficients. Let $\hat{\gamma}$ denote the vector of transition coefficients and let $\hat{\mathbf{V}}_{\gamma}$ denote its estimated covariance matrix, obtained from the inverse observed information matrix. For a given category, the corresponding transition probabilities can be written as

$$\hat{\pi} = g(\hat{\gamma}; \mathbf{x}),$$

where $\mathbf{x}$ contains the covariates of the model. We approximate the covariance matrix of these probabilities using

$$\hat{\mathbf{V}}_{\pi} = \mathbf{G} \hat{\mathbf{V}}_{\gamma} \mathbf{G}', \quad \mathbf{G} = \left. \frac{\partial g(\gamma; \mathbf{x})}{\partial \gamma'} \right|_{\gamma = \hat{\gamma}}.$$

Table 16: Initial Distribution of Latent Match States by Birth Cohort

Birth cohort	S1	S2	S3	S4	S5	S6	S7
Pre-1982	0.0000	0.0260	0.0000	0.0000	0.0046	0.0000	0.9694
1982–1984	0.0007	0.2065	0.0000	0.0315	0.0040	0.0000	0.7572
1985–1987	0.0161	0.4330	0.0000	0.0585	0.0047	0.0000	0.4876
1988–1990	0.0257	0.6135	0.0000	0.0775	0.0054	0.0000	0.2778
1991–1993	0.0375	0.7282	0.0000	0.0867	0.0071	0.0002	0.1403
1994–1996	0.0395	0.8115	0.0000	0.0907	0.0091	0.0004	0.0487
1997–1999	0.0327	0.8629	0.0005	0.0706	0.0114	0.0087	0.0132
2000–2002	0.0332	0.8872	0.0063	0.0286	0.0165	0.0184	0.0098
2003–2005	0.0612	0.8249	0.0173	0.0157	0.0267	0.0304	0.0238
2006–2008	0.0965	0.6553	0.0189	0.0095	0.0326	0.0870	0.1002
Missing	0.0561	0.3511	0.0000	0.0110	0.0087	0.0000	0.5732
Overall	0.0363	0.5818	0.0039	0.0437	0.0119	0.0132	0.3092

Notes: The table reports the estimated initial distribution over the seven latent match states by worker birth cohort. Each row reports the probability that a worker's first observed position is assigned to each latent state. The final row reports the overall initial-state distribution in the estimation sample.

The reported standard error of each transition probability is the square root of the corresponding diagonal element of $\hat{\mathbf{V}}_{\pi}$. By explicitly incorporating the Jacobian of the multinomial logit transformation, this procedure properly propagates the covariance among the estimated coefficients into the covariance of the transition probabilities, while respecting the adding-up constraint that each row of the transition matrix must sum to one.

9.5 Spell-level regression coefficients

9.6 VAR for match innovations

These two tables are now centered correctly:

9.7 Lagged firm outcomes (Full sample)

9.8 Lagged firm outcomes (Compustat)

Table 17: Worker age odds ratios by latent state

	S2	S6	S4	S3
≤ 20	60.277 (0.843)	7.782 (0.064)	1.680 (0.031)	0.501 (0.007)
20–25	13.398 (0.138)	3.494 (0.020)	1.819 (0.019)	0.630 (0.004)
25–30	2.424 (0.020)	1.612 (0.009)	1.288 (0.008)	0.852 (0.004)
35–45	0.638 (0.007)	0.726 (0.005)	0.750 (0.006)	0.993 (0.006)
45–55	0.581 (0.009)	0.645 (0.006)	0.515 (0.007)	0.815 (0.007)
55+	0.636 (0.018)	0.686 (0.012)	0.436 (0.009)	0.657 (0.010)
Missing	11.713 (0.198)	1.808 (0.024)	0.798 (0.015)	0.604 (0.010)

Table 18: Gender odds ratios by latent state

	S2	S6	S4	S3
F	1.065 (0.007)	1.064 (0.005)	1.091 (0.007)	0.987 (0.005)
Missing	1.112 (0.036)	1.068 (0.024)	1.188 (0.035)	1.017 (0.025)

Table 19: Education odds ratios by latent state

	S2	S6	S4	S3
High School	0.931 (0.014)	0.982 (0.013)	0.565 (0.010)	0.529 (0.009)
Associate	0.534 (0.007)	1.035 (0.010)	0.627 (0.009)	0.756 (0.008)
MBA	1.218 (0.014)	1.348 (0.010)	1.376 (0.017)	1.103 (0.010)
Master	1.789 (0.013)	1.412 (0.009)	1.019 (0.010)	0.992 (0.008)
Doctor	1.810 (0.032)	1.500 (0.022)	0.891 (0.014)	1.074 (0.012)
Missing	0.821 (0.092)	1.291 (0.117)	1.301 (0.198)	1.052 (0.142)

Table 20: Ethnicity odds ratios by latent state

	S2	S6	S4	S3
API	1.286 (0.019)	0.961 (0.009)	0.844 (0.011)	0.926 (0.014)
Black	1.120 (0.008)	1.055 (0.006)	0.827 (0.007)	0.828 (0.006)
Hispanic	1.154 (0.009)	1.050 (0.007)	0.879 (0.009)	0.858 (0.007)
Multiple	1.252 (0.043)	1.045 (0.031)	0.907 (0.039)	0.882 (0.034)
Native	1.187 (0.083)	1.078 (0.064)	0.821 (0.072)	0.874 (0.072)
Missing	1.287 (0.139)	1.087 (0.095)	0.919 (0.132)	0.944 (0.123)

Table 21: Firm size odds ratios by latent state

	S2	S6	S4	S3
11–30	0.931 (0.007)	1.015 (0.006)	1.399 (0.014)	1.053 (0.009)
31–50	0.878 (0.008)	1.006 (0.007)	1.685 (0.020)	1.112 (0.011)
51–200	0.840 (0.007)	1.002 (0.006)	1.973 (0.022)	1.167 (0.011)
200+	0.870 (0.010)	1.057 (0.008)	2.811 (0.037)	1.410 (0.015)
Missing	1.797 (0.057)	1.210 (0.027)	1.458 (0.053)	1.271 (0.038)

Table 22: Firm age odds ratios by latent state

	S2	S6	S4	S3
1–3 year	1.240 (0.027)	1.242 (0.020)	1.268 (0.029)	0.885 (0.017)
3–5 year	1.243 (0.028)	1.275 (0.022)	1.376 (0.035)	0.885 (0.018)
6–9 year	1.217 (0.026)	1.264 (0.020)	1.388 (0.034)	0.915 (0.018)
10–14 year	1.214 (0.026)	1.247 (0.020)	1.371 (0.034)	0.992 (0.020)
15–30 year	1.229 (0.027)	1.228 (0.020)	1.304 (0.031)	1.060 (0.021)
31–50 year	1.263 (0.030)	1.228 (0.021)	1.360 (0.039)	1.218 (0.029)
50+ year	1.409 (0.035)	1.285 (0.023)	1.598 (0.044)	1.490 (0.033)
Missing	1.296 (0.028)	1.241 (0.020)	1.299 (0.030)	1.098 (0.021)

Table 23: Sector odds ratios by latent state

	S2	S6	S4	S3
Admin and Waste Management and Remed Serv [NAICS 56]	1.093 (0.032)	1.239 (0.022)	0.803 (0.046)	0.755 (0.042)
Agriculture, Forestry, Fishing and Hunting [NAICS 11]	1.252 (0.091)	1.126 (0.045)	1.022 (0.081)	1.036 (0.085)
Arts, Entert, and Recr [NAICS 71]	1.898 (0.058)	1.400 (0.023)	0.792 (0.034)	0.763 (0.021)
Construction [NAICS 23]	1.016 (0.065)	1.010 (0.058)	0.842 (0.040)	0.948 (0.027)
Educational Services [NAICS 61]	2.073 (0.059)	1.636 (0.027)	0.693 (0.021)	0.819 (0.019)
Finance and Insurance [NAICS 52]	0.902 (0.027)	0.951 (0.016)	0.954 (0.032)	1.043 (0.024)
Health Care and Social Assistance [NAICS 62]	1.169 (0.046)	1.164 (0.022)	0.656 (0.018)	0.768 (0.017)
Information [NAICS 51]	1.012 (0.032)	1.074 (0.017)	1.036 (0.031)	0.922 (0.027)
Mng of Companies and Enterprises [NAICS 55]	0.931 (0.056)	0.968 (0.038)	0.873 (0.089)	0.925 (0.050)
Mining, Quar and Oil and Gas Extrac [NAICS 21]	1.055 (0.054)	1.024 (0.027)	1.305 (0.176)	1.079 (0.101)
Prof, Scien, and Tech Services [NAICS 54]	1.011 (0.035)	1.044 (0.020)	0.899 (0.023)	0.911 (0.021)
Real Estate and Rental and Leasing [NAICS 53]	0.920 (0.030)	0.935 (0.020)	0.725 (0.078)	0.786 (0.023)
Retail Trade [NAICS 44/45]	1.530 (0.052)	1.272 (0.025)	0.912 (0.060)	0.783 (0.032)
Trans and Warehousing [NAICS 48/49]	1.022 (0.031)	1.089 (0.018)	0.890 (0.041)	0.917 (0.036)
Utilities [NAICS 22]	0.922 (0.040)	0.999 (0.030)	1.168 (0.082)	1.354 (0.095)
Wholesale Trade [NAICS 42]	1.077 (0.048)	1.044 (0.025)	0.909 (0.038)	0.944 (0.030)
Missing	1.449 (0.138)	1.200 (0.088)	1.174 (0.136)	1.126 (0.119)

Table 24: Persistence of Match Innovations across Consecutive Employment Spells*Panel A: Different-firm transitions*

Previous spell	Subsequent spell						
	inn ₁	inn ₂	inn ₃	inn ₄	inn ₅	inn ₆	inn ₇
inn ₁	0.148	-0.052	0.035	0.057	-0.141	0.008	-0.054
inn ₂	-0.068	0.019	-0.011	0.004	0.147	-0.059	-0.032
inn ₃	0.044	-0.005	0.055	-0.017	-0.172	0.102	-0.007
inn ₄	0.015	0.067	-0.054	-0.023	0.026	-0.035	0.004
inn ₅	-0.063	0.078	0.004	-0.011	0.069	-0.075	-0.003
inn ₆	0.030	-0.059	0.030	0.042	-0.161	0.164	-0.045
inn ₇	-0.105	-0.048	-0.059	-0.052	0.232	-0.105	0.137

Panel B: Same-firm transitions

Previous spell	Subsequent spell						
	inn ₁	inn ₂	inn ₃	inn ₄	inn ₅	inn ₆	inn ₇
inn ₁	-0.024	-0.001	0.027	-0.063	0.115	-0.047	-0.006
inn ₂	-0.038	-0.022	-0.004	-0.019	0.090	0.031	-0.038
inn ₃	0.061	0.001	0.101	-0.067	-0.089	0.024	-0.031
inn ₄	0.095	-0.006	-0.039	0.022	-0.023	0.006	-0.056
inn ₅	0.024	0.041	-0.030	0.114	-0.139	0.004	-0.014
inn ₆	-0.018	0.016	-0.030	0.080	-0.119	0.088	-0.016
inn ₇	-0.100	-0.029	-0.025	-0.067	0.165	-0.106	0.161

Notes: The table reports the unrestricted persistence matrix for seven-dimensional match-innovation vectors across consecutive employment spells. Rows index the innovation associated with the previous spell and columns index the innovation associated with the subsequent spell. Estimation accounts for the linear dependence among the seven innovation components using six orthonormal Helmert coordinates. Each innovation component is demeaned by the subsequent spell's hire-quarter, pre-employment-gap category, and same-firm status prior to estimation. Panel A uses 1,651,815 transitions in which the worker changes firms. Panel B uses 988,987 transitions between positions within the same firm.

Table 25: Persistence of Latent-State Probabilities across Consecutive Employment Spells*Panel A: Different-firm transitions*

Previous spell	Subsequent spell						
	p_1	p_2	p_3	p_4	p_5	p_6	p_7
p_1	3.660	0.083	8.638	-4.758	-6.431	-0.547	-0.646
p_2	3.198	0.544	8.628	-4.604	-6.945	-0.175	-0.645
p_3	2.574	0.121	9.032	-4.657	-5.692	-0.714	-0.664
p_4	3.073	0.053	8.780	-3.515	-7.110	-0.631	-0.650
p_5	-19.330	-0.976	-52.605	26.769	39.638	2.916	3.586
p_6	3.238	0.114	8.676	-4.615	-6.527	-0.247	-0.639
p_7	3.588	0.061	8.851	-4.621	-6.934	-0.603	-0.343

Panel B: Same-firm transitions

Previous spell	Subsequent spell						
	p_1	p_2	p_3	p_4	p_5	p_6	p_7
p_1	0.791	-0.064	-0.079	-0.698	0.030	0.070	-0.050
p_2	-0.097	0.371	0.014	-0.076	-0.506	0.352	-0.058
p_3	-0.315	-0.079	0.429	-0.060	0.309	-0.213	-0.071
p_4	-0.183	-0.081	0.127	0.676	-0.331	-0.149	-0.059
p_5	-0.300	-0.060	-0.924	0.380	1.089	-0.171	-0.015
p_6	-0.004	-0.024	0.087	-0.234	-0.069	0.290	-0.047
p_7	0.107	-0.063	0.346	0.012	-0.523	-0.179	0.299

Notes: The table reports the unrestricted persistence matrix for seven-dimensional posterior latent-state probability vectors across consecutive employment spells. Rows index the state probability associated with the previous spell and columns index the state probability associated with the subsequent spell. Because the seven probabilities sum to one, estimation is conducted using six orthonormal Helmert coordinates, with the resulting coefficients mapped back to the seven-state representation shown in the table. Each probability component is demeaned by the subsequent spell's hire-quarter, pre-employment-gap category, and same-firm status prior to estimation. Panel A uses 1,651,815 different-firm transitions and Panel B uses 988,987 same-firm transitions.

Table 26: New-Hire Match Innovations and Firm Outcomes (Full Sample, Lag 2)

	Sep. (1)	Hires (2)	Growth (3)	Surv. (4)	Sep. (5)	Hires (6)	Growth (7)	Surv. (8)
inn_1 (Stepping-st)	−0.1031* (0.0010)	−0.0045* (0.0010)	0.1074* (0.0013)	0.0135* (0.0004)	−0.1055* (0.0010)	−0.0049* (0.0010)	0.1090* (0.0013)	0.0136* (0.0004)
inn_3 (Churning)	−0.1292* (0.0009)	−0.0212* (0.0009)	0.1189* (0.0011)	0.0022* (0.0003)	−0.1298* (0.0009)	−0.0218* (0.0009)	0.1198* (0.0011)	0.0023* (0.0003)
inn_5 (Early Gr)	−0.0488* (0.0009)	0.0120* (0.0009)	0.0725* (0.0011)	0.0109* (0.0003)	−0.0429* (0.0009)	0.0115* (0.0009)	0.0631* (0.0012)	0.0104* (0.0003)
inn_6 (Maturing Gr)	−0.2076* (0.0011)	−0.0370* (0.0013)	0.1812* (0.0016)	0.0132* (0.0003)	−0.2134* (0.0011)	−0.0371* (0.0013)	0.1874* (0.0016)	0.0137* (0.0003)
inn_7 (Stable Ongoing)	−0.1232* (0.0005)	−0.0170* (0.0006)	0.1147* (0.0007)	0.0085* (0.0002)	−0.1247* (0.0005)	−0.0169* (0.0006)	0.1162* (0.0007)	0.0087* (0.0002)
pred_1 (Stepping-st)					−0.0051* (0.0013)	0.0291* (0.0013)	0.0115* (0.0016)	−0.0029* (0.0004)
pred_3 (Churning)					−0.0056* (0.0016)	0.0306* (0.0017)	0.0036* (0.0021)	−0.0096* (0.0006)
pred_5 (Early Gr)					0.0619* (0.0017)	0.0234* (0.0018)	−0.0770* (0.0023)	−0.0053* (0.0006)
pred_6 (Maturing Gr)					−0.0588* (0.0036)	0.0681* (0.0038)	0.0646* (0.0048)	−0.0101* (0.0012)
pred_7 (Stable Ongoing)					−0.0424* (0.0015)	0.0393* (0.0015)	0.0522* (0.0019)	−0.0000 (0.0004)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predicted	No	No	No	No	Yes	Yes	Yes	Yes
Within R^2	0.0159	0.0019	0.0067	0.0038	0.0168	0.0021	0.0075	0.0040
N	6,902,126	6,902,126	6,930,601	6,989,518	6,902,126	6,902,126	6,930,601	6,989,518

Notes: Estimates relate lagged new-hire match-state innovations to firm outcomes in the full sample. Outcomes are annual separation and hiring rates, employment growth following Davis et al. (2013), and firm survival. All models include firm and 6-digit NAICS industry-by-year fixed effects. Separation and hiring models control for their lagged outcome; growth and survival models control for lagged employment growth. All lags are 2 years. Columns (5)–(8) also include lagged predicted state probabilities. State 4 (Transitional) is the reference for innovations and probabilities; state 2 (Stable/Stagnant) coefficients are estimated but not displayed. R^2 is within R^2 ; N counts firm-years. Standard errors are in parentheses. Coefficients and standard errors are rounded to four decimal places.

* $p < 0.10$, based on unrounded reported p -values. *Source:* Revelio Labs.

Table 27: New-Hire Match Innovations and Firm Outcomes (Full Sample, Lag 3)

	Sep. (1)	Hires (2)	Growth (3)	Surv. (4)	Sep. (5)	Hires (6)	Growth (7)	Surv. (8)
inn_1 (Stepping-st)	-0.0267* (0.0010)	-0.0078* (0.0010)	0.0301* (0.0012)	0.0083* (0.0003)	-0.0274* (0.0010)	-0.0087* (0.0010)	0.0297* (0.0012)	0.0082* (0.0003)
inn_3 (Churning)	-0.0933* (0.0010)	-0.0321* (0.0009)	0.0758* (0.0011)	0.0033* (0.0003)	-0.0939* (0.0009)	-0.0324* (0.0009)	0.0766* (0.0011)	0.0034* (0.0003)
inn_5 (Early Gr)	-0.0047* (0.0009)	0.0014 (0.0009)	0.0098* (0.0011)	0.0083* (0.0003)	0.0001 (0.0009)	-0.0005 (0.0009)	0.0009 (0.0012)	0.0078* (0.0003)
inn_6 (Maturing Gr)	-0.0802* (0.0011)	-0.0231* (0.0012)	0.0756* (0.0015)	0.0085* (0.0003)	-0.0826* (0.0011)	-0.0217* (0.0012)	0.0796* (0.0015)	0.0087* (0.0003)
inn_7 (Stable Ongoing)	-0.0598* (0.0005)	-0.0160* (0.0006)	0.0538* (0.0007)	0.0066* (0.0002)	-0.0602* (0.0005)	-0.0157* (0.0006)	0.0545* (0.0007)	0.0068* (0.0002)
pred_1 (Stepping-st)					-0.0027* (0.0013)	0.0322* (0.0013)	0.0213* (0.0016)	-0.0016* (0.0004)
pred_3 (Churning)					-0.0064* (0.0017)	0.0318* (0.0017)	0.0194* (0.0021)	-0.0067* (0.0006)
pred_5 (Early Gr)					0.0445* (0.0018)	0.0159* (0.0018)	-0.0546* (0.0022)	-0.0032* (0.0006)
pred_6 (Maturing Gr)					-0.0261* (0.0036)	0.0853* (0.0037)	0.0726* (0.0047)	-0.0083* (0.0012)
pred_7 (Stable Ongoing)					-0.0132* (0.0015)	0.0507* (0.0015)	0.0461* (0.0019)	0.0005 (0.0004)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predicted	No	No	No	No	Yes	Yes	Yes	Yes
Within R^2	0.0081	0.0005	0.0036	0.0018	0.0083	0.0008	0.0040	0.0019
N	6,318,902	6,318,902	6,344,316	6,394,277	6,318,902	6,318,902	6,344,316	6,394,277

Notes: Estimates relate lagged new-hire match-state innovations to firm outcomes in the full sample. Outcomes are annual separation and hiring rates, employment growth following Davis et al. (2013), and firm survival. All models include firm and 6-digit NAICS industry-by-year fixed effects. Separation and hiring models control for their lagged outcome; growth and survival models control for lagged employment growth. All lags are 3 years. Columns (5)–(8) also include lagged predicted state probabilities. State 4 (Transitional) is the reference for innovations and probabilities; state 2 (Stable/Stagnant) coefficients are estimated but not displayed. R^2 is within R^2 ; N counts firm-years. Standard errors are in parentheses. Coefficients and standard errors are rounded to four decimal places.

* $p < 0.10$, based on unrounded reported p -values. *Source:* Revelio Labs.

Table 28: Match Innovations and Firm Outcomes II (Compustat Firms, Lag 2)

	Emp. growth (1)	Survival (2)	Log sales (3)	Emp. growth (4)	Survival (5)	Log sales (6)
inn_1 (Stepping-st)	0.0957* (0.0382)	0.0649* (0.0189)	0.1339 (0.0941)	0.0944* (0.0389)	0.0681* (0.0191)	0.1565 (0.0964)
inn_3 (Churning)	0.0884* (0.0335)	0.0049 (0.0192)	-0.3118* (0.0907)	0.0912* (0.0336)	0.0032 (0.0192)	-0.3023* (0.0908)
inn_5 (Early Gr)	0.1835* (0.0279)	0.0637* (0.0148)	0.5261* (0.0833)	0.1830* (0.0285)	0.0650* (0.0148)	0.5248* (0.0844)
inn_6 (Maturing Gr)	0.2144* (0.0356)	0.0766* (0.0168)	0.2072* (0.0984)	0.2166* (0.0356)	0.0750* (0.0166)	0.2033* (0.0990)
inn_7 (Stable Ongoing)	0.1692* (0.0202)	0.0671* (0.0108)	0.1641* (0.0579)	0.1694* (0.0203)	0.0676* (0.0108)	0.1697* (0.0588)
pred_1 (Stepping-st)				-0.0136 (0.0420)	-0.0053 (0.0242)	-0.1039 (0.1072)
pred_3 (Churning)				-0.0395 (0.0623)	-0.0138 (0.0373)	-0.0970 (0.1534)
pred_5 (Early Gr)				-0.0583 (0.0545)	0.0539* (0.0301)	-0.3123* (0.1654)
pred_6 (Maturing Gr)				0.0077 (0.1141)	-0.0784 (0.0624)	-0.3203 (0.2942)
pred_7 (Stable Ongoing)				-0.0167 (0.0614)	-0.0182 (0.0325)	0.0112 (0.1422)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Predicted	No	No	No	Yes	Yes	Yes
Within R^2	0.0078	0.0040	0.2199	0.0079	0.0042	0.2203
N	54,192	59,475	48,759	54,192	59,475	48,759

Notes: Estimates relate lagged new-hire match-state innovations to Compustat firm outcomes. Outcomes are employment growth following Davis et al. (2013), firm survival, and log sales. All models include firm and 6-digit NAICS industry-by-year fixed effects. Growth and survival models control for lagged employment growth; sales models control for lagged log sales. Innovations, predicted probabilities, and outcome controls are lagged 2 years. Columns (4)–(6) additionally include predicted state probabilities. State 4 (Transitional) is the reference for innovations and probabilities; state 2 (Stable/Stagnant) coefficients are estimated but not displayed. R^2 is within R^2 ; N counts firm-years. Standard errors are in parentheses. Coefficients and standard errors are rounded to four decimal places.

* $p < 0.10$, based on unrounded reported p -values. *Source:* Revelio Labs and Compustat.

Table 29: Match Innovations and Firm Outcomes II (Compustat Firms, Lag 3)

	Emp. growth (1)	Survival (2)	Log sales (3)	Emp. growth (4)	Survival (5)	Log sales (6)
inn_1 (Stepping-st)	0.0900* (0.0369)	0.0255 (0.0187)	0.0763 (0.1025)	0.0940* (0.0372)	0.0273 (0.0189)	0.0962 (0.1046)
inn_3 (Churning)	0.1171* (0.0381)	−0.0233 (0.0188)	−0.3126* (0.0965)	0.1238* (0.0382)	−0.0227 (0.0188)	−0.3044* (0.0969)
inn_5 (Early Gr)	0.0564* (0.0289)	0.0659* (0.0154)	0.6062* (0.0954)	0.0573* (0.0291)	0.0672* (0.0154)	0.6026* (0.0969)
inn_6 (Maturing Gr)	0.1531* (0.0349)	0.0250 (0.0166)	0.1980* (0.1106)	0.1566* (0.0348)	0.0247 (0.0166)	0.1946* (0.1102)
inn_7 (Stable Ongoing)	0.0953* (0.0221)	0.0529* (0.0116)	0.2003* (0.0654)	0.0976* (0.0224)	0.0536* (0.0116)	0.2052* (0.0665)
pred_1 (Stepping-st)				−0.0342 (0.0410)	−0.0259 (0.0254)	−0.1900 (0.1238)
pred_3 (Churning)				−0.0912 (0.0631)	−0.0069 (0.0383)	−0.1821 (0.1703)
pred_5 (Early Gr)				−0.1385* (0.0522)	−0.0078 (0.0308)	−0.2464 (0.1905)
pred_6 (Maturing Gr)				−0.0329 (0.1062)	−0.0500 (0.0662)	−0.5940* (0.3435)
pred_7 (Stable Ongoing)				−0.0247 (0.0561)	−0.0115 (0.0389)	−0.0661 (0.1670)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Predicted	No	No	No	Yes	Yes	Yes
Within R^2	0.0050	0.0023	0.1088	0.0055	0.0024	0.1092
N	48,530	53,657	43,728	48,530	53,657	43,728

Notes: Estimates relate lagged new-hire match-state innovations to Compustat firm outcomes. Outcomes are employment growth following Davis et al. (2013), firm survival, and log sales. All models include firm and 6-digit NAICS industry-by-year fixed effects. Growth and survival models control for lagged employment growth; sales models control for lagged log sales. Innovations, predicted probabilities, and outcome controls are lagged 3 years. Columns (4)–(6) additionally include predicted state probabilities. State 4 (Transitional) is the reference for innovations and probabilities; state 2 (Stable/Stagnant) coefficients are estimated but not displayed. R^2 is within R^2 ; N counts firm-years. Standard errors are in parentheses. Coefficients and standard errors are rounded to four decimal places.

* $p < 0.10$, based on unrounded reported p -values. *Source: Revelio Labs and Compustat.*

Table 30: New-Hire Match Innovations and Firm Outcomes I (Compustat Firms, Lag 2)

	Sep. (1)	Hires (2)	Growth (3)	Surv. (4)	Sep. (5)	Hires (6)	Growth (7)	Surv. (8)
inn_1 (Stepping-st)	−0.1662* (0.0157)	0.0205 (0.0171)	0.2082* (0.0236)	0.0017 (0.0033)	−0.1727* (0.0160)	0.0212 (0.0173)	0.2137* (0.0239)	0.0017 (0.0034)
inn_3 (Churning)	−0.1658* (0.0142)	−0.0438* (0.0164)	0.1364* (0.0221)	−0.0013 (0.0036)	−0.1664* (0.0142)	−0.0421* (0.0164)	0.1378* (0.0220)	−0.0011 (0.0036)
inn_5 (Early Gr)	−0.1011* (0.0110)	0.0892* (0.0123)	0.2103* (0.0171)	0.0017 (0.0014)	−0.1015* (0.0110)	0.0875* (0.0124)	0.2087* (0.0172)	0.0019 (0.0015)
inn_6 (Maturing Gr)	−0.3125* (0.0143)	0.0177 (0.0169)	0.3514* (0.0228)	−0.0009 (0.0019)	−0.3126* (0.0142)	0.0174 (0.0168)	0.3515* (0.0227)	−0.0004 (0.0018)
inn_7 (Stable Ongoing)	−0.1994* (0.0084)	0.0404* (0.0094)	0.2540* (0.0128)	0.0009 (0.0012)	−0.2013* (0.0084)	0.0404* (0.0095)	0.2555* (0.0128)	0.0010 (0.0012)
pred_1 (Stepping-st)					−0.0033 (0.0174)	−0.0140 (0.0196)	−0.0132 (0.0274)	−0.0050 (0.0037)
pred_3 (Churning)					0.0040 (0.0271)	0.0057 (0.0281)	−0.0048 (0.0401)	−0.0107* (0.0049)
pred_5 (Early Gr)					0.0454* (0.0208)	−0.0748* (0.0234)	−0.1357* (0.0322)	−0.0003 (0.0048)
pred_6 (Maturing Gr)					−0.0062 (0.0457)	−0.0186 (0.0519)	−0.0055 (0.0727)	−0.0094 (0.0072)
pred_7 (Stable Ongoing)					−0.0649* (0.0222)	0.0149 (0.0251)	0.0732* (0.0342)	−0.0042 (0.0032)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predicted	No	No	No	No	Yes	Yes	Yes	Yes
Within R^2	0.0365	0.0101	0.0268	0.0010	0.0377	0.0110	0.0283	0.0015
N	69,014	69,014	69,026	69,056	69,014	69,014	69,026	69,056

Notes: Estimates relate lagged new-hire match-state innovations to firm outcomes in the Compustat-matched sample. Outcomes are annual separation and hiring rates, employment growth following Davis et al. (2013), and firm survival. All models include firm and 6-digit NAICS industry-by-year fixed effects. Separation and hiring models control for their lagged outcome; growth and survival models control for lagged employment growth. All lags are 2 years. Columns (5)–(8) also include lagged predicted state probabilities. State 4 (Transitional) is the reference for innovations and probabilities; state 2 (Stable/Stagnant) coefficients are estimated but not displayed. R^2 is within R^2 ; N counts firm-years. Standard errors are in parentheses. Coefficients and standard errors are rounded to four decimal places.

* $p < 0.10$, based on unrounded reported p -values. *Source:* Revelio Labs; Compustat sample.

Table 31: New-Hire Match Innovations and Firm Outcomes I (Compustat Firms, Lag 3)

	Sep. (1)	Hires (2)	Growth (3)	Surv. (4)	Sep. (5)	Hires (6)	Growth (7)	Surv. (8)
inn_1 (Stepping-st)	−0.0700* (0.0152)	0.0043 (0.0165)	0.0833* (0.0237)	0.0002 (0.0023)	−0.0716* (0.0155)	0.0063 (0.0167)	0.0888* (0.0239)	0.0003 (0.0023)
inn_3 (Churning)	−0.1290* (0.0146)	−0.0039 (0.0134)	0.1402* (0.0204)	−0.0006 (0.0027)	−0.1298* (0.0145)	−0.0015 (0.0135)	0.1427* (0.0204)	−0.0006 (0.0027)
inn_5 (Early Gr)	−0.0033 (0.0106)	0.0270* (0.0118)	0.0373* (0.0167)	0.0030 (0.0020)	−0.0014 (0.0106)	0.0245* (0.0119)	0.0331* (0.0168)	0.0028 (0.0019)
inn_6 (Maturing Gr)	−0.1661* (0.0131)	0.0291* (0.0151)	0.2047* (0.0208)	0.0019 (0.0017)	−0.1663* (0.0130)	0.0291* (0.0150)	0.2045* (0.0206)	0.0017 (0.0016)
inn_7 (Stable Ongoing)	−0.1018* (0.0082)	0.0390* (0.0089)	0.1568* (0.0126)	0.0018 (0.0012)	−0.1023* (0.0082)	0.0395* (0.0089)	0.1584* (0.0126)	0.0018 (0.0012)
pred_1 (Stepping-st)					−0.0193 (0.0167)	0.0095 (0.0195)	0.0098 (0.0269)	−0.0054 (0.0034)
pred_3 (Churning)					−0.0197 (0.0240)	−0.0053 (0.0273)	−0.0067 (0.0379)	−0.0025 (0.0041)
pred_5 (Early Gr)					0.0677* (0.0212)	−0.1010* (0.0232)	−0.1910* (0.0334)	−0.0065 (0.0045)
pred_6 (Maturing Gr)					−0.0536 (0.0449)	0.0149 (0.0516)	0.0105 (0.0704)	−0.0155 (0.0112)
pred_7 (Stable Ongoing)					−0.0516* (0.0227)	0.0201 (0.0263)	0.0631* (0.0353)	−0.0067 (0.0045)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predicted	No	No	No	No	Yes	Yes	Yes	Yes
Within R^2	0.0126	0.0020	0.0091	0.0014	0.0136	0.0035	0.0116	0.0020
N	64,971	64,971	64,986	65,014	64,971	64,971	64,986	65,014

Notes: Estimates relate lagged new-hire match-state innovations to firm outcomes in the Compustat-matched sample. Outcomes are annual separation and hiring rates, employment growth following Davis et al. (2013), and firm survival. All models include firm and 6-digit NAICS industry-by-year fixed effects. Separation and hiring models control for their lagged outcome; growth and survival models control for lagged employment growth. All lags are 3 years. Columns (5)–(8) also include lagged predicted state probabilities. State 4 (Transitional) is the reference for innovations and probabilities; state 2 (Stable/Stagnant) coefficients are estimated but not displayed. R^2 is within R^2 ; N counts firm-years. Standard errors are in parentheses. Coefficients and standard errors are rounded to four decimal places. * $p < 0.10$, based on unrounded reported p -values. *Source: Revelio Labs; Compustat sample.*