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Abstract

In job-ladder models, wage dispersion arises because firms trade off higher wages against the risk of losing workers to competitors. We measure an empirical "churn ladder"—the pattern in which workers move from low-wage, high-turnover firms to high-wage, low-turnover firms through job-to-job transitions. However, canonical models do not generate the data's steep churn gradient: poaching alone produces too little cross-firm dispersion in turnover. Lower-wage firms also lose more workers to nonemployment, substantially amplifying churn differences across the ladder. We introduce heterogeneity in both firm and worker separation rates, generating endogenous sorting and allowing the model to match observed joint patterns of wages and churn. Worker-level heterogeneity alone accounts for half of the firm-level variation in nonemployment separation. Ignoring wage-dependent separations to nonemployment biases firms' implied separation elasticities downward and overstates their labor market power.

JEL classification: E68
Key words: labor churn, job ladders, worker heterogeneity, labor monopsony

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1 Introduction

Most firms do not change size in most periods yet still hire and lose significant numbers of workers; this phenomenon, where gross flows exceed the net change, is known as "churn". This worker churn is fundamental in many theories of firm wage setting such as the model of on-the-job search in Burdett and Mortensen (1998). Firms paying a higher wage trade off a lower flow profit for an increase in the expected duration of their matches and a lower rate of churn. This mechanism generates heterogeneity across otherwise identical firms, forming the backbone of a broad class of "job ladder" models that explain residual wage dispersion in the presence of labor search frictions.

In this paper, we use the Census Bureau's Longitudinal Employer-Household Dynamics data to document the empirical shape of the job ladder in churn and wages. We find significant dispersion in churn over the cross-section of firms and, consistent with a broad set of job-ladder models, a negative relationship between churn and firms' wages. We also follow this wage and turnover ladder at the worker level, across their consecutive job transitions.[1] This controls for worker heterogeneity and potential selection, but the churn ladder is still apparent. As workers move from job to job, they move to higher-wage and lower-churn firms, climbing the wage ladder and descending the churn ladder.

Echoing Hornstein et al. (2011) on residual wage dispersion, we find that standard frictional labor market mechanisms are not sufficient to generate the dispersion observed in the data. Estimating the slope of the wage and churn ladder gives a quantitative benchmark that can be directly compared to calibrated models of on-the-job search. We compute and estimate a version of the Burdett and Mortensen (1998) model that incorporates the wage-retention tradeoff underlying wage and churn ladders, allowing for firm-level dispersion in turnover through on-the-job search. Crucially, on-the-job search itself does not generate enough dispersion in churn to match the data. To match the high turnover rates observed at the bottom rungs of the ladder, there must be high separations to nonemployment in

[1] This continuous employment spell with potentially multiple jobs was coined an "employment cycle" in Wolpin (1992). In this paper, we refer to these "employment cycles" simply as "employment spells" and "continuous employment spells," interchangeably.

addition to the elevated poaching rates implied by on-the-job search.

Our model incorporates two possible mechanisms to explain the observed dispersion in churn and the steepness of the churn ladder beyond what poaching alone can generate. First, we allow firms to set policies that make all workers more or less likely to separate from the job into nonemployment, conditional on wages. Second, we introduce latent worker heterogeneity in the probability of separating into nonemployment. This leads to workers differing in their expected employment spell lengths and therefore in their upward mobility from climbing the job ladder. This gives rise to endogenous sorting: workers with low separation risk are concentrated at high-wage, low-poaching firms, further lowering churn rates at the top of the ladder. In our calibrated model, worker heterogeneity accounts for roughly 60% of the decline in separations to nonemployment at the bottom half of the wage distribution, while firm policies account for 40% of the decline. Toward the top of the wage distribution, worker heterogeneity accounts for 40% of the gradient in separations to nonemployment. Poaching, meanwhile, accounts for a roughly constant quarter of total separations—in both its level and its contribution to the gradient—over the entire wage distribution.

The two explanations, firm policies and worker heterogeneity, also have implications that we can test empirically. We devise two test statistics using the means and variances of tenure conditional on firm-level wages. The intuition is that if firm policies alone drove the churn ladder, separation rates would be constant conditional on wage; therefore, tenure would be exponentially distributed. Worker heterogeneity increases average tenure and variance within the wage bin. We test the null hypothesis that separation rates are homogeneous conditional on the wage and reject it with both tests. This aligns with the findings in our calibrated model, which gives a role to both worker heterogeneity and firm policies in generating the cross-sectional dispersion in churn.

Our work is related to established models of the job ladder such as Burdett and Mortensen (1998) and Moscarini and Postel-Vinay (2017), which introduce the firm's retention motive into wage determination. In these models, a job ladder can exist both within ex-ante homogeneous firms and across heterogeneous levels of productivity.[2] Theory establishes a clear

[2]The latter somewhat weakens the strict one-to-one relationship between wage and turnover but maintains

link between wage rungs and churn rungs of a job ladder, and we explore the empirical magnitude of this effect and how a model of the job ladder can deliver it.

Understanding this relationship is also critical for measuring labor market power. Manning (2003) links the poaching threat faced by the firm to the elasticity of separations with respect to wages and the implied wage markdown in a Burdett and Mortensen (1998) model. Bassier et al. (2022) build on this intuition to causally estimate the labor supply elasticity facing a single firm, focusing on separations to other employers. We show that this measurement exercise often misses an important component of the relevant separation elasticity: separations to nonemployment. The firm's labor supply elasticity depends on how wages affect all margins of worker retention, not just job-to-job moves. If higher wages also reduce exits to nonemployment, then approaches that rely only on poaching flows will understate the separation elasticity and therefore overstate firms' monopsony power through an excessively large implied markdown. Incorporating wage-dependent separations to nonemployment raises the measured elasticity and can bring it closer to empirical estimates from dynamic monopsony frameworks and quasi-experimental designs.

In terms of measuring the job ladder in labor market data, seminal work by Topel and Ward (1992) highlighted the importance of job-to-job transitions to workers' wage gains. Moscarini and Postel-Vinay (2008, 2012) first documented a link between job transitions and firm characteristics in the existence of a job ladder in firm size. We extend this measurement of the ladder to firm dynamics, via the churn rate, closely related to Bagger and Lentz (2019) and Sorkin (2018).

We then combine the structure of a partial equilibrium model of on-the-job search along with detailed microdata to back out the distribution of wage offers and resulting worker flows and turnover. Engbom et al. (2026) use a similar approach with wages from the CPS to measure the long-run decline of job transition rates and their cause. Gottfries and Teulings (2023) use match duration and employment histories in NLSY data to measure the contribution of on-the-job search in wage growth and dispersion throughout an "employment

the general correlation because wages are still correlated with productivity, which itself has a one-to-one relationship with turnover.

cycle."[3] With matched employer-employee data, we can study the interaction of the firm distribution of wages and churn and the worker's job ladder.

Also related is recent work incorporating both worker and firm heterogeneity. Ozkan et al. (2023), Lentz et al. (2023), and Lamadon et al. (2026) identify latent heterogeneity in firms and workers, and the sorting between them. They use mobility for identification but focus primarily on the importance of this heterogeneity to wages, which is complementary to our focus on the distribution of turnover patterns across firms.

Understanding the source of separation heterogeneity has important implications for the role of the job ladder. We find evidence for the firm-specific differences in separation rates that are crucial to the premise of a "slippery" job ladder. This mechanism has been proposed to explain persistent earnings losses after job displacement via repeated unemployment risk in Pinheiro and Visschers (2015) and Jarosch (2023). However, we also reject the hypothesis that it is the only source of heterogeneity in separation rates. Worker-level latent heterogeneity and endogenous sorting produce a meaningful distinction between wage and earnings inequality and their sources. It is also consistent with the findings in Borovičková and Macaluso (2025) that workers with high and low end-of-career earnings experience similar numbers of job transitions, but of differing quality in terms of earnings gain. This paper and our findings also align with a growing literature on latent heterogeneity across workers in their flow patterns. For example, Hall and Kudlyak (2019); Gregory et al. (2025), and Ahn et al. (2023). While these papers primarily focused on the dynamics of worker flows in and out of employment, we find these insights about heterogeneity in workers' separation rates to extend to the distribution of employed workers. This latent worker heterogeneity is also critical in replicating the distribution of their employers, both in their wages and their gross flows.

[3]Rather than use the wage distribution, they infer the offer distribution from order statistics and the sequence of wage records, expanding on Barlevy (2008).

2 Empirical estimates of wage and job ladders

2.1 Data

This paper's data come from LEHD, a matched employer-employee panel consisting of administrative data collected from quarterly state unemployment insurance files. These files cover most of wage and salary employment in the United States with the exception of federal employees, the self-employed, gig workers, and others not typically covered by the unemployment insurance system. Our sample consists of a random 15% sample of workers from a 17-state sample over the time period spanning 1998–2013.[4]

At the employer, we observe firm identifiers at the State–Employer Identification Number (SEIN) level, through which we can link and observe employment and earnings of workers at the firm in that state.[5] We use several measures of establishment characteristics and dynamics from the Quarterly Workforce Indicators (QWI) files. We use employment weights to aggregate establishments within the state to the SEIN level. For each firm, we compute hires as employer-level "accessions," which includes all new employees and does not exclude recalls. We exclude firms that start up or shut down in that quarter as well as those with more than 200% turnover within a quarter.

From our 15% sample of workers, we use the job history file (JHF), which lists earnings at each job spell during a worker's lifetime. For each period in which the worker has earnings, we follow Hahn et al. (2017) by selecting a "dominant" employer as the job with maximum earnings over two quarters. A job-to-job transition is measured as a change in dominant job from one period to the next when the new dominant job had positive earnings in the same quarter as the old dominant job. This measure will potentially misclassify a worker as having made a job transition when they have worked continuously at two jobs where the dominant job fluctuates between the two employers. Similarly, this measure also misses some

[4]Our sample includes data from California, Colorado, Hawaii, Idaho, Illinois, Indiana, Kansas, Maine, Maryland, Missouri, Montana, Nevada, North Dakota, Tennessee, Texas, Virginia and Washington. These states represent 42% of national employment.

[5]Multi-state firms will be counted as separate firms in each state. The firm-level data covers the firms' entire workforce, not just our 15% sample.

true job-to-job transitions that occur over a weekend at the seam of two quarters since we require overlapping earnings. Time aggregation also implies that some job-to-job transitions we measure are transitions into nonemployment for up to 11 weeks before transitioning to a new job.

We restrict our job transition sample in two principal ways. On the worker side, we restrict to workers who are between 25 and 65 years old when their job begins. This truncation by age is consistent with much of the earnings risk literature to reduce the prevalence of very short job spells. On the firm side, we remove transitions involving firms with fewer than 10 employees to eliminate large percentage changes from discrete employment changes. We accumulate worker earnings and firm growth and turnover into annual measures before and after a transition. Our sample restrictions result in 1.2 million job-to-job transitions.[6] We deflate earnings in all quarters to 2009 dollars.

2.2 Definitions

Our primary focus is on measuring a firm's "churn," the gross flows above and beyond net employment growth. To measure churn, we measure excess hires, $C_{i,t}$, as the number of hires beyond the ones needed for firm i's net employment growth in that period. This is equivalent to the churn measure in Elsby et al. (2025):

$$\begin{aligned} C_{i,t} =& H_{i,t} - \max(\Delta L_{i,t}, 0) = \min(H_{i,t}, S_{i,t}) \\ =& \frac{1}{2}\left(H_{i,t} - \max(\Delta L_{i,t}, 0) + S_{i,t} + \min(\Delta L_{i,t}, 0)\right) \ . \end{aligned} \tag{2.1}$$

where $\mathbb{H}_{i,t}$ and $\mathbb{S}_{i,t}$ denote firm i's counts of gross hires and separations in quarter t and $L_{i,t}$ its average employment during the quarter (`Ebar` in the QWI), rather than the total number of workers who ever appear on its payroll.[7] For the origin firm of a transition, indexed

[6] In order to measure annual earnings growth and firm dynamics, we require the origin and destination match to last 6 quarters. This restriction drops a substantial number of observations which is consistent with Hyatt and Spletzer (2017), who report that about $\frac{1}{3}$ of all job matches last less than 1 quarter.

[7] See the QWI documentation at https://lehd.ces.census.gov/data/lehd-snapshot-doc/latest/sections/employer_level/qwi.html.

$i = \ell$, and the destination firm, indexed $i = d$, the hiring rates are $H_{\ell,t} = \frac{\sum_{k=1}^{4} \mathbb{H}_{\ell,t-k}}{\frac{1}{2}(L_{\ell,t}+L_{\ell,t-4})}$ and $H_{d,t} = \frac{\sum_{k=1}^{4} \mathbb{H}_{d,t+k}}{\frac{1}{2}(L_{d,t}+L_{d,t+4})}$, and the separation rates are $S_{\ell,t} = \frac{\sum_{k=1}^{4} \mathbb{S}_{\ell,t-k}}{\frac{1}{2}(L_{\ell,t}+L_{\ell,t-4})}$ and $S_{d,t} = \frac{\sum_{k=1}^{4} \mathbb{S}_{d,t+k}}{\frac{1}{2}(L_{d,t}+L_{d,t+4})}$.[8] Net employment growth is then simply the difference between these rates, $\Delta L_{\ell,t} = H_{\ell,t} - S_{\ell,t}$ and $\Delta L_{d,t} = H_{d,t} - S_{d,t}$.

For a transition in period t, we look 4 quarters prior to the transition and 4 quarters after the transition. So that our measure is not mechanically affected by the transition of the worker we observe, firm characteristics indexed t skip the period of transition, i.e., $t+1$ to $t+4$ and $t-1$ to $t-4$; we construct the firm's average earnings below with the same convention.

Our final firm-level measure, average earnings, is central to everything that follows: it is the empirical counterpart of the wage w that indexes a firm's rung on the job ladder, and all of our firm-level wage rankings, deciles, and percentiles refer to it. We define it as the log of the average real earnings that firm i pays its employees over the same four-quarter window used for the flow measures:

$$\bar{w}_{i,t} = \ln\left(\frac{\sum_{k=1}^{4} \mathbb{W}_{i,t-k}}{\sum_{k=1}^{4} L_{i,t-k}}\right), \tag{2.2}$$

where $\mathbb{W}_{i,t}$ denotes the total real earnings, in 2009 dollars, that firm i pays its workforce in quarter t. Here, it becomes important that our measure for $L_{i,t}$ is average employment within the quarter, `Ebar` in the QWI, rather than the total count of workers who ever appear on payroll during the quarter. This distinction matters because with total count in the denominator, higher churn would mechanically inflate the number of payroll records and depress measured average earnings, building a negative relationship between churn and wages into the measurement itself. As with the flow measures, the average is computed over the firm's entire workforce rather than our 15% worker sample, destination firms use the window $t+1$ to $t+4$, and the transition quarter is skipped so that the transitioning worker's partial-quarter pay does not mechanically affect the origin or destination firm's measured earnings.

[8] Since these annual measures are chosen to go with a transition at time t, we suppress the t notation for the firm and just denote them with d and ℓ.

3 Empirical evidence on the churn-wage relationship

We first want to consider the relationship between earnings and churn at the firm level. Figure 1 plots the annual excess hire rate, or churn rate, of firms over their percentile rank in terms of average wages. We observe a strong monotonic decline in churn over the distribution of firms' average wages. Churn rates are very high at low-wage firms, while at the top of the firm wage distribution the churn rate is substantially lower. This lines up well with the intuition behind most job-ladder models, that firms face a tradeoff between their wage policy and worker retention. It is also consistent with the idea that high-wage firms poach from firms with lower wages.

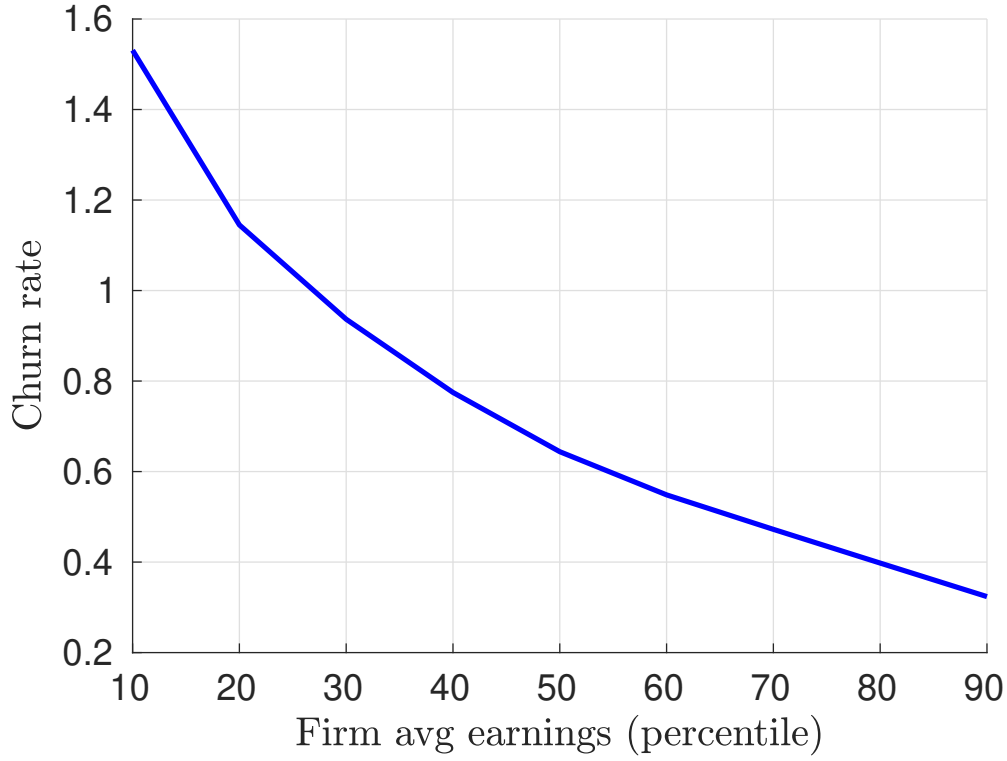

Figure 1: The firm-weighted mean of excess accession or "churn" rate (annual) at each pseudo-decile bin of the average firm-level wage distribution.

3.1 Worker-level estimation: churn

While this strong negative relationship between churn rates and firm wages is suggestive of a churn ladder, this correlation can reflect differences in worker composition across firms without necessarily being related to individuals moving up a job ladder. To address this, we document that looking within continuous employment spells, workers move up a wage ladder and down a churn ladder, from low-wage and high-turnover firms into higher-wage and low-turnover firms with each job transition. Because we look within a worker, this movement does not reflect sorting on the characteristics of the worker. Further, we look within a continuous employment spell, which controls for the starting point out of unemployment. Rather, the pattern we find on the change in earnings and firm turnover with each job transition reflects the worker's marginal gain in wage from searching on the job and making a transition, and the firm's implied tradeoff between match duration and its share of match surplus for the same worker.

We run the following regression on our sample of job transition observations:

$$X_{ij} = \beta_0 + \sum_{k=2}^{N_g} \beta_k \mathbb{I}_{j=job_k} + \gamma_g + \varepsilon_{ij}, \tag{3.1}$$

where X_{ij} is one of three measures: $X_{ij} = \bar{w}_{ij}$ and $X_{ij} = \bar{L}_{ij}$ are the average earnings and number of employees at firm j in the year before worker i separates from it. $X_{ij} = EAR_{ij}$ is the excess accession rate of firm j in the year before the worker i's separation. The indicator $\mathbb{I}_{j=job_k}$ is equal to one if job j is the kth job within a spell of employment, indexed by g. Including employment spell fixed effect γ means these coefficients are relative to the average for the employment spell. If a worker's first employer out of nonemployment is quite good, e.g. low churn or high wage, then we want to look at that as the base from which we look for changes.

The coefficients β_k reflect the change in churn, wage or size from the transition to the kth job in a spell from the baseline level of churn in the first job (which is normalized to 0). The inclusion of the employment spell fixed effect is particularly important because there

is substantial heterogeneity not just across individuals, but across employment spells. By controlling for that heterogeneity, we isolate the effect of moving up the job ladder in a strict sense and quantify the change in the firm's characteristic with each move on the worker's job ladder. It is important to note that the employment spell fixed effect does not control for heterogeneity that creates differences in employment duration. That is, there is still a potential composition effect due to the survivorship of employment spells necessary to reach higher consecutive job transitions.

Figure 2 plots the coefficients from the above regression, giving us a visual representation of the churn ladder, size ladder and earnings ladder. Each begins at 0, which is a normalization because we are running this with fixed effects. Another way to see the normalization is that workers take their first job as a random draw on the distribution, and movements thereafter on the ladder are based on changes from this position.

For graphical comparability, we look at logs of each variable, log earnings, log size and the log churn rate. The most striking trend is the monotonic decline in the log churn rate (the black dashed line), which falls by approximately 40 log points after seven job transitions. This downward trajectory indicates that with every move, workers successfully transition into firms characterized by higher stability and lower turnover. This descent of the churn ladder occurs simultaneously with a steady climb up the earnings ladder (the blue dotted line), confirming that workers generally move toward higher-paying employers over time. Here, the rise is about 30 log points over seven transitions.

In contrast to the clear slopes of earnings and churn, firm size (the red dashed line) remains relatively flat across the job sequence. This suggests that while workers are effectively optimizing for higher pay and better retention, firm size itself is a less direct indicator of a job's position on the ladder compared to churn and wages. It rises, as would be predicted by theory, but only very modestly. If the central logic of the job ladder is that firms trade off higher earnings for better retention, then the black and blue lines are necessary outcomes. Size is a secondary implication and is also affected by mitigating factors, like differences in the production function, which weaken the relationship.

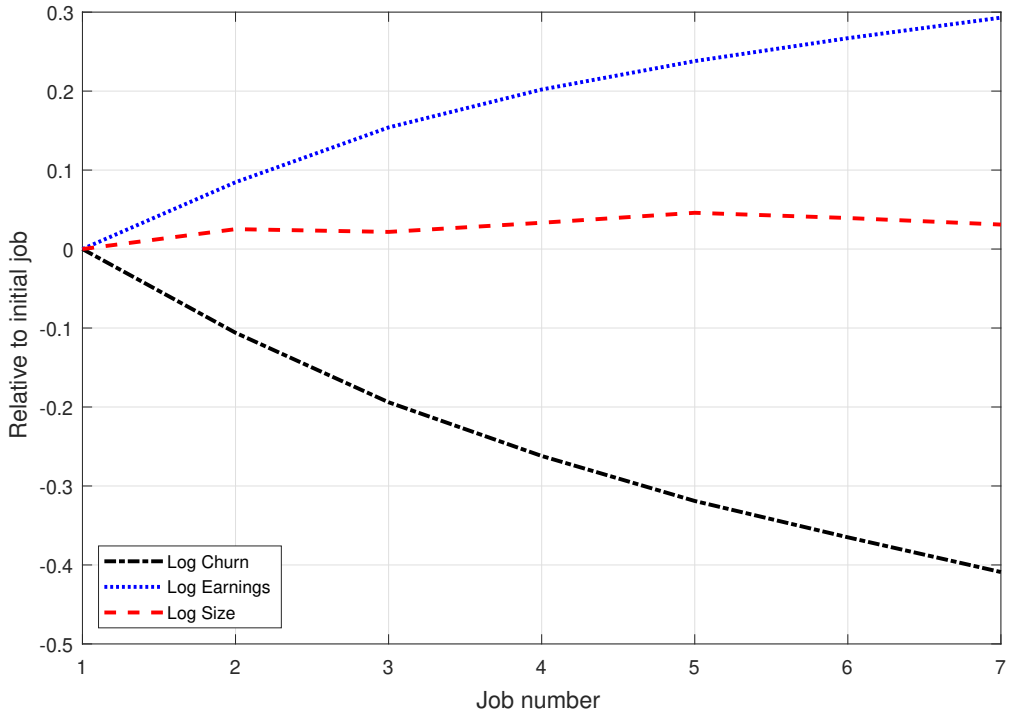

Figure 2: The firm's churn rate, size, and average earnings over the index of job transitions within a worker's employment spell. Each measure is normalized to 0 for the initial job in the spell.

3.2 Empirical tests for separation heterogeneity within wage

A declining churn rate over the wage distribution can arise for at least two distinct reasons: higher-wage firms may offer more stable jobs, or there may be a more stable collection of workers at the firm.[9] Firm-level data on separation rates cannot distinguish these explanations, because a firm effect and a workforce composition that produce the same average separation rate are observationally equivalent in the first moment. They are not equivalent, however, in the distribution of tenure. If all workers at a given wage face the same separation hazard, tenure at that wage is exponentially distributed, with its mean and variance pinned down by the observed separation rate. If instead workers with different separation risks

[9]This is not meant to be an exhaustive statement. For example, firms paying the same wage could differ in separation rates for reasons outside the canonical model, such as amenities. Or, instead of worker heterogeneity, match-quality heterogeneity that sorts across the wage distribution could cause a similar phenomenon; we explore this alternative within the model in Appendix F.2.

coexist at the same wage, average tenure exceeds the exponential benchmark and tenure is too dispersed. In this section we use these two conditional moments of tenure to test for separation-rate heterogeneity within wage levels without imposing the structure of our model.

The distinction also matters for the shape of the firm distribution itself: if workers differ in their underlying propensity to separate to nonemployment, these types will sort endogenously across the wage distribution, as low-separation workers accumulate at high-wage firms through longer employment spells. The two tests we develop below use the mean and variance of tenure at each wage level to help distinguish between these explanations. It is probably not surprising that we reject homogeneity of tenure, but it is informative that there is *more* homogeneity at the top of the wage distribution, consistent with types sorting on the job ladder.

Before constructing the tests, we fix notation, which is standard and anticipates the fuller model of Section 4.1. Workers differ in a separation type δ_j, the rate at which a type-j worker separates from employment into nonemployment, and $s_j(w)$ is the share of type-j workers employed at wage w. Firms also affect separations through a wage-specific component $\delta^f(w)$, so that a type-j worker employed at wage w separates into nonemployment at rate $\delta^f(w)\delta_j$. In the model of Section 4.1 this firm component is the separation policy $\varphi(w)$, which we parameterize as $\varphi(w) = e^{\varepsilon_\delta(w-\bar{w})}$, normalized so that $\varphi(\bar{w}) = 1$ at the top wage $\bar{w}$, when we calibrate the model, but the tests do not rely on this functional form. While employed, workers also receive outside offers drawn from the wage-offer distribution F, arriving at rate λ_e if the offer can be rejected and at rate λ_r if it cannot.

To set up both tests, imagine first there is no worker-level heterogeneity in δ_j. Then, there should be no within-wage variation in separation probabilities. For notational simplicity, suppose the only reason for separation is into nonemployment, $\delta(w)$.[10] In this case, without worker heterogeneity, tenure at a given wage level is exponentially distributed with

[10]Note, of course, that without on-the-job search there is no mechanism for dispersion in the wage offer distribution in our model anymore. So there would be only a single offered wage, with tenure exponentially distributed at that wage. For purposes of exposition, we are temporarily suspending our understanding of the Diamond Paradox.

expectation $\tau(w) = \frac{1}{\delta(w)}$. If instead the true data-generating process involves heterogeneous workers with separation types δ_j, then the observed separation rate averages over the types employed at that wage, $\delta(w) = \delta^f(w)\left[\sum_j s_j(w)\delta_j\right]$, and expected tenure averages the types' expected tenures, $\tau(w) = \sum_j s_j(w)\frac{1}{\delta^f(w)\delta_j}$. The two data-generating processes produce the same average separation rate but different tenure distributions. Here we state the logic of each test and its resulting statistic; Appendix C contains the full derivations.

First-moment test: Now we can compare our null hypothesis, $s_1(w) = 1$ and $s_j(w) = 0$ for $j \neq 1$, $\forall w$, to a case where δ incorporates heterogeneity. Since $\frac{1}{x}$ is a strictly convex function, by Jensen's inequality the expectation of tenure in the no-heterogeneity case is strictly smaller than the expectation of tenure in the case with heterogeneity. That is,

$$\frac{1}{\delta(w)} < \sum_j s_j(w)\frac{1}{\delta^f(w)\delta_j}, \tag{3.2}$$

where $\delta(w)$, the average separation rate at wage w, is the object we observe in the data. Our test is then against the null hypothesis that the expectation of tenure is consistent with the no-heterogeneity case. We can reject the null if the empirical mean of tenure is sufficiently greater than $\frac{1}{\hat{\delta}(w_i)}$, its counterpart implied by the empirical separation rate, at each w_i. We implement the test on a finite set of wage levels $\{w_1, \ldots, w_N\}$, using $\hat{\delta}_i$ and $\hat{\tau}_i$ to denote the estimated rate of separation into nonemployment and the average tenure among the n_i observations at each w_i.[11]

Under the null hypothesis, tenure is exponentially distributed, which delivers an exact χ^2 distribution for the joint test statistic. On-the-job search complicates the tenure distribution, but a stable feature of the data—separations to nonemployment are a roughly constant fraction of all separations, which we call $1-\ell$, as shown later in the right panel of Figure 6—lets us rescale the null so that the total separation rate at w_i is $\frac{\hat{\delta}_i}{1-\ell}$. As we derive in Appendix

[11] Because our data is collected in discrete time, τ and δ are not measured as continuous variables. We will treat them as such for notational and analytical simplicity but it does not change our qualitative conclusions.

C, the joint test statistic in its final form is

$$\sum_{i=1}^{N} \frac{2\hat{\delta}_i n_i \hat{\tau}_i}{1-\ell} \sim \chi^2_{2\sum_{i=1}^{N} n_i - N} \,. \tag{3.3}$$

Second-moment test: Similarly, we can devise a statistical test using the variance of tenure and not just the mean. The intuition is straightforward: worker heterogeneity in separation rates tends to be largest at the bottom of the wage distribution, pushing up dispersion in tenure. However, these low-wage jobs also have the highest separation rates, pushing down the dispersion of tenure. Hence, if there is no heterogeneity, only the latter force operates. Under the null, tenure is exponentially distributed, so its variance at each w_i is also pinned down by the observed separation rate; under heterogeneity, tenure is a mixture of exponentials, which is over-dispersed relative to that benchmark. In Appendix C we derive the variance of tenure in both cases, formalize the over-dispersion result, and apply the same $1-\ell$ rescaling to account for on-the-job search. The resulting test statistic at each w_i is the difference between the estimated variance of tenure and its value under the null:

$$\widehat{\text{Var}(\tau|w_i)} - \frac{(1-\ell)^2}{\hat{\delta}_i^2}. \tag{3.4}$$

The distribution of this test statistic is difficult to characterize analytically. Hence, we bootstrap the distribution and use it to generate p-values.

In Figure 3, we present, across the wage domain, the average duration and the variance of tenure in the data minus their counterparts under the null of homogeneous separation rates within wage level. The joint test statistic of each has a p-value indistinguishable from 0 both because our sample size is so large and because the deviation at each point is so large. In the first moment, the actual tenure is considerably longer than that implied by a constant separation rate within firms. For the second moment, there is considerably more dispersion in tenure than would be predicted. Both are suggestive of heterogeneity in separation rates within each wage bin.

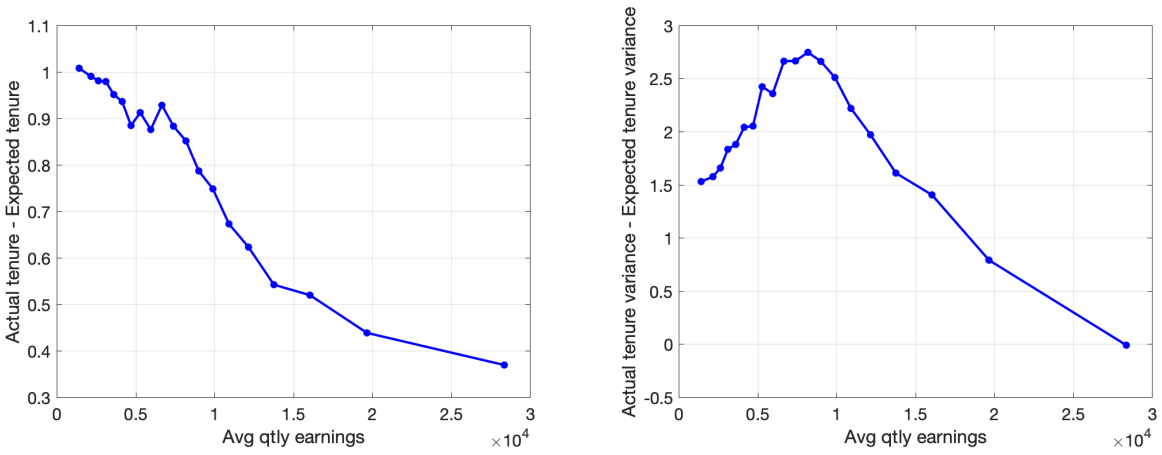

Figure 3: Deviations of average tenure (LEFT) and the variance of tenure (RIGHT) from their values under the null of homogeneous separation rates within wage level. Both tests reject the null.

Together, these rejections establish that the firm's wage alone cannot account for the distribution of tenure: separation rates must be heterogeneous within wage levels. The tests do not, on their own, identify the source of that heterogeneity. Our model interprets it as worker-level risk that sorts endogenously across the wage distribution as low-separation workers survive longer employment spells and climb higher on the ladder. This is not merely a statistical footnote: the magnitude of the deviations in Figure 3 is large, not just statistically significant, so the within-wage heterogeneity to be explained is quantitatively substantial. In what follows, we build a model that incorporates exactly this structure—heterogeneity in both worker and firm separation rates alongside the standard poaching mechanism—and use it to decompose how much of the observed churn ladder each source explains.

4 Churn in a job-ladder model with heterogeneous separations

We start with a framework based on Burdett and Mortensen (1998). This job-ladder model has a simple flow-balance condition that characterizes the distribution of firm size via hires

and separations so that for a firm offering wage w to the worker, its size L is characterized by:

$$(\delta + \lambda_e(1 - F(w)))L(w) = \lambda_u u + \lambda_e G(w)(1 - u) \tag{4.1}$$

where δ is the separation rate, λ_e is the rate of contact of employed workers, F is the distribution of offers from other firms, G the distribution of values among currently matched workers. We take u to be the mass of unemployed workers, λ_u their rate of contacting firms, and the overall measure of workers and firms to be 1. The left-hand side is the number of workers exiting from a match with wage w and the right-hand side is the number of workers entering it. In this simple version, wage w summarizes the match value. In equilibrium the size of the firm, $L(w)$, is characterized by the firm indifference condition $L(w)(p - w) = \bar{\pi}$ where $\bar{\pi}$ is some constant level of profit and p is the productivity level of all firms. While we will not impose this equilibrium condition, it provides some useful intuition as to why the job ladder's wage-churn relationship is so general. Here, wages influence worker retention and thereby affect firm size and firm churn rates. A firm with lower turnover rates maintains a larger firm size by keeping its workers longer, resulting in a higher expected surplus from the same per-worker profit flow, $p - w$. Although higher-wage firms earn less flow profit on each worker, they are compensated by reduced turnover.

Given the implied assumption that workers transit to higher-paying firms, $1 - F(w)$ defines the dominating offers, and known distributions and parameters, Equation 4.1 defines a relationship between wages and flows. This implies that one can take the empirical distribution of size and excess hires and infer the distribution of offered values or vice-versa.

Specifically, we can define the per-worker excess hires rate, $c(w)$, the hires above and beyond the growth rate of the firm, as

$$c(w) = \delta + \lambda_e(1 - F(w)) = \frac{\lambda_u u + \lambda_e G(w)(1 - u)}{L(w)} \ . \tag{4.2}$$

Because we are considering firms in steady-state, every hire is an "excess" hire and all gross

worker flows are churn. Thus, $c(w)$ equals both the hire rate and the separation rate, whereas more generally it would be the minimum of the two. To obtain an empirical relationship from this model, the first equation, $c(w) = \delta + \lambda_e(1 - F(w))$, is most useful.

Specifically, it is easy to see the monotonicity of churn on wages. Taking the derivative of $c(w)$ yields

$$c'(w) = -\lambda_e f(w) \tag{4.3}$$

which is weakly negative everywhere because $f(w)$, being a density, is non-negative everywhere. Both empirically and in one of the most famous results of Burdett and Mortensen (1998), there is positive mass on $f(w)$ over the entire domain of wages. This means that $c(w)$ strictly declines with wages.

Furthermore, we can define the flows in and out of the distribution below $F(w)$, given an earnings distribution $G(w)$. This flows equation relates the distributions $F(w)$ and $G(w)$ by:

$$F(w) = \frac{G(w)(\delta + \lambda_e)(1 - u)}{\lambda_u u + \lambda_e(1 - u)G(w)} \ . \tag{4.4}$$

This holds by equating the mass of workers falling down the job ladder to those who are climbing the job ladder, the same logic as presented in Jolivet et al. (2006). This last relationship is particularly useful empirically because $G(w)$ can be directly observed in the data, as can δ.

4.1 Heterogeneous separations and the job ladder

Our empirical results suggest that separations are a key component of churn, so we allow δ to vary across both workers and firms. Focusing first on worker heterogeneity, the intuition is that different workers fall off the job ladder into nonemployment at different rates. This implies a pattern of sorting in which higher-wage firms at the top of the ladder accumulate low separation rate types. Low-wage firms that hire more directly from unemployment have more separations as the unemployed consist of many high-separation types. Going up the

wage ladder, firms consist of more low-separation types who were able to remain employed for consecutive job-to-job transitions as high-separation types move back to unemployment.

We model firm-level differences in δ as a bundle of wage and the stability of the job they offer. There are several reasons this may happen; for instance, if there are diminishing returns from monetary remuneration, longer-lived jobs might be more valuable. Mechanically, then we can build in a relationship whereby high-wage employers also offer lower δ values. Alternatively, if the value of non-work is a random variable, higher wages make it less likely that this option will dominate. Our approach, tying δ to wage, presents a reduced-form version of these more structural explanations.

In addition to these two dimensions of heterogeneity, to empirically match the distribution of worker turnover and the relationship between wages and churn in job transitions, we must account for the possibility of workers moving to jobs that are dominated by the previous employer's wage level. We introduce a reallocation shock with an arrival rate of λ_r, in which a worker moves to a new job drawn from the entire offer distribution F regardless of the wage.[12]

To add these three concepts, suppose the distribution of workers' separation rates is $D(\delta)$ and each worker gets a draw from this distribution, $\delta_i \in [0, \bar{\delta}]$, that is fixed forever. The firm-side heterogeneity is a wage-specific separation policy $\varphi(w)$ that scales the separation rate of every worker at a firm paying w, with $\varphi'(w) < 0$ so that higher-wage firms offer more stable jobs. This implies that, conditional on δ_i, one could derive the same job-churn relationship from Equation 4.2 at the firm level; however, a firm at a particular wage will have a $\delta(w)$ that depends on its accumulation of δ_i types and its own contribution to the separation rate through $\varphi(w)$. The separation rate at wage w is therefore $\delta(w) = \varphi(w) \int_0^{\bar{\delta}} s dD(s|w)$.

The reservation wage of every worker at a firm paying w is still w, although there is the possibility of a reallocation shock with probability λ_r. This means the mass of potential poaching offers is still $(1 - F(w))$ for on-the-job search. This comes because we forced all firm-side heterogeneity to be perfectly correlated with the wage, so as wages increase, the

[12]This reallocation or "Godfather" shock is an offer that the worker cannot refuse and induces a move to anywhere in the offer distribution regardless of the worker's current wage.

firm component of the separation risk also gets more favorable.

This means that our new expression for churn, $c(w)$, is now

$$c(w) = \varphi(w) \int_0^{\bar{\delta}} s dD(s|w) + \lambda_r + \lambda_e(1 - F(w)) \tag{4.5}$$

We now present a modified version of Equation 4.4, including both heterogeneity in workers and firms and our new reallocation shock, λ_r.

$$\int_{\underline{w}}^{w} \int_0^{\bar{\delta}} (s\varphi(z) + \lambda_r(1 - F(w)) + \lambda_e(1 - F(w)))(1 - u)h(z, s)dsdz =$$
$$\lambda_u u F(w) + F(w) \int_w^{\bar{w}} \int_0^{\bar{\delta}} \lambda_r(1 - u)h(z, s)dsdz \tag{4.6}$$

To see how this compares to our initial setup, just set $\delta_i = \delta$ and $\varphi(w) = 1$ and we recover G as the marginal distribution, integrating over δ_i and from $z = \underline{w}$ to w: $G(w) = \int_{\underline{w}}^{w} \int_0^{\bar{\delta}} h(z, s)dsdz$.[13] Note that we are integrating over wages, using z to index them. Hence, the joint relationship between δ and w appears on the left-hand side of Equation 4.6 as the accumulation of firms' separation effect below wage w.

4.2 Mapping model to data

Suppose wages are defined on a discrete interval, $\{w_1, \ldots, w_W\}$ and there is a discrete set of types $\{\delta_1, \ldots, \delta_J\}$, which defines discrete densities h.[14] Then for wage value w_k we have the

[13] Using this style of notation, we did not need to use the joint density h; we could equivalently have written Equation 4.6 in terms of the conditional distributions $G(w|\delta)$ and type-specific unemployment rates, integrating over types only.

[14] We will abuse notation somewhat, continuing to use notation F, h to describe the distributions and densities associated with w although they are now discrete instead of continuous above.

following:

$$\sum_{i=1}^{k}\sum_{j=1}^{J}(\delta_j\varphi(w_i)+(\lambda_r+\lambda_e)(1-F(w_k)))(1-u)h(w_i,\delta_j)=$$
$$\lambda_u\sum_{j=1}^{J}u_jp_jF(w_k)+F(w_k)\sum_{i=k+1}^{W}\sum_{j=1}^{J}\lambda_r(1-u)h(w_i,\delta_j) \tag{4.7}$$

Here the effective nonemployment separation rate is $\phi(w_k)$ times the employment-weighted average of the worker-type separation parameters, δ_j, at that wage.

We can use Equation 4.7 to solve for $F(w_k)$

$$F(w_k)=\frac{\sum_{i=1}^{k}\sum_{j=1}^{J}(\delta_j\varphi(w_i)+\lambda_r+\lambda_e)(1-u)h(w_i,\delta_j)}{(\lambda_r+\lambda_e)\sum_{i=1}^{k}\sum_{j=1}^{J}(1-u)h(w_i,\delta_j)+\lambda_u\sum_{j=1}^{J}u_jp_j+\sum_{i=k+1}^{W}\sum_{j=1}^{J}\lambda_r(1-u)h(w_i,\delta_j)} \tag{4.8}$$

And then our densities $h(w_i,\delta_j)$, $W\times J$ values, are restricted by the following system of $W\times 2$ equations, which pins them down exactly in our case of $J=2$ types:

$$\delta(w_i)=\left(\sum_{j=1}^{J}\delta_j\frac{h(w_i,\delta_j)}{g(w_i)}\right)\varphi(w_i) \tag{4.9}$$
$$g(w_i)=\sum_{j=1}^{J}h(w_i,\delta_j) \tag{4.10}$$
$$\text{for } i\in\{1,...,W\}$$

and we can solve for the probability of each type by using the steady-state unemployment rate:

$$u=\sum_{j=1}^{J}u_jp_j$$

where u_j is the steady-state unemployment rate for type-j workers, which involves integrating over employment. Define the conditional density $g(w_i|\delta_j) = \frac{h(w_i,\delta_j)}{\sum_{s=1}^{W} h(w_s,\delta_j)}$. Then for type j, their unemployment rate is

$$u_j = \frac{\delta_j \sum_{i=1}^{W} \varphi(w_i) g(w_i|\delta_j)}{\lambda_u + \delta_j \sum_{i=1}^{W} \varphi(w_i) g(w_i|\delta_j)} \tag{4.11}$$

Of course, with $J = 2$ types, we can use Equations 4.9, 4.10 and 4.11 to solve for this entire system, as given in Appendix D.

5 Calibration and quantitative results

In this section, we calibrate our model and compare the model-implied relationship between churn and wages with the corresponding patterns in the data. Our baseline is the full model, which combines on-the-job search, reallocation shocks, wage-dependent separations, and permanent heterogeneity in workers' separation rates. We show that this richer specification can jointly account for the worker churn ladder, the firm-level churn gradient, the distribution of job tenure, and the composition of separations into job-to-job and nonemployment transitions. We then use restricted counterfactuals to isolate the role of the different mechanisms. The first is the Burdett-Mortensen benchmark, which replaces wage-dependent separations with a constant separation rate. In Appendix F, the second counter-factual removes worker heterogeneity while retaining wage-dependent firm separation policies and reallocation, and a third makes the worker heterogeneity match-specific rather than permanent. Together, these counterfactuals show what pure on-the-job search can generate, and why worker heterogeneity is necessary to match the joint distribution of churn, tenure, and the firm distribution in the data.

We set the model to quarterly frequency to match the data. We take the normalized empirical CDF of employment-weighted firm average wages as a direct input for the employment wage distribution, $G(w)$. For the firm separation policy we adopt the parametric form

$\varphi(w) = e^{\varepsilon_\delta(w-\bar{w})}$, normalized so that $\varphi(\bar{w}) = 1$ at the top wage $\bar{w}$, so that a single parameter, ε_δ, the elasticity of $\varphi(w)$ with respect to the wage, governs how much more stable jobs are at higher-wage firms. In the full model, we then solve the system in Equations (4.8)–(4.11) to recover the offer distribution $F(w)$, the joint distribution of wages and worker separation types in employment, the worker separation parameters δ_j, and the reallocation rate λ_r. Holding fixed the population shares of the two worker types, p_1 and p_2, the remaining parameters are chosen to minimize the distance between the model and the data along several dimensions.

Table 1: Calibrated model parameters. The population share of the second worker type is $p_2 = 1 - p_1$.

Parameter	Value	Target
p_1	0.8	Ahn et al. (2023)
λ_u	0.394	Avg. quarterly NE rate, Gregory et al. (2025)
λ_e	0.060	est. - worker ladder
λ_r	0.023	est. - worker ladder
ε_δ	-0.414	est. - worker ladder
δ_1	0.037	est. - tenure distribution
δ_2	0.69	

We choose the five estimated parameters to minimize the distance between model and data for the following moments: (i) the worker-level churn ladder, measured as the change in churn experienced at each job index; (ii) the share of workers with less than one year of tenure across the firm wage distribution; (iii) the fraction of separations that are to nonemployment rather than to other employers across the firm wage distribution; (iv) the overall churn rate across the firm wage distribution; and (v) the schedule of separations to nonemployment, $\delta(w)$, across the firm wage distribution. The finding rate λ_u is not estimated: we set it to the average quarterly rate at which nonemployed workers find employment in the LEHD sample of Gregory et al. (2025), and the nonemployment share is an untargeted outcome of the calibration ($u = 0.25$).

5.1 Baseline results: the full model

We begin with the full calibrated model. Relative to the standard job ladder, this model allows separations to nonemployment to vary with wages through two channels: a firm-level wage-dependent separation policy and permanent worker heterogeneity in ex ante separation risk. These two forces jointly lower the effective separation rate at high-wage firms and raise it at low-wage firms. Low-separation workers survive longer employment spells, accumulate more opportunities to move up the ladder, and therefore sort toward high-wage firms. High-separation workers are disproportionately concentrated at low-wage firms and in unemployment. This endogenous sorting amplifies the decline in churn over the wage distribution, even though search remains random conditional on contact.

Underlying the endogenous relationships in our model, we back out $F(w)$ via the system of Equations 4.8–4.11. As in any job ladder model, $G(w)$ first-order stochastically dominates $F(w)$, but here, the sorting across types and wage-specific firm policies strengthens the pattern: mass at the top of the earnings distribution requires relatively few offers because these jobs are mostly filled by low separation type workers (see Figure 21 in Appendix E).

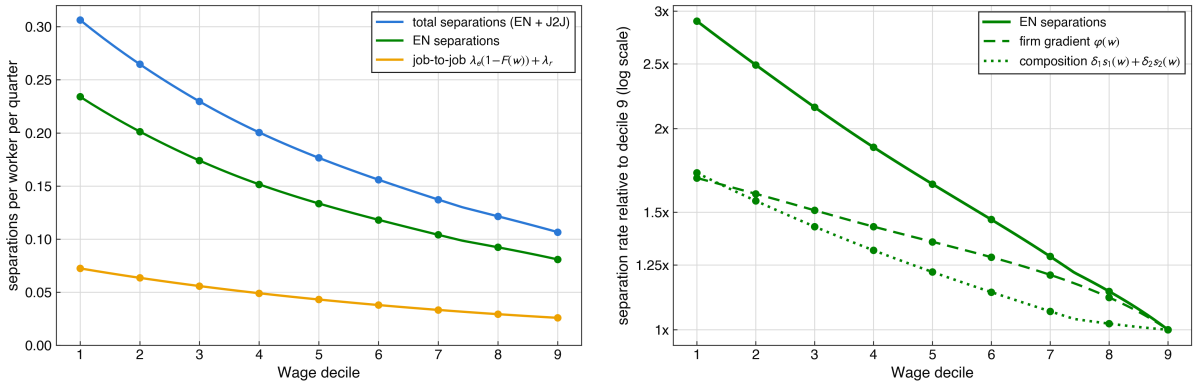

Figure 4: LEFT: Total quarterly separations per worker and their additive components—separations to nonemployment, $\delta(w)$, and job-to-job transitions—at each decile of the firm average wage distribution in the calibrated model. RIGHT: Decomposition of the decline in separations to nonemployment, $\delta(w)$ (log scale, relative to the ninth decile), into the firm-level gradient $\varphi(w)$ and the worker-type composition $\delta_1 s_1(w) + \delta_2 s_2(w)$.

The left panel of Figure 4 shows the declining separation rates in our model. In most job ladder models, the decline in poaching as wages rise is the only force driving this pattern.

This accounts for the slope of the yellow line in the figure, and along with forced reallocation (λ_r), it accounts for only 20–25% of separations throughout the wage distribution. On the other hand, $\delta(w)$ makes the separation rate to nonemployment (EN) decline with w as well, the green line.

In the right panel of Figure 4 we decompose EN separations, $\delta(w)$, into the portion that comes from the firms themselves, $\varphi(w)$, and the part driven by endogenous sorting across types, whereby the high δ are concentrated at low levels of w. Because of our functional structure, $\delta(w) = \varphi(w)\left[\delta_1 s_1(w) + \delta_2 s_2(w)\right]$ where $s_j(w) = h(w, \delta_j)/g(w)$ is the share of type-j workers employed at wage w, this is linearly separable in logs. Hence, we plot the relative magnitudes in this figure.

Overall, both the firm component and composition component contribute about equally to the decline in $\delta(w)$. At the bottom of the wage distribution, the composition dominates, but once we get to the very top of the distribution, the composition of high δ types has stabilized, and so it no longer contributes to the decline in EN separations.

The composition effect is driven by endogenous sorting in the model. We show this directly in the Appendix: the left panel of Figure 19 plots the composition of worker types and separation probabilities over the firms' average wage distribution. At the lowest-wage firms, the share of high-separation-rate workers is about 60% higher than in employment overall. These firms are small and mostly recruit from unemployment, which low-δ workers rarely experience. At the top of the wage distribution are mostly low-δ workers, though a smaller share of lucky high-δ types are employed there.

Figure 5 shows two of our calibration targets. On the left panel, it compares the slope of the worker churn ladder in our model relative to our estimates in the data. The decline in churn with each job transition is similar in magnitude in our model, which is derived from the shape of the distribution of offers over firms' wage levels and churn rates. Workers mostly move up the job ladder, and these steps up coincide with changes in churn arising from the wage-dependent nonemployment separation rate $\varphi(w)$ and endogenous sorting via the job-to-job mechanism.

In the right panel, we show the distribution of short-tenured matches. As introduced in

our empirical tests, while we might match the distribution of turnover with firm-effects that vary purely with w, $\varphi(w)$, if all of the separation rates are homogeneous conditional on w, we would miss tenure. Hence, the fit with Figure 5 suggests that the worker heterogeneity is disciplined by the tenure distribution.

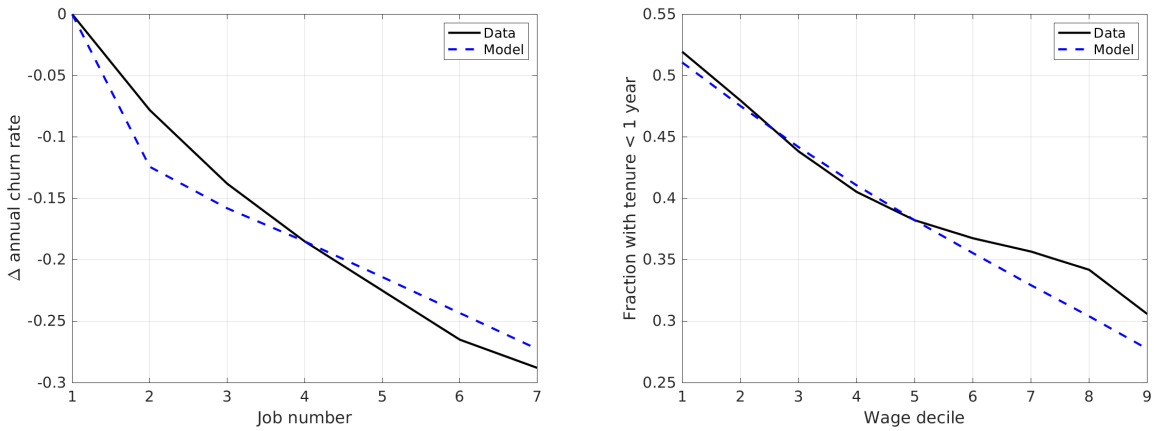

Figure 5: LEFT: The change in annual churn rate of the employer relative to the initial job across job-ladder transitions in the data and the calibrated model. The average churn rate of the initial job is normalized to 0. RIGHT: The fraction of workers with less than one year of tenure at each decile of the firm wage distribution in the data and the calibrated model.

At the worker level, the composition of workers who remain employed through several job transitions consists mostly of those with a low separation probability. This variation in composition mirrors the type of selection present in our regressions with employment-spell fixed effects. This sorting through the longevity of employment is present despite the fixed-effects specification controlling for heterogeneity across jobs within the employment spell and across workers.

Figure 6 (LEFT) plots the annual churn rate against the earnings decile of the firm, comparing the data (solid black line) to the calibrated model with worker heterogeneity (dashed blue line).[15] This is also a calibration target, and we match it well. Both lines begin around 1.2 at the lowest wage decile and decline monotonically to roughly 0.4–0.5 at the top

[15]Unlike the firm-weighted relationship in Figure 1, Figure 6 weights firms by employment to provide a comparison with the model's distribution of workers across firms. This weighting accounts for the differences in the levels of churn between the two figures.

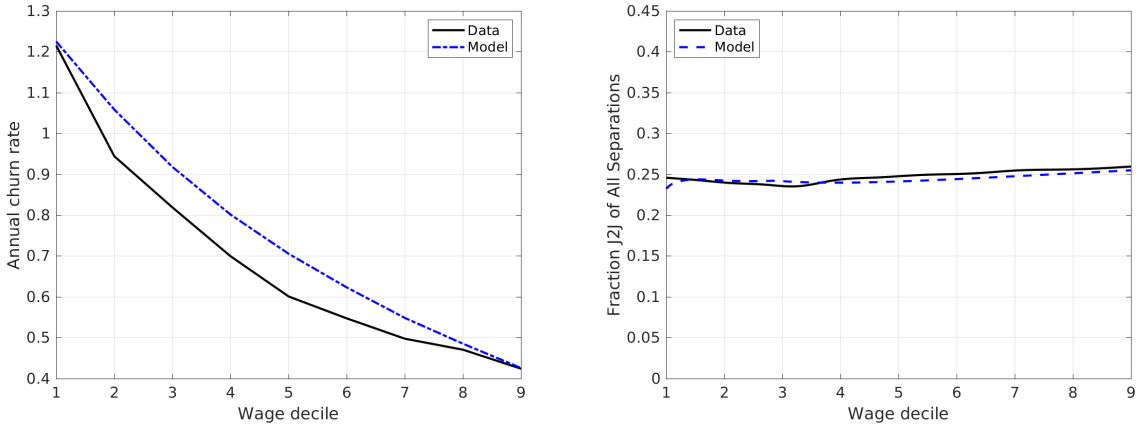

Figure 6: LEFT: The mean annual churn rate at each employment-weighted decile of the firm earnings distribution in the data and the calibrated model with worker heterogeneity. RIGHT: The fraction of separations to other employers (job-to-job) out of all separations at each percentile of the firm earnings distribution in the data and the calibrated model with worker heterogeneity.

of the distribution. The most notable feature of this figure, especially in contrast to Figure 7 shown later, is how closely the model now tracks the data across the entire wage distribution. The fit covers both extremes—the model replicates both the high churn rates at the bottom of the ladder and the much lower rates at the top of the firm average wage distribution. This stands in sharp contrast to our counterfactual exercises without heterogeneity and without wage-dependent separations. The tight fit reflects the two mechanisms we have added that vary separations over the wage distribution: worker composition shifts toward low-separation types as one moves up the wage distribution, and firms' own separation policies also become more favorable at higher wages. Together, these compress the churn rate at the top of the distribution.

In Figure 6 (RIGHT), the model also targets the fraction of separations going to another employer. Interestingly, this share is nearly constant over the wage distribution. While separations decline dramatically over the wage distribution, their composition in terms of the share leaving to other firms versus nonemployment stays roughly the same. This relationship between separations to nonemployment vs. job-to-job is key to identifying the elasticity of the firm separation policy $\varphi(w)$, and the magnitude of the selection effect for workers. If

separations to nonemployment are primarily generated by the firm policy $\varphi(w)$ instead of worker composition, then job-to-job transitions contribute too much to turnover at the top of the wage distribution. Figure 6 shows how the calibrated model matches this fraction quite well.

Having shown that the baseline model matches the joint patterns in the data, we now use three restricted counterfactuals to isolate the contribution of its main ingredients. Our main counterfactual is the canonical Burdett-Mortensen benchmark, presented in Subsection 5.2, which allows churn to vary with wages only through on-the-job search. Appendix F then studies two intermediate counterfactuals that retain wage-dependent firm separation policies and reallocation but alter the worker heterogeneity: the first (Appendix F.1) removes it altogether, and the second (Appendix F.2) makes it match-specific rather than permanent.

5.2 Counterfactual: the Burdett-Mortensen job ladder

For our first counterfactual scenario, we consider the Burdett-Mortensen (BM) benchmark model, which sets the separation rate to a constant over the wage distribution. In this case, churn varies with wages only through poaching and job transitions, with a common separation rate to nonemployment for all workers. This benchmark is useful because it isolates how much of the observed churn-wage relationship can be generated by on-the-job search alone.

Figure 7 (LEFT) plots the worker churn ladder and the (RIGHT) panel plots the average churn rate of firms in each decile of firm average earnings in the data, our calibrated baseline model, and the BM counterfactual. The BM counterfactual actually tracks the worker churn ladder closely: the proportional decline in churn across job transitions is generated by poaching alone. The firm-level churn distribution, however, is where the BM benchmark fails most clearly. While the model with just job transitions can generate a negative relationship between earnings and churn, the gradient is much steeper in the data. While workers do move from higher-churn to lower-churn jobs as they move up the ladder, in a proportional sense, the overall magnitude of churn in the economy is too low.

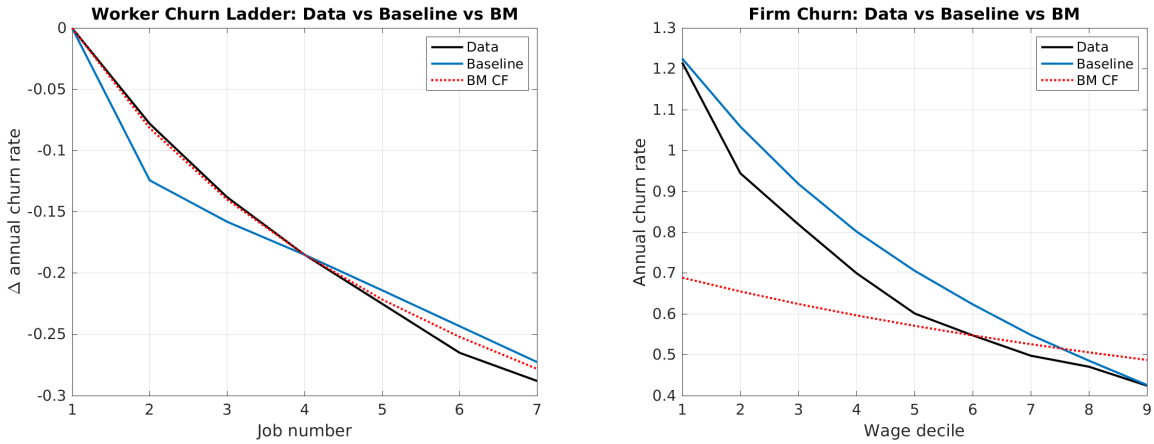

Figure 7: LEFT: The change in annual churn rate of the employer relative to the initial job across job-ladder transitions in the data, the calibrated baseline model, and the Burdett-Mortensen counterfactual. The average churn rate of the initial job is normalized to 0. RIGHT: The mean annual churn rate at each decile of the firm earnings distribution in the data, the calibrated baseline model, and the BM counterfactual.

To understand the mechanics of the simple model and why it fails to generate sufficient variation in churn, it is helpful to look at equation (4.2): $c(w) = \delta + \lambda_e(1 - F(w))$. It is clear that churn is increasing in the contact rate λ_e of employed workers searching on the job, but this increase depends on the offer distribution. As λ_e increases, the initial churn rate of employers hiring low-wage workers at the bottom of the job ladder increases, reflecting a high rate of poaching. But at the top of the job ladder, the churn rate of firms does not move much with λ_e since $(1 - F(w))$, the probability of the offer being higher than the worker's current wage, is small. The reason for this high baseline value of churn is evident in the appearance of a constant δ in equation (4.2). Separation rates to nonemployment are another determinant of churn, and in this benchmark that rate is identical for all workers. As long as δ is a constant, it imposes this floor on churn even at the highest wage rates.

To achieve enough variation in churn across the job ladder and the firm distribution, separation rates to nonemployment must also be correlated with wages. Indeed, when we decompose worker separation rates at the firm into separations to other employers (EE) versus separations to nonemployment (EN), we find that EN rates are also negatively correlated with wage rank and positively correlated with churn.

The distribution of job tenure in the Burdett-Mortensen model shows how constant separation rates limit the fit of the model. Figure 8 plots the fraction of workers with tenure under one year across firm wage deciles. The BM counterfactual predicts too many short-tenure matches over most of the wage distribution, with the discrepancy pronounced at higher-wage firms. This failure follows from the model's central restriction: without reallocation shocks or heterogeneity in separation risk, the only force generating churn differences across firms is poaching along the job ladder. As a result, the model can produce declining churn with wages, but only by making high-wage firms increasingly insulated from separations. That mechanism is too weak to generate the observed dispersion in tenure while also matching the firm-level churn gradient.

The composition of separations provides even sharper evidence against the BM benchmark. The right panel of Figure 8 plots the fraction of all separations that are job-to-job across the wage distribution. In the data, the J2J share of separations is roughly flat. The BM counterfactual predicts the opposite: a steep decline, from above the data at the bottom to essentially zero at the top. This reversal is the direct implication of a model in which separations differ across firms only because of poaching. At low-wage firms, nearly all separations are attributed to workers moving up the ladder, while at high-wage firms the absence of better outside offers drives the J2J margin toward zero. But that is not what the data show. High-wage firms see proportional declines in separations to nonemployment, in lockstep with the drop in job-to-job separations. Similarly, low-wage firms' elevated churn is not primarily a poaching phenomenon. The BM model therefore gets the level and slope of firm churn wrong for the same reason that it distorts the EN/EE decomposition: it lacks the nonemployment and heterogeneity margins that, in the baseline, generate substantial turnover at low-wage firms without forcing the entire adjustment onto job transitions.

5.3 Measuring labor supply elasticity and monopsony

An important application of our churn ladder is how it informs the measurement of labor market power. In most job-ladder models, poaching is the driving feature that makes the

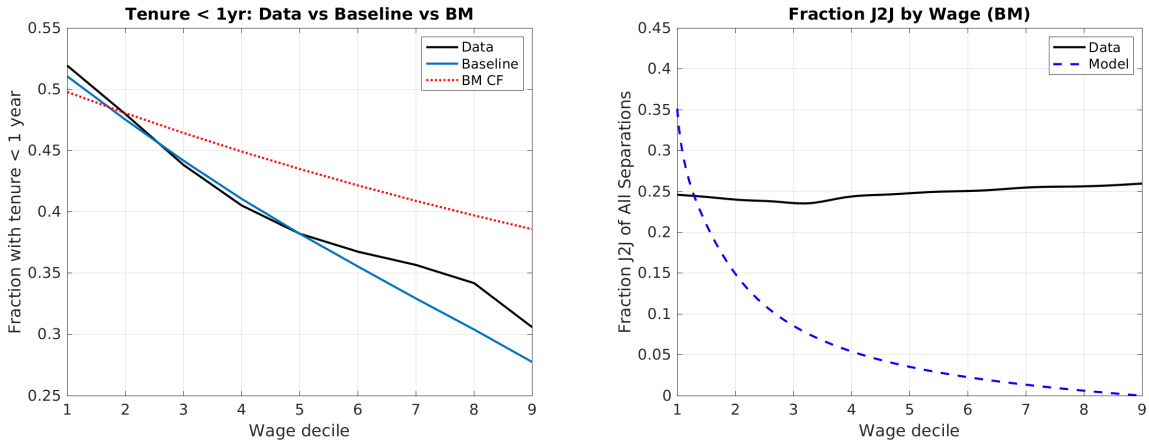

Figure 8: LEFT: The fraction of workers with less than one year of tenure at each decile of the firm wage distribution in the data, the calibrated baseline model, and the Burdett-Mortensen counterfactual. The BM counterfactual produces too many short-tenure matches throughout the upper part of the wage distribution. RIGHT: The fraction of all separations that are job-to-job transitions at each decile of the firm earnings distribution in the data and the BM counterfactual. The BM counterfactual produces too many separations to nonemployment relative to job transitions at the top of the wage distribution.

labor supply faced by firms dependent on wages. Labor supply depends on wages both in how firms use them to retain workers and in how they use them to recruit from other firms. Further, labor supply elasticity directly informs the firms' monopsonistic markdown. For a higher elasticity of supply, firms enjoy less market power and must pay more competitive wages. This is parsimoniously demonstrated in Manning (2003) and Bassier et al. (2022), in which the firm's separation elasticity with respect to the wage is the key element to measure. The crucial insight to this literature from our work is the same finding that allows us to match the churn ladder: separations to nonemployment vary systematically with wages, so poaching is not the only factor moving the elasticity.

To derive the separation elasticity with the notation in Manning (2003), the rate of outflow from firms is a function of the wage level and identical to our measure of the churn rate in Equation 4.2, $\delta + \lambda(1 - F(w))$. Similarly, we can derive the recruiting inflow to be $\lambda u + \lambda G(w)(1 - u)$. In steady state, at every w, $L(w) = \frac{\lambda u + \lambda G(w)(1-u)}{\delta + \lambda(1-F(w))}$. In this simpler model, akin to the one presented in Manning (2003), we can derive a labor supply elasticity which directly relates to the monopsonistic markdown. With δ constant in w, it is $\frac{dL}{dw}\frac{w}{L} =$

$\frac{2\lambda f(w)w}{\delta+\lambda(1-F(w))}$, but once $\delta'(w) \neq 0$, it becomes $\frac{w\delta'(w)}{\delta(w)}\frac{\lambda(1-F(w))-\delta(w)}{\lambda(1-F(w))+\delta(w)} + \frac{2\lambda f(w)w}{\delta(w)+\lambda(1-F(w))}$.[16] The last term is the same in both cases, but the first term when $\delta'(w) \neq 0$ is a positive number. It is the elasticity of δ with respect to wages, a negative number, times a fraction that is -1 at the maximum wage and a negative number of smaller magnitude below that, so long as $\lambda(1-F(w))$ does not exceed $\delta(w)$. Empirically this condition holds: separations to nonemployment are roughly three times poaching separations at every wage.

Using our full model from Section 4.1, we can show that $\delta'(w) < 0$ makes the overall labor supply elasticity larger at a given wage and thereby reduces monopsonistic markdowns, just as in the simplified model from Manning (2003). Here the $\delta(w)$ might come from composition or from firm effects. Our labor supply with respect to w is

$$L(w) = \frac{\lambda_u u + (\lambda_r + \lambda_e G(w))(1-u)}{\delta(w) + \lambda_r + \lambda_e(1-F(w))} \tag{5.1}$$

Equation 5.1 characterizes the relationship between firm employment and wages in the model's steady-state allocation. Importantly, the nonemployment separation rate $\delta(w)$ incorporates both firms' wage-dependent separation policies and the endogenous sorting of workers across the wage distribution. The resulting labor supply elasticity therefore reflects both mechanisms through their contribution to worker retention. Solving first for the elasticity of labor in the case where $\delta'(w) = 0$, we would get[17]

$$\frac{dL}{dw}\frac{w}{L} = w\left(\frac{\lambda_e(1-u)g(w)}{\lambda_u u + (\lambda_r + \lambda_e G(w))(1-u)} + \frac{\lambda_e f(w)}{\delta + \lambda_r + \lambda_e(1-F(w))}\right) . \tag{5.2}$$

If, however, we calculate it in Equation 5.1 with $\delta'(w) < 0$, then we get for $\frac{dL}{dw}\frac{w}{L}$

$$\frac{dL}{dw}\frac{w}{L} = w\left(\frac{\lambda_e(1-u)g(w)}{\lambda_u u + (\lambda_r + \lambda_e G(w))(1-u)} + \frac{\lambda_e f(w) - \delta'(w)}{(\delta(w) + \lambda_r + \lambda_e(1-F(w)))}\right) . \tag{5.3}$$

Equation 5.3 makes it quite clear that, because $\delta'(w) < 0$ and it is subtracted in the numer-

[16] Our model in Section 4.1 nests the latter case with $\delta'(w) \neq 0$ if $\lambda_u = \lambda_e$ and $\lambda_r = 0$.

[17] All of our derivations are in Appendix Section G.

ator, the second term is larger as long as the constant δ is not sufficiently smaller than $\delta(w)$. Because $\delta(w)$ must integrate up to δ, this cannot be the case everywhere. In practice, as we show, the δ' term dominates and signs the bias, while the magnitude of the bias depends on the wage level. Indeed, with a fairly large magnitude of $\delta'(w)$, this bias can be very large. One way to algebraically get a sense of the size of the bias is to relate the fraction of separations from poaching to the fraction of separations to nonemployment: if the latter is higher, then the bias is larger.

With a simplification that is broadly consistent with the data, we can clarify the nature of the bias: relative to the $\delta'(w) = 0$ case, the elasticity is shifted up proportionally, with the shift increasing in w. Let $\delta(w) = \kappa(\lambda_r + \lambda_e(1 - F(w)))$, where κ is approximately 3 because poaching transitions are about $\frac{1}{4}$ of transitions. Then $\delta'(w) = -\kappa\lambda_e f(w)$ and then Equation 5.3 becomes:

$$\begin{aligned}\frac{dL}{dw}\frac{w}{L} &= w\left(\frac{\lambda_e(1-u)g(w)}{\lambda_u u + (\lambda_r + \lambda_e G(w))(1-u)} + \frac{\lambda_e f(w)(1+\kappa)}{(1+\kappa)(\lambda_r + \lambda_e(1-F(w)))}\right) \\ &= w\left(\frac{\lambda_e(1-u)g(w)}{\lambda_u u + (\lambda_r + \lambda_e G(w))(1-u)} + \frac{\lambda_e f(w)}{\lambda_r + \lambda_e(1-F(w))}\right) . \end{aligned} \tag{5.4}$$

Notice the only difference between the two is that the second term of Equation 5.3 has a $-\delta'(w)$ in its numerator. Because $\delta'(w) < 0$, this is a positive term; the labor supply elasticity faced by the firm is now larger. Dividing the second terms of Equations 5.2 and 5.4 we can get that

$$\frac{\lambda_e f(w)}{\lambda_r + \lambda_e(1-F(w))} \Bigg/ \frac{\lambda_e f(w)}{\delta + \lambda_r + \lambda_e(1-F(w))} = \frac{\delta}{\lambda_r + \lambda_e(1-F(w))} + 1 \tag{5.5}$$

Equation 5.5 shows that the second elasticity term of the $\delta'(w) \neq 0$ case is proportionally higher and depends on w through the distribution in the denominator. The derivative of this bias with respect to w is $\frac{\delta\lambda_e f(w)}{(\lambda_r+\lambda_e(1-F(w)))^2} > 0$. So the true elasticity is shifted upward by a proportional term that is increasing in w, so that generally higher wages have even higher

labor supply elasticities and lower markdowns than the standard, $\delta'(w) = 0$ model would predict. The overall labor supply elasticity also includes the recruitment component, which is unchanged in this comparison. We assess the quantitative importance of this bias in the retention margin for the total elasticity using our calibrated model in Figure 9.

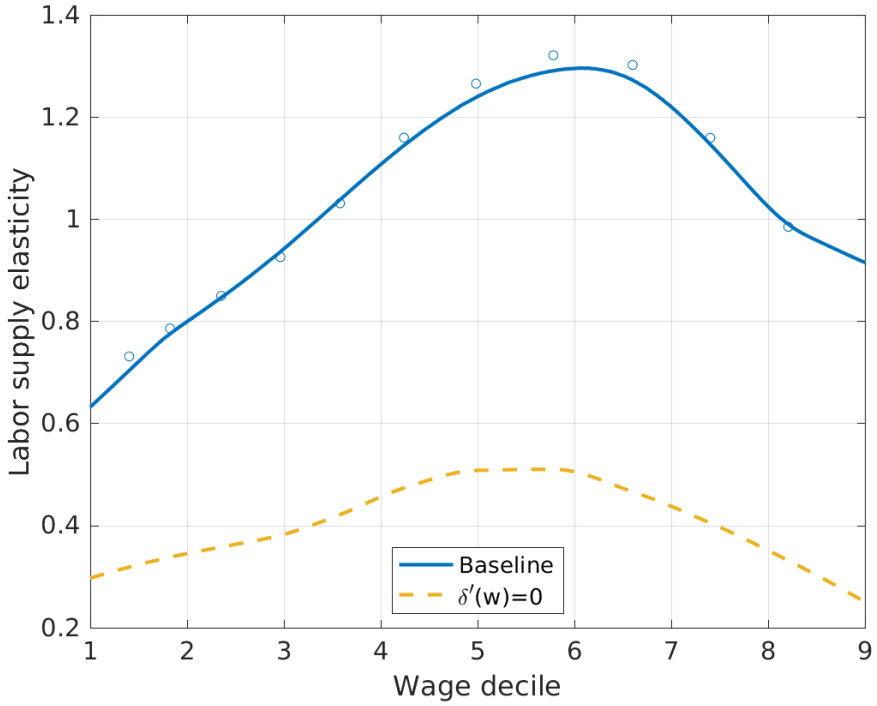

Figure 9: The labor supply elasticity faced by the firm at each level of the wage distribution, computed in the calibrated model with wage-dependent separations ($\delta'(w) < 0$) and in a restricted version that holds δ constant at its mean value.

To show this bias graphically, we compute the labor supply elasticity in our calibrated model from Equation 5.2 and from Equation 5.3, allowing $\delta'(w)$ to fluctuate freely. Figure 9 plots the labor supply elasticity faced by the firm across the wage distribution under two assumptions: our baseline calibrated model, in which the separation rate declines with wages ($\delta'(w) < 0$), and a restricted version that holds δ constant at its mean value. The gap between the two curves is striking. Across virtually the entire wage distribution, the baseline elasticity is between two and five times larger than the constant-δ case, with the absolute

gap most pronounced in the middle of the distribution where both the density of offers and the slope of $\delta(w)$ are large. This gap directly translates into lower implied markdowns: firms face a more wage-elastic labor supply than a model based solely on poaching flows would suggest. The shape of the baseline elasticity is also informative. It rises steeply from the bottom of the wage distribution, peaks near the median wage, and then declines toward the top, suggesting that labor market power varies substantially over the wage distribution and is higher at both tails of the distribution. The initial rise in elasticity reflects the increasing density of the offer distribution and the steepest portion of the $\delta(w)$ gradient, where both the poaching margin and the nonemployment separation margin respond most sharply to wages. The decline at the top of the distribution reflects the diminishing mass of potential poachers–$1 - F(w)$ approaches zero–and the flattening of $\delta(w)$ as the composition of workers stabilizes at nearly all low-separation types. The constant-δ curve, by contrast, rises more modestly with a much lower peak and subsequent decline, implying greater monopsony power overall.

It is useful to interpret the magnitude of our labor supply elasticity estimates in light of this decomposition. Estimates based exclusively on job-to-job flows capture only the poaching component of worker retention. When separations to nonemployment are wage-sensitive, this partial elasticity understates the wage responsiveness of total retention and overstates the implied markdown. In our calibrated model, the omitted nonemployment margin is quantitatively large, accounting for most of the gap between the poaching-only and total-retention elasticities throughout the wage distribution. At the same time, our resulting total labor supply elasticities remain low relative to several recent estimates in the applied micro literature that use movers, firm wage policies, or quasi-experimental variation (Bassier et al., 2022; Kroft et al., 2025). They are much closer, however, to the magnitudes in Webber (2015), who estimates firm-level labor supply elasticities using LEHD data and finds average elasticities near one.

This point applies broadly to the Burdett–Mortensen class of dynamic monopsony models rather than to any single implementation. In canonical wage-posting models (Burdett and Mortensen, 1998; Bontemps et al., 2000), sequential-auction and bargaining variants

(Postel-Vinay and Robin, 2002; Cahuc et al., 2006), and recent granular-employer extensions (Gottfries and Jarosch, 2026), wages affect firm size through recruitment and retention along the job ladder. These models therefore provide a natural framework for studying monopsony power in dynamic labor markets. Our results suggest, however, that quantitative applications of this framework should allow separations to nonemployment to vary with the wage. When the nonemployment separation rate is held constant, the resulting labor supply elasticity captures the poaching margin but omits an additional wage-sensitive retention margin. The implied markdown is therefore based on a partial elasticity whenever exits to nonemployment decline with wages.

5.4 Discussion: different dimensions for measuring the job ladder

Theory suggests that on-the-job search creates a job ladder and thereby shapes the relationship between firm size, wages, and churn. Here, we find strong support for this mechanism: wages and churn vary across workers and firms in a manner broadly consistent with the canonical job-ladder model. The main discrepancy is quantitative, as the model understates the magnitude of the gradient. The theoretical relationship is driven by high-wage firms poaching from low-wage firms, increasing churn at the bottom of the ladder. But this poaching mechanism yields a familiar finding in the search literature: the dispersion we observe in the data is much greater than that predicted by frictional labor market models. Nevertheless, frictions are still essential for generating the dispersion we observe because they facilitate sorting across firms by wage and across workers by separation risk. This sorting mechanism, working through on-the-job search, helps to explain the empirical patterns we document.

The importance of nonemployment separations informs how job-ladder models rank firms. On the one hand, job ladders create a natural ranking of firms, and we suggest another dimension by which they can be measured. On the other hand, our results suggest caution in selecting the appropriate dimension to measure.

This exercise has lessons for methods of measuring rank, using firm characteristics such as wage, productivity or size (see, e.g. Moscarini and Postel-Vinay (2012) or Haltiwanger

et al. (2018)). Again, the position on the churn ladder does not change the rank order, but it provides a more direct measure than size. In a model, higher rank firms poach from lower rank firms and thereby become larger. However, size can also be affected by other factors, e.g. production functions and the Coasean contracting environment. So rather than looking at this second-order implication, we suggest looking at churn itself.

Firm-level differences in separation rates have been crucial to the "slippery" job-ladder mechanisms that try to explain persistent earnings losses after job loss. This literature uses a steeply declining firm separation policy $\varphi(w)$ to explain the experience of displaced workers, who suffer repeated unemployment spells (see Pinheiro and Visschers (2015) or Jarosch (2023)). The churn ladder offers a complementary perspective on this phenomenon: high separation rate firms at the bottom rungs of the job ladder, those that make earnings losses more persistent for separated workers, are one ingredient of the churn ladder. But the degree to which a steep gradient of $\delta(w)$ is because of firms themselves, $\varphi(w)$, or worker sorting, $s(w)$, informs the literature's notions of job-ladder slipperiness. Our estimates suggest that a sizeable portion of the high separation rates at these firms reflects their concentration of high-separation workers. Thus, the slow earnings recovery is not only because of the firms with which displaced workers match, but also because these workers were unlikely to climb the ladder in the first place.

Unobservable worker-level heterogeneity is a key driver for our churn ladder and shapes the cross-sectional distribution of firms. Similar worker-side differences in job separation rates have also been central in the recent discussion of heterogeneous unemployment rates. This work has, with worker-side data, shown large differences in the separation and unemployment rates across workers (see Hall and Kudlyak (2019), Ahn et al. (2023), or Gregory et al. (2025)) to better understand business cycle fluctuations in unemployment. Not only do high-separation workers drive the unemployment rate, they also elevate worker churn rates at the bottom of the job ladder.

6 Conclusion

In this paper, we present new evidence on the empirical shape of the churn ladder from both worker- and firm-side observations. This evidence is qualitatively consistent with a prediction common to a broad class of models: the churn ladder exists in tandem with the wage ladder. We estimate the firm-side negative relationship between earnings and churn and document the significant dispersion of churn in the cross-section. Estimating the slope of both wage and churn over the job ladder gives a quantitative relationship that can be directly compared to calibrated workhorse models of on-the-job search.

The failure of the job-ladder model to generate the dispersion in turnover that we see in the data is informative about an important missing mechanism. To match the turnover rates at the top of the firm ranking, firms must experience far fewer separations, both from poaching and to nonemployment. We demonstrate that there is substantial heterogeneity in separation rates across employers within our data, and more importantly, separations to nonemployment decline strongly with firms' wage rank. Heterogeneity in worker separations and their implied sorting is consistent with a growing literature identifying latent heterogeneity in workers' attachment to employment and the reconciliation of worker flows. Our finding elaborates on this literature: heterogeneity in workers' separation rates seems to play a key role in the distribution of gross flows across the firm distribution as well.

Our paper confirms the job-ladder model's central prediction that turnover declines with earnings, while showing that the canonical mechanism generates too little dispersion in turnover. The missing force in the canonical job-ladder framework is wage-dependent separation to nonemployment, operating through both firm policies and worker sorting. Our results, however, show that this firm-level heterogeneity can be induced by worker-level heterogeneity and the job ladder. We think this is an important insight: that the firm distribution is inherently shaped by worker-level heterogeneity and sorting induced by the job ladder.

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A Appendix: additional descriptive statistics on the churn ladder

A.1 Summary statistics by size and industry

In this section we present a few more facts about the distribution of these joint churn and wage ladders. There is a great amount of heterogeneity across firms in both churn and average wages, and most of it exists within observable characteristics.

First, we break down the wage and churn distributions across firm size and firm size changes. We show in Table 2 that annual churn is decreasing in size and lowest among firms that do not change their size.

Table 2: Mean and variance of churn by employment size and growth

	Mean Churn	Var. of churn within group
Small (< 50)	0.821	2.465
Med (50–1000)	0.794	1.358
Large (1000+)	0.616	0.706
Shrinking ($< -2\%$)	0.814	1.975
Stable $[-2\%, 2\%]$	0.567	0.508
Growing ($> 2\%$)	0.875	2.78

We also note that there is considerable variation in churn across industries. Table 3 lists the mean and variance of the annual churn rate for firms within each sector. Note that there is considerable variation across industries in both the mean and variance of churn rates. However, this variation in churn across industries appears to be largely driven by differences in wages. In Figure 10, we plot sector-level means of churn rates against sector-level means of firms' average quarterly earnings. We get a familiar negative relationship between wages and churn and similar dispersion in churn rates across the wage distribution, just as we see in the unconditional relationship in Figure 1.

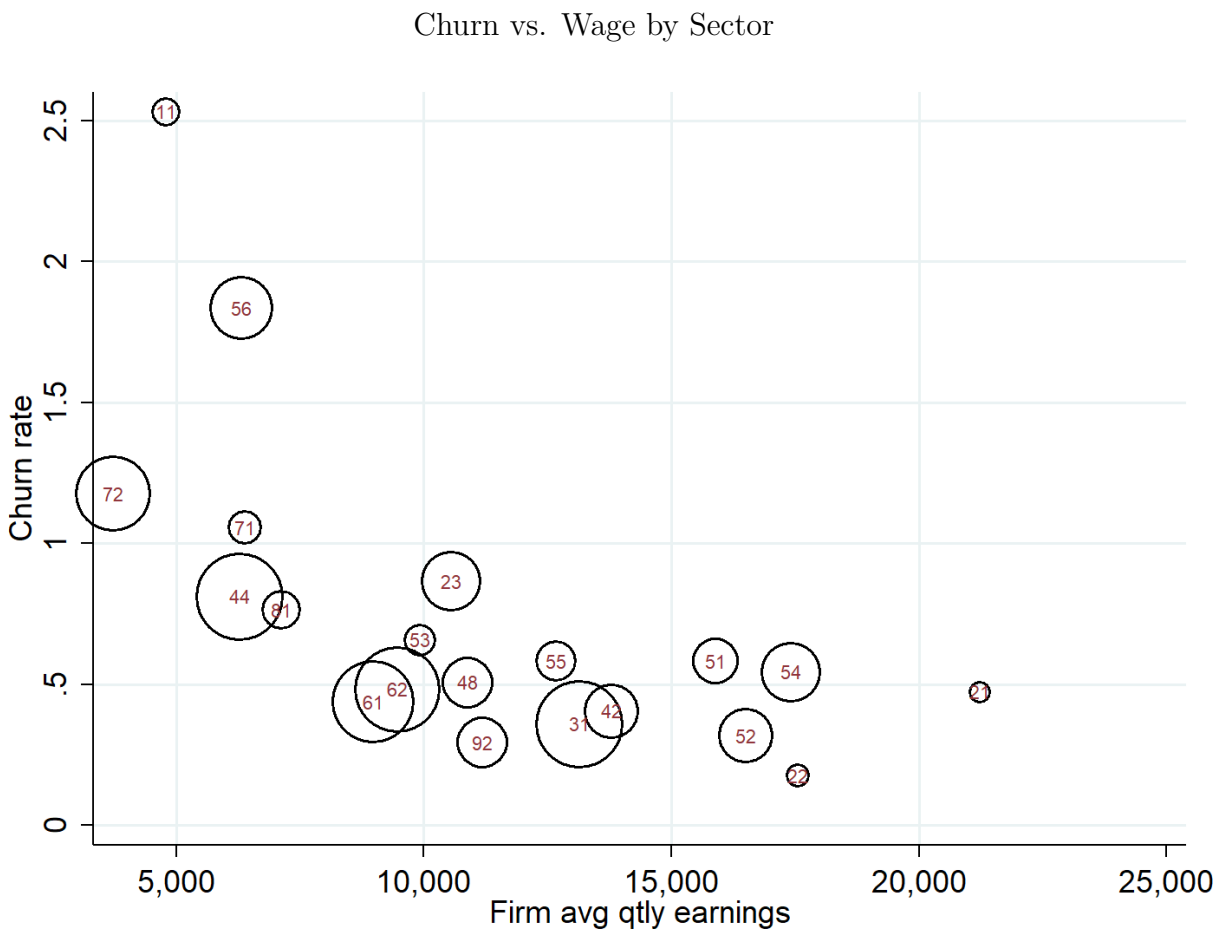

Figure 10: Employment-weighted mean of annual churn rate of firms within each sector, plotted against the employment-weighted mean of firms' average quarterly earnings. Bubble size represents the employment weight of the sector. Sector labeled 31 represents Manufacturing (31-33), Sector 44 represents Retail Trade (44-45), and Sector 48 represents Transportation and Warehousing (48-49).

Table 3: Mean and variance of churn by industry sector.

	Mean Churn	Var. of churn within group
NAICS 11: Ag., Forestry, Fishing, Hunting	2.443	21.76
NAICS 21: Mining, Quarrying, Oil & Gas Extr.	0.685	0.716
NAICS 22: Utilities	0.268	0.350
NAICS 23: Construction	0.980	1.239
NAICS 31-33: Manufacturing	0.515	0.647
NAICS 42: Wholesale Trade	0.458	0.576
NAICS 44-45: Retail Trade	0.812	1.202
NAICS 48-49: Transport. & Warehousing	0.728	1.099
NAICS 51: Information	0.597	8.649
NAICS 52: Finance & Insurance	0.400	1.148
NAICS 53: Real Estate & Rental & Leasing	0.662	1.063
NAICS 54: Prof., Sci., & Tech. Services	0.520	1.310
NAICS 55: Mgmt. of Companies & Enterprises	0.581	5.612
NAICS 56: Admin. & Supp. etc. Services	1.347	5.986
NAICS 61: Education	0.663	2.515
NAICS 62: Health Care & Social Assistance	0.620	1.218
NAICS 71: Arts, Entertainment, & Recreation	1.311	5.383
NAICS 72: Accommodation & Food Services	1.266	1.250
NAICS 81: Other Services	0.765	1.192
NAICS 99: Public Administration	0.484	0.653

B Appendix: robustness of the worker churn ladder

In this section, we plot the worker-level churn ladder across different groups. The churn ladder is remarkably robust across observable characteristics of the worker. The decline in churn across job indices within workers' continuous employment spells is consistent in slope across sex, race, education level, and age. There are significant variations in the levels of churn over these employment cycles, but the decline across job transitions is remarkably consistent.

Of note as well is that the slope of the worker churn ladder is very similar across workers' lifetime income profiles. In Figure 15, we plot the churn ladder for each tercile of lifetime earnings, conditioning on birth cohort. High- and low lifetime earnings workers experience similar churn ladders.

We also note that the worker-level churn ladder holds across firm characteristics such as size and growth, despite the variation in churn levels in these firms that we found in Tables 2 and 3. While we see significant differences in the initial levels of churn across sectors, the worker-level coefficients at each job index within sectors display very similar negative slopes in terms of percentage changes.

Churn Ladder: Sex

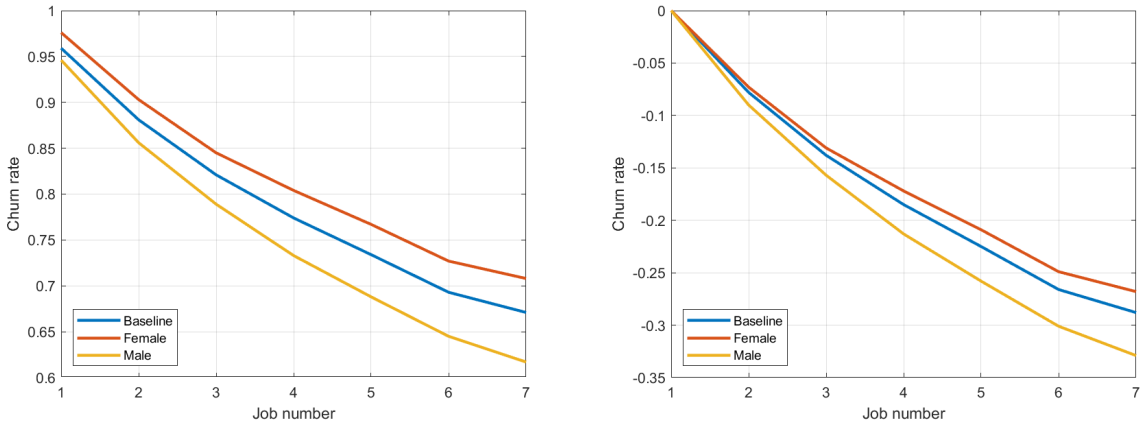

Figure 11: Worker-level churn ladder estimates in levels (LEFT) and relative to initial job (RIGHT).

Churn Ladder: Race

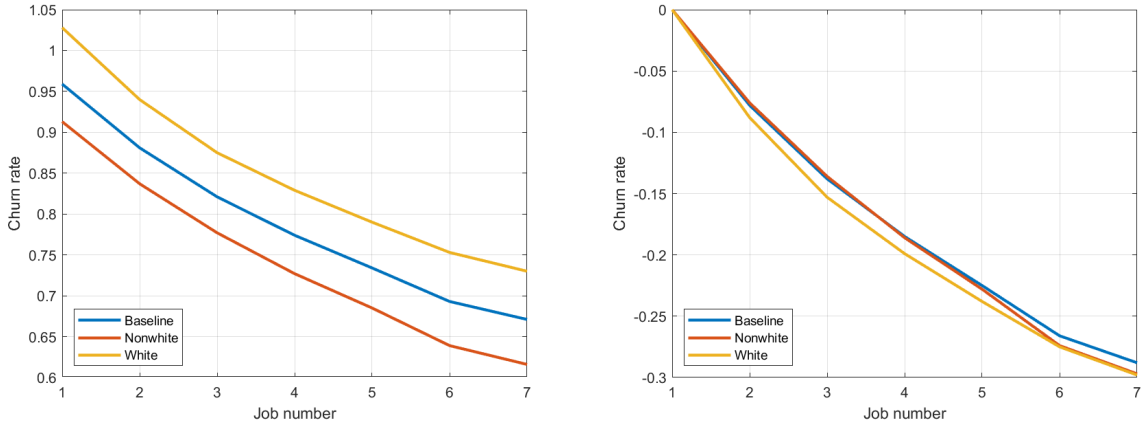

Figure 12: Worker-level churn ladder estimates in levels (LEFT) and relative to initial job (RIGHT).

Churn Ladder: Age

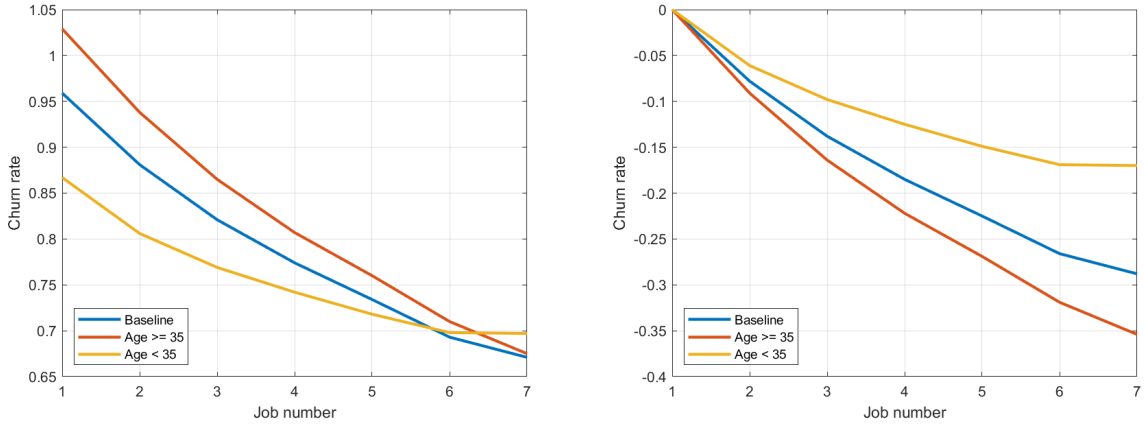

Figure 13: Worker-level churn ladder estimates in levels (LEFT) and relative to initial job (RIGHT).

Churn Ladder: Education

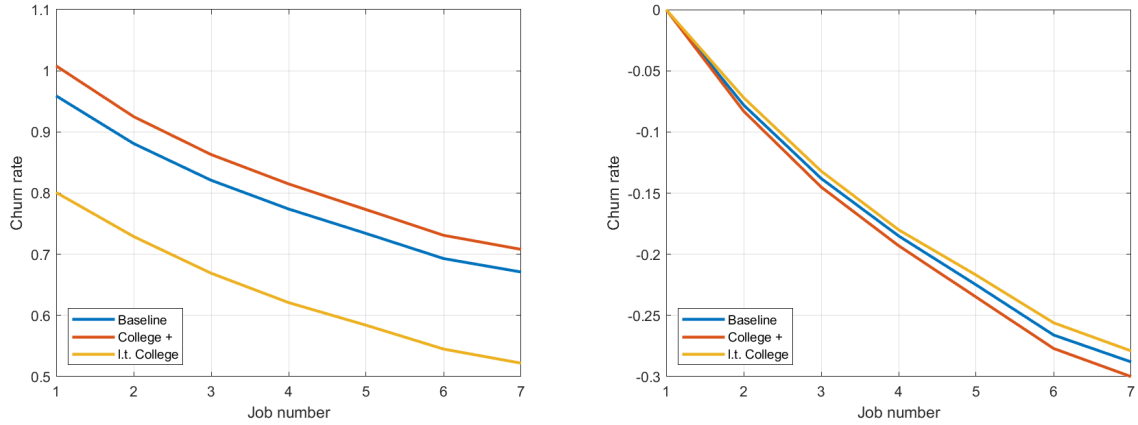

Figure 14: Worker-level churn ladder estimates in levels (LEFT) and relative to initial job (RIGHT).

Churn Ladder: Lifetime Income Terciles (cond. on cohort)

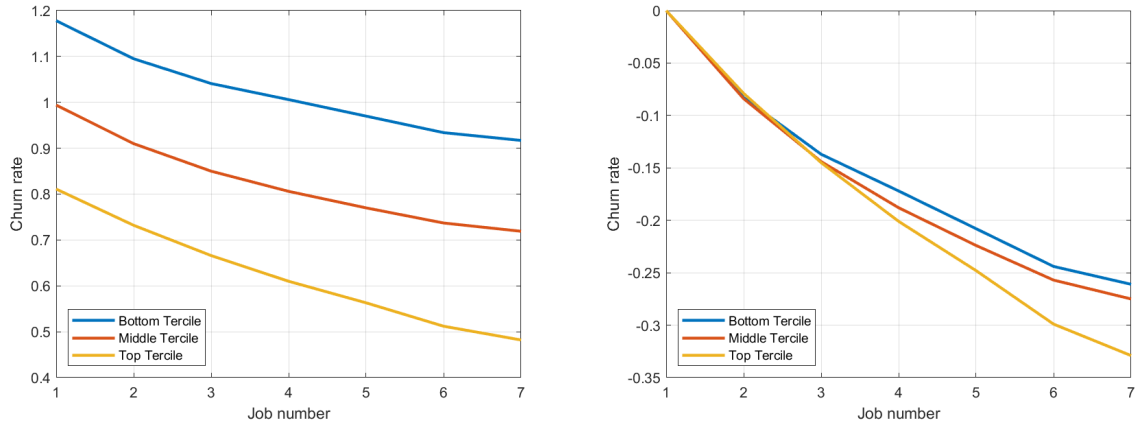

Figure 15: Worker-level churn ladder estimates in levels (LEFT) and relative to initial job (RIGHT).

Churn Ladder: Firm Size

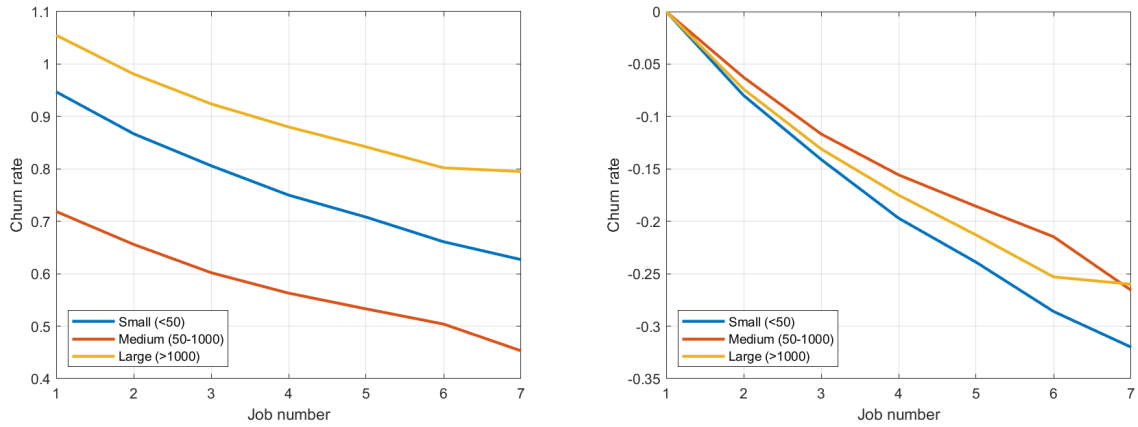

Figure 16: Worker-level churn ladder estimates in levels (LEFT) and relative to initial job (RIGHT).

Churn Ladder: Firm Growth

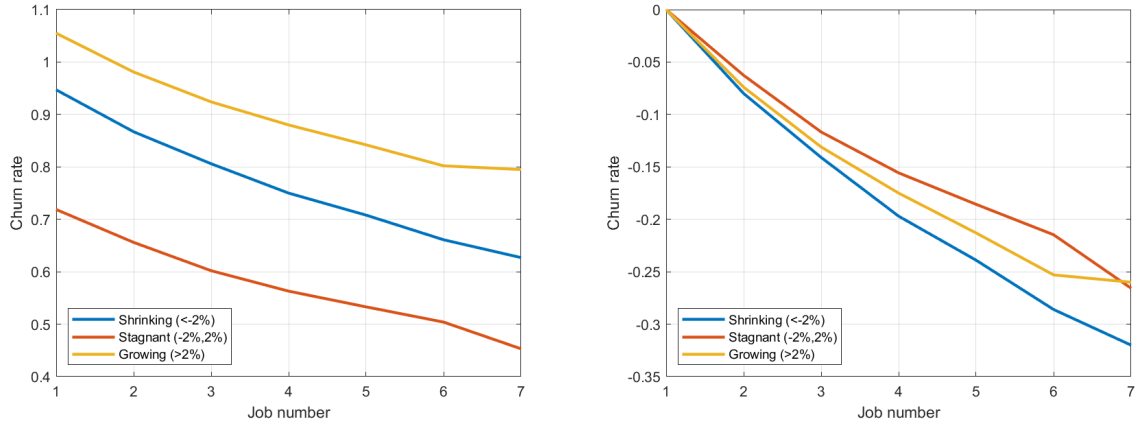

Figure 17: Worker-level churn ladder estimates in levels (LEFT) and relative to initial job (RIGHT).

Churn Ladder: By Sectors

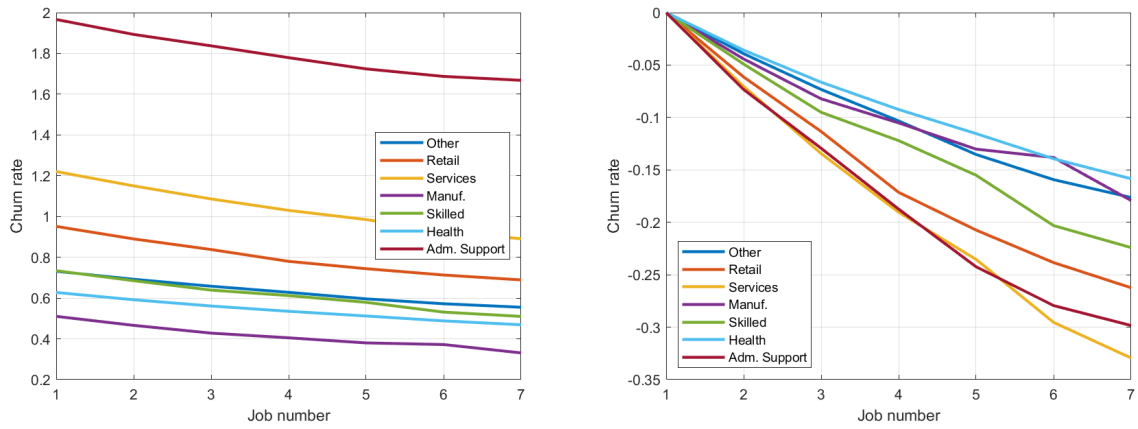

Figure 18: Worker-level churn ladder estimates in levels (LEFT) and relative to initial job (RIGHT).

C Appendix: derivations of the tenure-based heterogeneity tests

This appendix collects the derivations behind the first- and second-moment tests of Section 3.2. Recall the setting: a type-j worker employed at wage w separates into nonemployment at rate $\delta^f(w)\delta_j$, and $s_j(w)$ is the share of type-j workers employed at wage w, so the observed separation rate into nonemployment at w averages over the types employed there:

$$\delta(w) = \delta^f(w)\left[\sum_j s_j(w)\delta_j\right]. \tag{C.1}$$

The null hypothesis of homogeneity is $s_1(w) = 1$ and $s_j(w) = 0$ for $j \neq 1$, $\forall w$. We derive each test first in the simplified environment in which separation into nonemployment is the only reason a match ends, and then incorporate job-to-job transitions.

C.1 First-moment test

With separations only into nonemployment, tenure at wage w for a type-j worker is exponentially distributed with rate $\delta^f(w)\delta_j$, so expected tenure at w mixes over the types employed there:

$$\tau(w) = \sum_j s_j(w)\frac{1}{\delta^f(w)\delta_j}. \tag{C.2}$$

Under the null, this collapses to $\tau(w) = \frac{1}{\delta(w)}$. Under heterogeneity, because $\frac{1}{x}$ is strictly convex, Jensen's inequality applied to Equation (C.1) delivers the strict inequality in Equation (3.2): expected tenure exceeds the inverse of the observed separation rate.

Absent job-to-job transitions, the first-moment test can therefore be formulated as $H_0 : E[\tau|w_i] = \frac{1}{\hat{\delta}_i}\ \forall w_i \in \{w_1, \ldots, w_N\}$, where we test on a finite set of w_i at which we have estimated the empirical $\hat{\delta}_i$s. At each w_i, we compare $\hat{\tau}_i$ to $\frac{1}{\hat{\delta}_i}$. Under the null hypothesis, the match tenure is driven by a homogeneous Poisson process, so it is distributed exponentially with rate parameter δ_i, $\tau \sim \text{Exp}(\delta_i)$. This means $2\delta_i\tau \sim \chi^2_2$ for each of the n_i tenure observations at w_i and hence, summing across observations, our test statistic at each w_i is $2\hat{\delta}_i n_i \hat{\tau}_i \sim \chi^2_{2n_i-1}$, where one degree of freedom is lost to estimating $\hat{\delta}_i$. To make this into a joint hypothesis, notice that in this simplified form, with only separations to nonemployment, $\delta(w_i)$ are independent across each w_i. Thus, the joint test statistic is distributed $\chi^2_{2\sum_{i=1}^N n_i - N}$.

This problem gets more complicated in our true model with on-the-job search, in which the total separation rate from a firm of wage w is

$$\sigma(w) = \delta(w) + (1 - F(w))\lambda_e + \lambda_r\ . \tag{C.3}$$

This is a competing-risks problem: the time before separation is still distributed as an exponential, but now depends on $\delta(w)$ and the on-the-job-search components. However, the endogenous function $F(w)$, moving freely, presents two problems. First, the null hypothesis

for each w_i becomes difficult to characterize, as a function of w_i itself. More difficult, however, is that each w_i is no longer independent. But we can simplify this with an approximation: separations to nonemployment are a constant fraction of all separations, which we call $1-\ell$. This pattern is evident in the data, as shown in the right panel of Figure 6. Under the null hypothesis that firm heterogeneity is the data-generating process, $\sigma(w) = \frac{\delta(w)}{1-\ell}$ and thus our null for the mean of tenure is proportional to our earlier H_0: $E[\tau|w_i] = \frac{1-\ell}{\hat{\delta}_i}$ $\forall w_i$. The joint test statistic scales the same way, replacing $\hat{\delta}_i$ with the total separation rate $\frac{\hat{\delta}_i}{1-\ell}$, which delivers Equation (3.3) in the main text.

C.2 Second-moment test

Again suppose first that separations to nonemployment are the only determinant of tenure, i.e. no on-the-job search. Conditional on type j and wage w, tenure is exponential with rate $\delta^f(w)\delta_j$, so its second raw moment is $\frac{2}{(\delta^f(w)\delta_j)^2}$. Mixing over types and subtracting the square of Equation (C.2), the variance of tenure as a function of wage is

$$\text{Var}(\tau|w) = \sum_j \frac{2s_j(w)}{\left(\delta^f(w)\delta_j\right)^2} - \left(\sum_j \frac{s_j(w)}{\delta^f(w)\delta_j}\right)^2 \tag{C.4}$$

If $s_1(w) = 1$ so that there is no heterogeneity, then tenure is exponentially distributed at each w and this expression collapses to the exponential variance, $\frac{1}{\delta(w)^2}$. Under heterogeneity, the variance instead strictly exceeds this benchmark, formalizing the over-dispersion claim in the main text. To see this, write $m(w) \equiv \sum_j \frac{s_j(w)}{\delta^f(w)\delta_j}$ for expected tenure. The first term of Equation (C.4) is twice the second raw moment, across types, of $\frac{1}{\delta^f(w)\delta_j}$, which is weakly greater than $m(w)^2$. Hence

$$\text{Var}(\tau|w) \geq 2m(w)^2 - m(w)^2 = m(w)^2 > \frac{1}{\delta(w)^2}\ , \tag{C.5}$$

where the final strict inequality is Equation (3.2).

Of course, we can actually observe $\delta(w)$ in the data, so, absent job-to-job transitions, our null hypothesis is

$$H_0 : \text{Var}(\tau|w_i) = \frac{1}{\hat{\delta}_i^2}\ \forall w_i \tag{C.6}$$

We can again test on a finite set of $w_i \in \{w_1, \ldots, w_N\}$ and the empirical $\hat{\delta}_i$ estimated at each w_i. This yields a test statistic at each w_i that is the difference between the estimated variance and the one constructed from separation rates using the estimated exponential distribution: $\widehat{\text{Var}(\tau|w_i)} - \frac{1}{\hat{\delta}_i^2}$.

Incorporating on-the-job search, tenure under the null is exponential with the total sep-

aration rate in Equation (C.3), so its variance is

$$\text{Var}(\tau|w) = \frac{1}{(\delta(w) + (1 - F(w))\lambda_e + \lambda_r)^2} = \frac{1}{(\sigma(w))^2} \tag{C.7}$$

Incorporating the same approximation as in the first-moment test, $\sigma(w) = \frac{\delta(w)}{1-\ell}$, our null hypothesis is now that $\text{Var}(\tau|w) = \frac{(1-\ell)^2}{\delta(w)^2}$ and the rest of the analysis is the same, which delivers the test statistic in Equation (3.4) of the main text. Because the distribution of this statistic is difficult to characterize analytically, we bootstrap its distribution to generate the p-values reported in Figure 3.

D Appendix: identification with discrete types

D.1 Mapping model to data

Suppose wages are defined on a discrete interval, now with discrete densities h. Then for discrete wage value w_k from range $w \in \{w_1, \ldots, w_W\}$ and $\delta_j \in \{\delta_1, \ldots, \delta_J\}$ we have the following equation (4.7):

$$\sum_{i=1}^{k}\sum_{j=1}^{J}(\delta_j\varphi(w_i) + (\lambda_r + \lambda_e)(1 - F(w_k)))(1-u)h(w_i, \delta_j) = \lambda_u u F(w_k) + F(w_k)\sum_{i=k+1}^{W}\sum_{j=1}^{J}\lambda_r(1-u)h(w_i, \delta_j)$$

Here $\delta(w_k) = \varphi(w_k)\sum_{j=1}^{J}\delta_j\frac{h(w_k,\delta_j)}{g(w_k)}$, that is, the effective separation rate for a firm at wage w_k is the worker-weighted average of separation rates δ_j for each j type of worker at wage w_k, scaled by the firm-level policy $\varphi(w_k)$.

With two types, δ_1, δ_2 with underlying probability $p_1, 1-p_1$ our identification comes from solving a fairly straightforward system.

We can write (4.7) as:

$$\begin{aligned}\sum_{i=1}^{k}&(\delta_1\varphi(w_i) + \lambda_r(1 - F(w_k)) + \lambda_e(1 - F(w_k)))(1-u)h(w_i, \delta_1) + \\ &(\delta_2\varphi(w_i) + \lambda_r(1 - F(w_k)) + \lambda_e(1 - F(w_k)))(1-u)h(w_i, \delta_2) = \\ &\lambda_u u F(w_k) + F(w_k)\sum_{i=k+1}^{W}\lambda_r(1-u)h(w_i, \delta_1) + F(w_k)\sum_{i=k+1}^{W}\lambda_r(1-u)h(w_i, \delta_2)\ .\end{aligned}$$

Given a $G(w)$ and $\delta(w)$, our joint densities $h(w_i, \delta_j)$ are defined by the $2 \times W$ conditions:

$$\begin{aligned}\delta(w_i) &= \left(\delta_1\frac{h(w_i,\delta_1)}{g(w_i)} + \delta_2\frac{h(w_i,\delta_2)}{g(w_i)}\right)\varphi(w_i) \\ g(w_i) &= h(w_i, \delta_1) + h(w_i, \delta_2) \\ &\text{for } i \in \{1, ..., W\}\end{aligned}$$

Now to get the masses p_1 and $(1 - p_1)$ of each worker type $j \in \{1, 2\}$, we can use the relationship between the aggregate unemployment rate u and the unemployment rate for each type, u_j, and their steady-state relationship to inflows and outflows. Define the overall

separation rates $\bar{\delta}_j = \frac{\sum_{i=1}^{W} \varphi(w_i) h(w_i, \delta_j) \delta_j}{\sum_{i=1}^{W} h(w_i, \delta_j)}$ then

$$u = \sum_j u_j p_j = u_1 p_1 + u_2(1 - p_1) = \frac{\bar{\delta}_1}{\bar{\delta}_1 + \lambda_u} p_1 + \frac{\bar{\delta}_2}{\bar{\delta}_2 + \lambda_u}(1 - p_1)$$

$$u = \left(\frac{\bar{\delta}_1}{\bar{\delta}_1 + \lambda_u} - \frac{\bar{\delta}_2}{\bar{\delta}_2 + \lambda_u} \right) p_1 + \frac{\bar{\delta}_2}{\bar{\delta}_2 + \lambda_u}$$

And it should be that for the employed, the following holds:

$$\frac{p_j(1 - u_j)}{1 - u} = \sum_{i=1}^{W} h(w_i, \delta_j) \text{ for } j \in \{1, 2\}$$

E Additional model figures

This appendix collects additional figures from the calibrated baseline model. Figure 19 shows the endogenous sorting at the heart of the model: the left panel plots the composition of worker types over the firm wage distribution—high-δ workers are concentrated at the lowest-wage firms, which recruit mostly from nonemployment, while the top of the distribution is populated almost entirely by low-δ workers—and the right panel plots the resulting separation schedule $\delta(w)$ together with the job-to-job transition rate. Figure 20 decomposes total turnover into the contributions of worker types, the firm separation policy, and job-to-job transitions. Figure 21 plots the employment wage distribution $G(w)$, taken from the data, together with the offer distribution $F(w)$ recovered from Equations (4.8)–(4.11). Finally, Figures 22 and 23 show the sorting in motion: high-δ workers are heavily over-represented in both hiring and separation flows relative to their share of the employment stock, and their jobs rarely survive long enough to end in a job-to-job move, which is why they accumulate at the bottom of the ladder and in nonemployment.

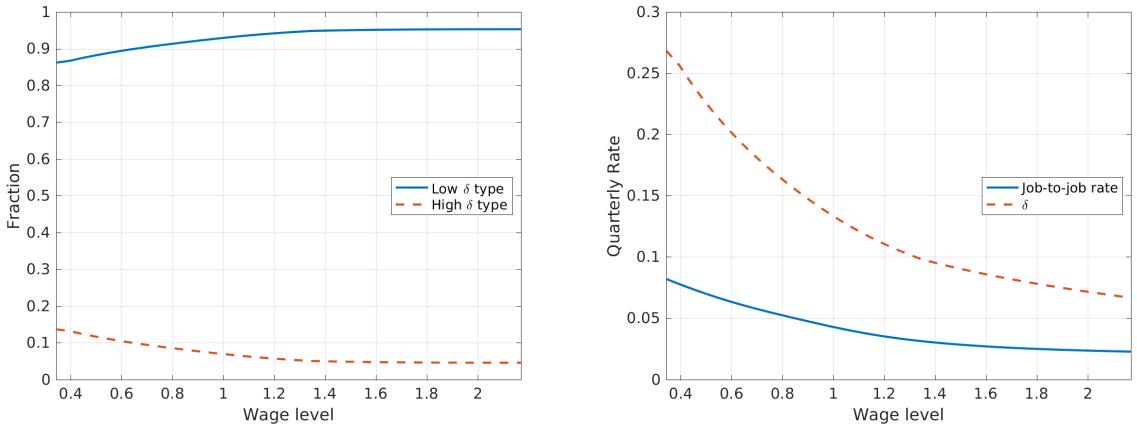

Figure 19: LEFT: The fraction of low- and high-separation-rate worker types at each level of the firm wage distribution in the calibrated model. RIGHT: The quarterly rate of job-to-job transitions (including both on-the-job search and reallocation) and the average separation rate $\delta(w)$ integrated over all worker types at each level of the firm wage distribution in the calibrated model.

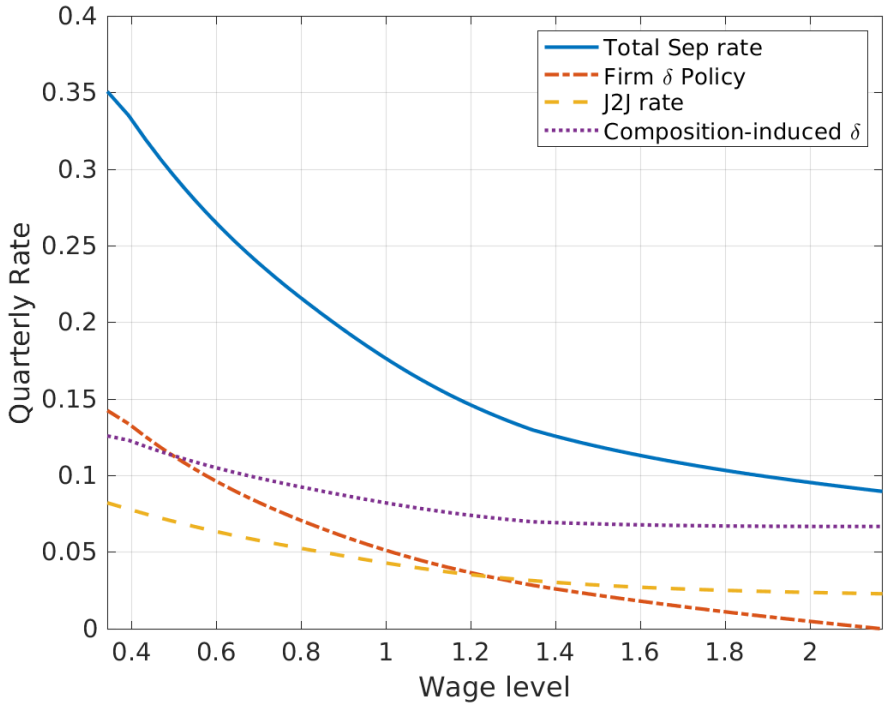

Figure 20: The contribution of worker types, firms, and job-to-job transitions to total turnover over the wage distribution.

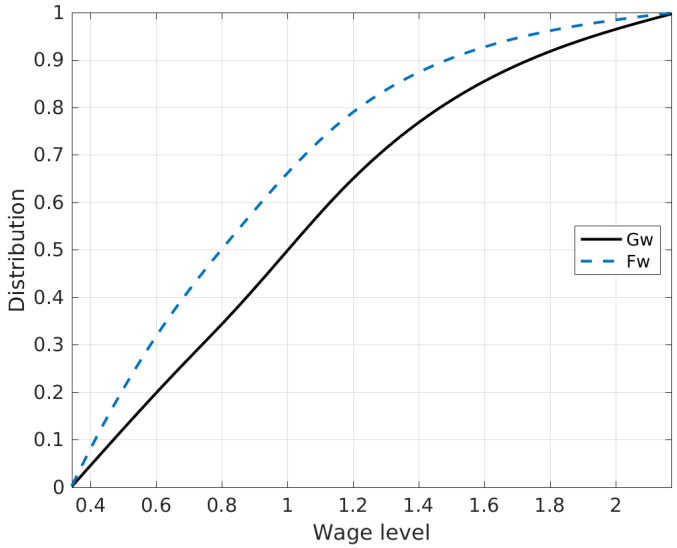

Figure 21: The employment wage distribution $G(w)$ and the equilibrium offer distribution $F(w)$ in the calibrated model. $G(w)$ first-order stochastically dominates $F(w)$: high-wage jobs are mostly filled by low-separation workers with few outflows, so relatively few offers are required to sustain the mass of employment at the top.

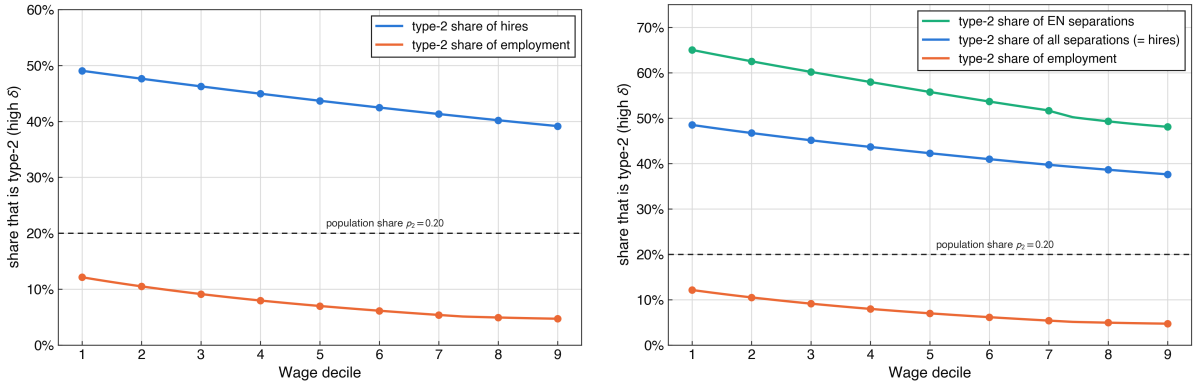

Figure 22: LEFT: The share of hires at each wage decile that are high-δ workers, compared with their share of the employment stock and their population share. RIGHT: The corresponding shares of separations, to nonemployment and in total. High-δ workers flow through both margins of the firm at roughly four times their stock share: low-wage firms churn through high-δ hires rather than accumulating them.

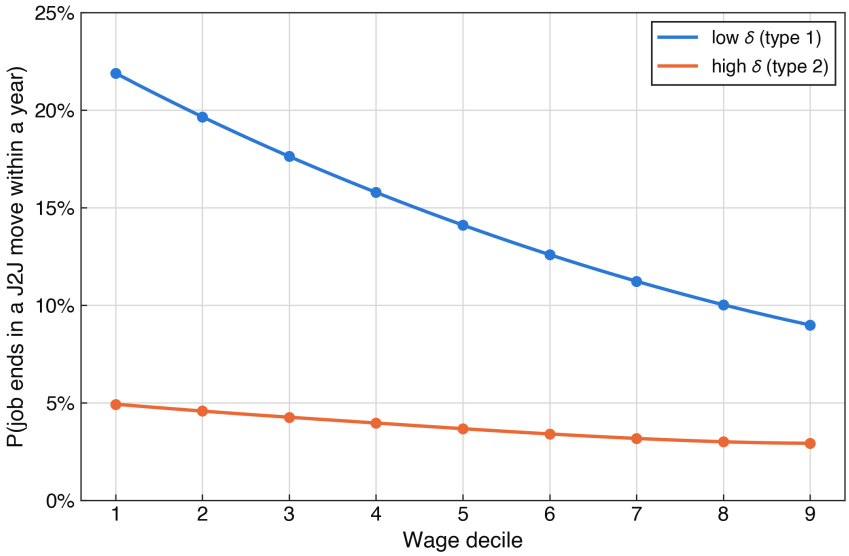

Figure 23: The probability that a job ends in a job-to-job move within one year, by worker type and wage decile. Both types face the same job-offer hazard $\lambda_e(1 - F(w)) + \lambda_r$; the gap reflects the EN hazard arriving first for high-δ workers, whose jobs rarely last long enough for an acceptable outside offer.

F Counter-factual models with other forms of δ heterogeneity

F.1 The model without worker heterogeneity

Our model generates $\delta(w)$ through two distinct mechanisms. The first is a firm effect, the separation policy $\varphi(w)$ with elasticity ε_δ, that ties the separation rate directly to the wage offer. The second is latent worker heterogeneity in ex ante δ, which sorts low-separation workers toward high-wage firms through the natural selection of longer employment spells and repeated on-the-job transitions. Section 3.2 provided the empirical basis for this second channel: we rejected the null that separation rates are homogeneous conditional on the wage, consistent with a role for worker-level heterogeneity.

To quantify the contribution of worker heterogeneity, we simulate a counterfactual that removes it entirely. We collapse both types to a single common separation rate and re-calibrate, relying solely on the firm-level policy $\varphi(w)$ to replicate the $\delta(w)$ gradient. This restricted version resembles slippery job-ladder specifications such as Pinheiro and Visschers (2015) and Jarosch (2023), which generate churn dispersion entirely through firm-level policies. While parsimonious and theoretically coherent, it cannot simultaneously match the churn ladder and the cross-sectional distribution of tenure—a tension the heterogeneous-worker baseline resolves through the additional degree of freedom that endogenous compositional sorting provides.

Figure 24 (LEFT) compares the worker churn ladder across the data, the baseline model, and the no-heterogeneity counterfactual. The no-heterogeneity counterfactual tracks the slope of the ladder reasonably well: the rate of decline in churn across job transitions is broadly similar across all three, with only modest divergence appearing at higher job indices. This closeness is by design, as the elasticity of $\varphi(w)$, ε_δ, is recalibrated to match this target. The lesson, however, is not that heterogeneity is unimportant—it is that the worker churn ladder, measured as a proportional slope across transitions, is insufficiently informative on its own to distinguish the two mechanisms. The following figures show that the model without heterogeneity achieves this partial fit only by failing along other margins.

The firm-level churn gradient shows how the no-heterogeneity counterfactual achieves this partial fit. The right panel of Figure 24 plots the annual churn rate against firm wage decile for the data, baseline, and no-heterogeneity counterfactual. Recalibrated with a much steeper firm separation policy (ε_δ roughly -0.70, against -0.41 in the baseline), the counterfactual approximates the level and slope of firm churn, understating it only at the very bottom of the distribution. In the baseline, low-wage firms accumulate high-δ workers who separate frequently to nonemployment; without that compositional channel, the firm policy alone must generate the entire gradient mechanically. The next two margins show the cost of that substitution.

The distribution of job tenure makes the failure most direct, and connects most clearly to the tests developed in Section 3.2. Figure 25 plots the fraction of workers with tenure under one year across firm wage deciles. The baseline model tracks the data closely, while the no-heterogeneity counterfactual overshoots uniformly—predicting too many short-tenure matches at every point in the wage distribution, with the excess concentrated at lower wages. The reason is precisely the tension identified in Section 3.2: with a single separation rate within each wage bin, churn and tenure are linked one-for-one, leaving no degrees of freedom to match both simultaneously. The baseline breaks this link through the mixture of high- and

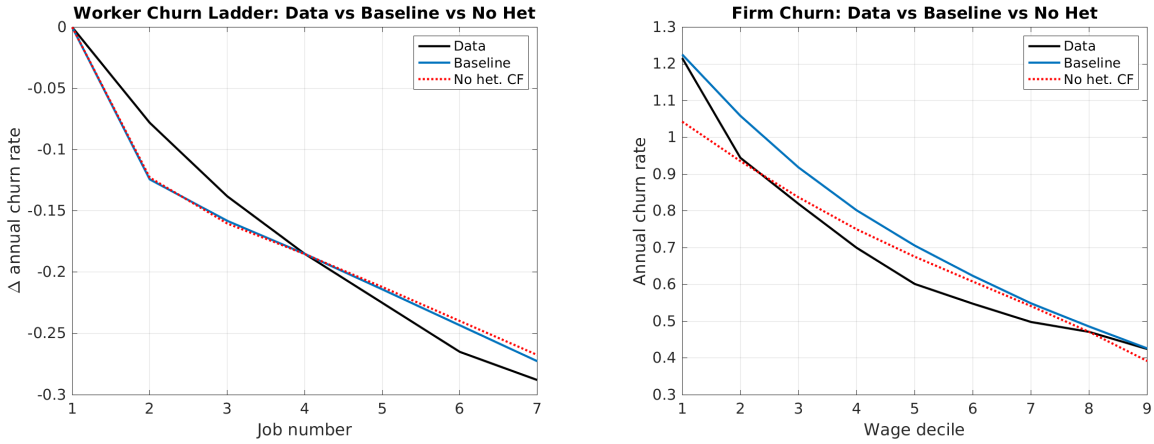

Figure 24: LEFT: The change in annual churn rate of the employer relative to the initial job across job-ladder transitions in the data, the calibrated baseline model, and the no-heterogeneity counterfactual. The average churn rate of the initial job is normalized to 0. RIGHT: The mean annual churn rate at each decile of the firm earnings distribution in the data, the calibrated baseline model, and the no-heterogeneity counterfactual.

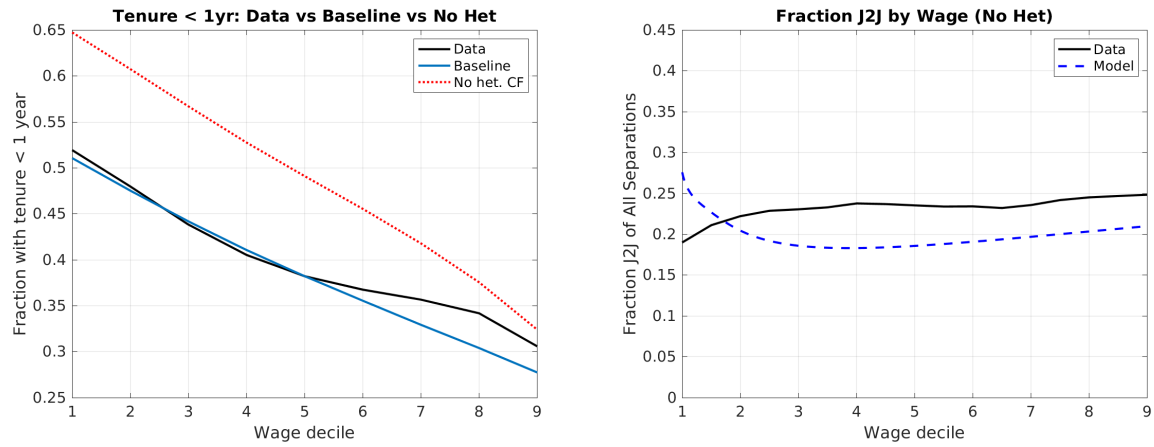

Figure 25: LEFT: The fraction of workers with less than one year of tenure at each decile of the firm wage distribution in the data, the calibrated baseline model, and the no-heterogeneity counterfactual. The no-heterogeneity counterfactual overpredicts short-tenure matches throughout the distribution, with the excess most pronounced at lower wages. RIGHT: The fraction of all separations that are job-to-job transitions at each decile of the firm earnings distribution in the data and the no-heterogeneity counterfactual.

low-δ types at each wage level, whose differing survival rates generate the excess dispersion in tenure the data require. Without this mixture, the firm effect must set higher separation rates at the bottom to approach the observed churn gradient, which in turn inflates the predicted short-tenure fraction beyond what we observe.

The composition of separations provides the most decisive evidence against the no-heterogeneity model. Figure 25 (RIGHT) plots the fraction of all separations that are job-to-job, by firm wage decile, comparing the no-heterogeneity model to the data. In the data, the J2J share of separations is roughly flat across the wage distribution, even rising modestly at the top. The no-heterogeneity model cannot keep it flat: it overstates the J2J share at the bottom of the distribution and understates it through the middle and top, producing a non-monotone profile the data do not exhibit. The failure at the bottom is the informative one. Elevated churn at low-wage firms is, in the baseline, driven primarily by nonemployment separations among the concentrated high-δ workers, not by poaching. Without that compositional force, the no-heterogeneity model attributes too much of the churn at the bottom to J2J transitions, distorting the ratio of EN to EE separations relative to the data.

Taken together with the Burdett-Mortensen benchmark of Section 5.2, this counterfactual establishes that worker heterogeneity is not a peripheral calibration device. Removing it produces a model that can approximately replicate the worker churn ladder and even the firm-level churn gradient—at the cost of a counterfactually steep firm separation policy—but fails on the margins that identify the heterogeneity: the tenure distribution within wage bins and the composition of separations across the ladder. The baseline model's success across all four dimensions reflects the structural role of endogenous sorting: as low-δ workers accumulate at high-wage firms through longer employment spells, they simultaneously compress firm churn at the top, generate excess dispersion in tenure within wage bins, and keep the J2J share of separations roughly constant across the wage distribution—exactly the joint pattern the data exhibit.

Of course, there are other ways to introduce heterogeneity in worker-firm separation rates. Probably the clearest alternative is via idiosyncratic employer-employee match quality, which has been used in a variety of frameworks with recent related examples such as Gottfries and Teulings (2023) or Clymo et al. (2026). We explore this in the next subsection, replacing permanent worker heterogeneity with a fresh draw of δ_j at each employer match. Definitionally, the first step down the churn ladder is exactly the same, but then it flattens somewhat thereafter in this model. Where the two models notably distinguish themselves, however, is that the match-quality model does not induce the same amount of firm-level heterogeneity in churn; that is, it produces a flatter version of our Figure 1.

F.2 Match-specific δ heterogeneity

In the baseline, each worker carries a permanent separation type δ_i, drawn once from $D(\delta)$ and fixed for life. This appendix studies the natural alternative in which the separation type is a property of the *match* rather than of the worker: at each new firm–worker match, the worker draws a fresh $\delta \sim D(\delta)$, independent of the firm's wage and of the worker's history. This is the idiosyncratic match-quality formulation used, for example, by Gottfries and Teulings (2023) and Clymo et al. (2026). We hold every calibrated parameter at its baseline value (Table 1); only the assignment of δ changes. Note that if the draw were instead taken once, on exit from nonemployment, and held for the remainder of the employment spell, we would essentially recover the baseline: the type would persist across every job-to-job

transition within the spell, differing from the baseline only in the type composition of flows out of nonemployment. The match-quality and baseline specifications therefore differ in a single respect: whether the type persists *across* job-to-job transitions within a spell.

Firm-level composition. Because every hire arrives with an independent draw, the share of low-separation types in a firm's *inflow* is p_1 at every wage, with no dependence on w. The endogenous cross-match sorting that, in the baseline, concentrates low-δ workers at high-wage firms is thus switched off. What remains is a much weaker, non-compounding within-match selection: at any instant a firm's *stock* is tilted toward the type that survives the current match longer. Writing the total rate at which a type-j worker leaves a wage-w match as

$$\sigma_j(w) \;=\; \delta_j\,\varphi(w) \;+\; \lambda_r \;+\; \lambda_e\big(1-F(w)\big), \tag{F.1}$$

the stock share of the low type is the duration-weighted inflow share,

$$s_q(w) \;=\; \frac{p_1/\sigma_1(w)}{p_1/\sigma_1(w)+p_2/\sigma_2(w)}, \tag{F.2}$$

so that the firm's separation rate and churn become

$$\delta_q(w) \;=\; \varphi(w)\big[s_q(w)\,\delta_1+(1-s_q(w))\,\delta_2\big], \qquad c_q(w) \;=\; \delta_q(w)+\lambda_r+\lambda_e\big(1-F(w)\big). \tag{F.3}$$

The contrast with the baseline is entirely in the composition term. In the baseline, the low-type share $s(w)$ is the fixed point of the sorting system in Equations (4.8)–(4.11) and rises steeply with w as low-δ workers accumulate at the top of the ladder over many transitions. In (F.2), by contrast, $s_q(w)$ departs from p_1 only through the within-match survival ratio $\sigma_2(w)/\sigma_1(w)$, and that departure does not compound across transitions. The firm-level dispersion in $\delta(w)$, as well as in churn, is correspondingly muted.

Figure 26 plots the annual firm churn rate across the earnings distribution for the data, the baseline, and the match-quality model. As the algebra anticipates, the match-quality gradient is a flatter version of the baseline relationship in Figure 6: it begins well below the data at the bottom of the distribution and falls only modestly thereafter. The reason is as we described above. In the baseline, the high churn of low-wage firms comes largely from the high-δ workers concentrated there. Once types are reshuffled at every match, high-δ matches end quickly at *every* firm and thus accumulate nowhere; no rung, including the bottom, carries the high-δ concentration that drives the baseline's elevated churn at low wages. The match-quality model, therefore, generates too little cross-firm heterogeneity in churn, which is the firm-side dimension on which the two heterogeneity structures most clearly part ways.

The worker churn ladder tells the complementary story. Figure 27 reports the change in firm churn across consecutive jobs within an employment spell. Index the matches in a spell by n. In both models, the first match draws $\delta^{(1)} \sim D(\delta)$, and this draw governs the worker's hazards out of the first job nearly identically; the specifications diverge significantly only at $n \geq 2$, where the baseline retains $\delta^{(1)}$ while the match-quality model draws a fresh $\delta^{(2)}$. The first rung of the ladder is therefore common to the two models, and they separate only from the second transition onward. Persistent worker heterogeneity generates cumulative selection toward low-separation types among workers reaching higher job indices, producing

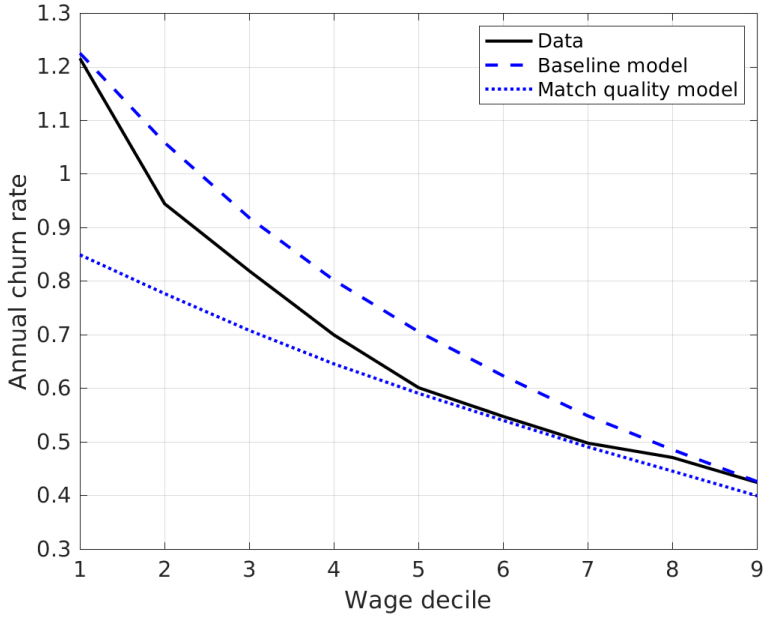

Figure 26: Annual firm churn rate across the earnings/wage decile distribution in the data, the baseline model, and the match-quality model. The match-quality gradient is a flatter version of Figure 6 (LEFT): it lies well below the data at the bottom of the distribution and declines only gently.

a steeper churn ladder. In contrast, redrawing types at each match limits this cumulative selection, and the match-quality ladder becomes progressively flatter. This is exactly what the figure shows: the match-quality ladder lies on top of the baseline at the first transition and then flattens, ending roughly 0.025 above the baseline after the seventh consecutive job in a spell.

That flattening is a selection effect. In the baseline, the persistence of $\delta^{(1)}$ means that workers who survive to high job indices are increasingly drawn from the low-δ pool—the same survivorship that the employment-spell fixed effect does not absorb (Section 3.1)—and these survivors continue to sort into ever-lower-churn firms. Resampling the type at each match erases that accumulating selection: reaching a high job index conveys no information about the current match's δ, so the descent past the first rung reflects only wage-climbing through poaching and the firm policy $\varphi(w)$, not a compounding compositional shift.

Taken together, the two figures make the same point from the worker and the firm sides. Match-specific heterogeneity reproduces the first step of the churn ladder and the qualitative direction of the descent, but it generates neither the steepness of the ladder beyond the first transition nor the firm-level dispersion in churn. Both features require a type that persists across matches, so that endogenous sorting can compound as workers climb. This is why we favor permanent worker heterogeneity over idiosyncratic match quality as the source of the churn ladder.

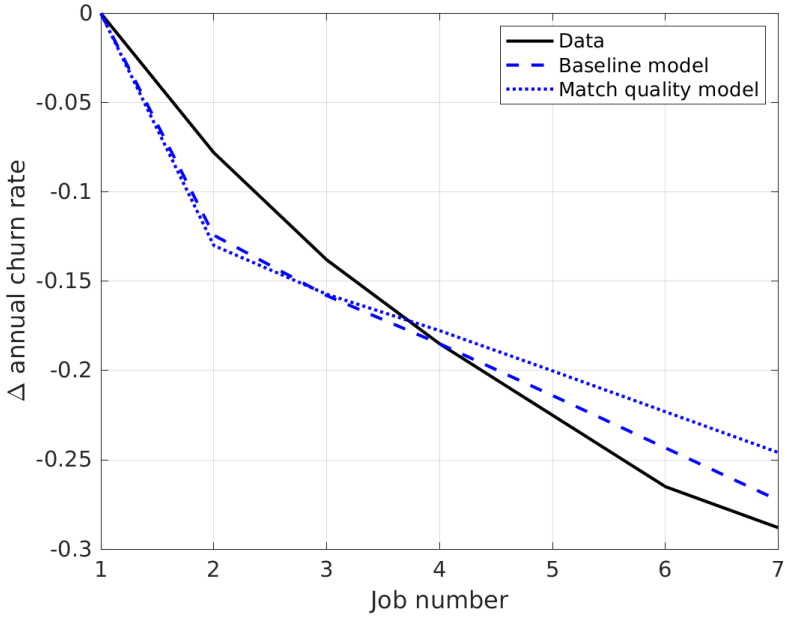

Figure 27: The change in annual churn rate of the employer relative to the initial job across job-ladder transitions in the data, the baseline model, and the match-quality model. The average churn rate of the initial job is normalized to 0. The match-quality ladder coincides with the baseline at the first transition and flattens thereafter.

G Labor supply elasticity derivations

The firm's size is determined by flow balances:

$$\big(\delta(w) + \lambda_r + \lambda_e(1 - F(w))\big)L(w) = \lambda_u u + \big(\lambda_r + \lambda_e G(w)\big)(1 - u).$$

Define:

$$N(w) \equiv \lambda_u u + \big(\lambda_r + \lambda_e G(w)\big)(1 - u), \qquad D(w) \equiv \delta(w) + \lambda_r + \lambda_e(1 - F(w)),$$

so that $L(w) = N(w)/D(w)$.

Case 1 ($\delta'(w) = 0,\ \delta(w) = \delta$): take the log-derivative of $L(w) = N(w)/D(w)$.

$$\begin{aligned}\varepsilon_L(w) &= \frac{\partial L(w)}{\partial w}\frac{w}{L(w)} = w\left(\frac{N'(w)}{N(w)} - \frac{D'(w)}{D(w)}\right) \\ &= w\Bigg(\underbrace{\frac{\lambda_e(1-u)g(w)}{\lambda_u u + (\lambda_r + \lambda_e G(w))(1-u)}}_{\text{inflow channel}} + \underbrace{\frac{\lambda_e f(w)}{\delta + \lambda_r + \lambda_e(1 - F(w))}}_{\text{outflow channel}}\Bigg). \end{aligned} \tag{G.1}$$

In (G.1), the first term is the inflow (recruitment) channel, and the second is the outflow (retention) channel.

Case 2 ($\delta'(w) \neq 0$): the derivative of $D(w)$ adds a separation-elasticity term.

$$\begin{aligned}
\varepsilon_L(w) &= w\left(\frac{N'(w)}{N(w)} - \frac{D'(w)}{D(w)}\right) \\
&= w\left(\frac{\lambda_e(1-u)g(w)}{\lambda_u u + (\lambda_r + \lambda_e G(w))(1-u)} - \frac{\delta'(w) - \lambda_e f(w)}{\delta(w) + \lambda_r + \lambda_e(1-F(w))}\right) \\
&= w\Bigg(\underbrace{\frac{\lambda_e(1-u)g(w)}{\lambda_u u + (\lambda_r + \lambda_e G(w))(1-u)}}_{\text{inflow channel}} + \underbrace{\frac{\lambda_e f(w)}{\delta(w) + \lambda_r + \lambda_e(1-F(w))}}_{\text{outflow channel}} \qquad \text{(G.2)} \\
&\qquad - \underbrace{\frac{\delta'(w)}{\delta(w) + \lambda_r + \lambda_e(1-F(w))}}_{\text{separation-elasticity correction}}\Bigg). \qquad \text{(G.3)}
\end{aligned}$$

G.1 Flows from Manning

For comparison, Manning's firm size is

$$L(w) = \frac{\delta\lambda}{(\delta + \lambda(1-F(w)))^2}$$

Case 1 with constant δ: We derive the wage elasticity.

$$\frac{\partial L(w)}{\partial w} = \frac{2\delta\lambda^2 f(w)}{(\delta + \lambda(1-F(w)))^3}.$$

Therefore, multiplying by $w/L(w)$ gives

$$\begin{aligned}
\varepsilon_L(w) &= \frac{w}{L(w)}\frac{\partial L(w)}{\partial w} = \frac{w}{L(w)}\frac{2\delta\lambda^2 f(w)}{(\delta + \lambda(1-F(w)))^3} \\
&= \frac{2\lambda f(w) w}{\delta + \lambda(1-F(w))}. \qquad \text{(G.4)}
\end{aligned}$$

Case 2 with $\delta'(w) \neq 0$:

$$\begin{aligned}\frac{\partial L(w)}{\partial w} &= \frac{\lambda\delta'(w)}{\left(\delta(w)+\lambda(1-F(w))\right)^2} - \frac{2\lambda\delta(w)\left(\delta'(w)-\lambda f(w)\right)}{\left(\delta(w)+\lambda(1-F(w))\right)^3} \\ &= \frac{\lambda\delta'(w)\left(\delta(w)+\lambda(1-F(w))\right) - 2\lambda\delta(w)\left(\delta'(w)-\lambda f(w)\right)}{\left(\delta(w)+\lambda(1-F(w))\right)^3}.\end{aligned}$$

Multiplying by $w/L(w)$ gives the elasticity

$$\begin{aligned}\varepsilon_L(w) &= \frac{w}{L(w)} \frac{\lambda\delta'(w)\left(\delta(w)+\lambda(1-F(w))\right) - 2\lambda\delta(w)\left(\delta'(w)-\lambda f(w)\right)}{\left(\delta(w)+\lambda(1-F(w))\right)^3} \\ &= \frac{\delta'(w)\left(\delta(w)+\lambda(1-F(w))\right) - 2\delta(w)\left(\delta'(w)-\lambda f(w)\right)}{\delta(w)+\lambda(1-F(w))} \frac{w}{\delta(w)} \\ &= \frac{\lambda(1-F(w))-\delta(w)}{\delta(w)+\lambda(1-F(w))} \frac{w\delta'(w)}{\delta(w)} + \frac{2\lambda f(w)w}{\delta(w)+\lambda(1-F(w))}.\end{aligned}$$

Equivalent rearrangement:

$$\varepsilon_L(w) = \frac{w\delta'(w)}{\delta(w)} \frac{\lambda(1-F(w))-\delta(w)}{\lambda(1-F(w))+\delta(w)} + \frac{2\lambda f(w)w}{\delta(w)+\lambda(1-F(w))}. \tag{G.5}$$

In (G.5), the second term is the baseline wage elasticity from (G.4). The first term is the correction from endogenous separations: $w\delta'(w)/\delta(w)$ is typically negative; as w rises and $1-F(w) \to 0$, the multiplier approaches -1, which increases overall elasticity. If $\lambda(1-F(w)) < \delta(w)$ for all w, as holds empirically, the multiplier remains negative throughout.