Heterogeneous Wage Cyclicality and Unemployment Fluctuations*

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Abstract

Wage rigidity as an amplification mechanism for the volatility of unemployment requires that jobs with rigid wages actually hire unemployed workers (rather than poach them from other firms). I differentiate jobs based on their hiring pool: whether they hire mostly unemployed or employed workers - and separately estimate their wage cyclicality. Using French matched employer-employee panel data, I find that wage rigidity varies significantly across jobs, with those engaging in worker poaching exhibiting more cyclical wages. I develop a labor search model with separation of search and heterogeneous wage cyclicality to measure the importance of distinguishing jobs by their hiring pool. The model reveals that rigid wages in jobs hiring unemployed workers have a disproportionately large effect on unemployment volatility compared to jobs poaching workers. Incorporating this heterogeneity yields a 20% increase in unemployment volatility.

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1 Introduction

Standard labor search models, calibrated to business cycle frequency, significantly underdeliver in the volatility of unemployment when compared to the data (Shimer (2005)). Wage rigidity, the inverse of the sensitivity of wages to aggregate productivity, has been widely proposed as a solution (Hall (2005)): if wages are rigid, during a recession, wages are stuck at high levels, thus firms are disincentivized from searching for workers, increasing unemployment. However, understanding which specific types of rigidity impact unemployment volatility remains a crucial question in economic research. This paper suggests that a job's hiring pool is fundamental for understanding the impact of wage rigidity on unemployment fluctuations.

Consider the following thought experiment. Imagine an economy with two sets of jobs: one set hires only unemployed workers, while the other poaches workers from the first set, with job search incentives determined via free-entry of vacancies. While it is commonly assumed that wage rigidity amplifies unemployment fluctuations, in this scenario, it is only the rigidity in the first set of jobs that significantly impacts unemployment volatility. If in recession rigidity lowers vacancy posting incentives in the first set of jobs, this lowers the chances of the unemployed workers getting hired, thus raising unemployment. Conversely, rigidity in the second set of jobs only affects unemployment indirectly by influencing the incentives of the first set to post vacancies. If in recession wage rigidity reduces poaching incentives, the first set of jobs is less concerned about losing their workers. This incentivizes these jobs to post vacancies, resulting in a lower unemployment rate. Thus, wage rigidity in the second set of jobs actually dampens unemployment fluctuations, contrary to the standard intuition. This raises two questions: how diverse is wage cyclicality across different job types empirically? And, given this heterogeneity, how does it translate into real-world unemployment fluctuations, considering that actual economies rarely exhibit such stark differences in hiring pools across jobs?

To address the first question, I utilize the French matched employer-employee panel data DADS. This dataset allows for the separate estimation of wage cyclicality for jobs hiring from unemployment and employment, crucially accounting for the heterogeneity in hiring pools. By tracking the work history of each worker and matching it with employer data, I can classify jobs based on proportion of their hires from unemployment and estimate wage rigidity separately for each bracket. For the estimation, I take the empirical design of Carneiro, Guimarães, and Portugal (2012), widely used in papers with matched employer-employee data. It consists of level wage regression with two-sided fixed effects (Abowd, Kramarz, and Margolis (1999)), a time trend, and a business cycle proxy. To incorporate the hiring pool dimension into the estimation, I interact the job brackets with both the time trend and the business cycle proxy.

My analysis reveals significant differences in wage cyclicality between jobs that hire unemployed workers and those that poach workers: the latter exhibit up to 50% more cyclical wages than the former. These differences hold true for both incumbent workers and new hires, underscoring the importance of job-level heterogeneity in understanding unemployment fluctuations. Furthermore, incorporating the worker dimension (whether a worker themselves is a job-to-job transitioner) does not significantly affect cyclicality, indicating that heterogeneity in wage cyclicality comes from jobs' hiring practices rather than workers' outside options.

Building upon these empirical findings, I develop a labor search model to quantify the relative importance of wage cyclicality across jobs with different hiring pools. This model is grounded in the intuition that jobs hiring unemployed workers and those poaching workers have mechanically different effects on unemployment. To incorporate this intuition, I build a model with on-the-job search and separation of search: workers search in different submarkets depending on their current employment status, with locations following a job ladder structure. This differs from the directed search models as Menzio and Shi (2011) in two ways: number of submarkets is finite and the wage exogenously imposed. More precisely, each job is tied to a specific submarket in which they can post vacancies. Workers choose in which submarket to search, and then workers and firms randomly match within a submarket. Submarkets take the interpretation of the rungs of the job ladder, where higher rungs pay more and attract workers with better outside options. This in turn implies that the higher rungs hire more job-to-job transitioners and fewer unemployed workers. The discreteness of the market allows for a more direct connection with the data, where jobs are split into brackets based on their hiring pools.

I let each submarket have its own wage determination mechanism, defined by its wage level and wage cyclicality, borrowing the functional form from Blanchard and Galı (2010) and Michaillat (2012). The intention of the model is to quantify effects of jobs of different hiring pools, so I abstract from explaining wage cyclicality: both wage level and cyclicality are exogenously imposed on each submarket. The key underlying assumption is that the cyclicality observed in the data and its heterogeneity indeed stem from exogenous factors or hiring practices that would affect hiring incentives. For example, rigidity stemming from heterogeneous wage-equity constraints as in Rudanko (2023) would apply, but heterogeneous Nash Bargaining weights, following Hagedorn and Manovskii (2013), would not.

In the quantitative analysis, I restrict attention to three submarkets, corresponding to job brackets from the empirical exercise. The focus of the calibration is to match the hiring pools and wages, both in level and cyclicality, of the submarkets to those of the job brackets. Since in the data each job bracket poaches from every bracket, including itself, I incorporate preference shocks in workers' search behaviors to facilitate hiring from both unemployment and other submarkets. A single submarket version of this model is essentially that of Diamond-Mortensen-Pissarides, so I take the estimates unrelated to heterogeneity, like the matching function, from Murtin and Robin (2018).

Simulation reveals that rigid wages in the lowest submarket have a 50% larger effect on the standard deviation of unemployment than rigidity in the second submarket, and 5 times larger than the third. Thus, the direct effect of jobs hiring unemployed workers is stronger than the indirect effect generated by rigidity in jobs that poach workers. Moreover, this indirect effect gets weaker the higher up the job ladder the submarket is. The more steps the submarket has to go through to affect the hiring incentives of jobs actually hiring the unemployed, the smaller the impact on the volatility of unemployment. To quantify the effect of heterogeneous wage rigidity across submarkets, I compare my calibration with the case where wages are equally cyclical in all the jobs. I show that accounting for this heterogeneity increases unemployment volatility by 20%.

Related Literature: I focus on distinguishing between jobs based on their hiring pools, both empirically, by estimating their wage cyclicality, and theoretically, by analyzing their effects on unemployment volatility. This dimension of heterogeneity is new to the literature.

On the empirical side, the majority of the literature studied new hire and incumbent wage cyclicality[1], focusing on job composition and procyclical match upgrading biases. These biases primarily affect new hire estimation, while my empirical result holds for both new hires and incumbents. Instead, this paper estimates heterogeneous wage cyclicality across jobs (Cervini-Plá, López-Villavicencio, and Silva (2018) and Teramoto (2023) estimate wage cyclicality across workers), with the precise focus on how that heterogeneity may affect unemployment.

Still, even within the new hire cyclicality literature, Haefke, Sonntag, and Van Rens (2013) and Gertler, Huckfeldt, and Trigari (2020) are quite close in their methodology as they distinguish between previously unemployed workers and job switchers in order to control for match upgrading bias. Haefke, Sonntag, and Van Rens (2013) find strong procyclicality in wages of previously unemployed, while Gertler, Huckfeldt, and Trigari (2020) find that these wages are as rigid as wages of incumbent workers and suggest that the observed new hire wage procyclicality in other papers is entirely due to high cyclicality in wages of job switchers.

[1]The list includes Bils (1985), Shin (1994), Devereux and Hart (2006), Gertler and Trigari (2009), Carneiro, Guimarães, and Portugal (2012), Hagedorn and Manovskii (2013), Stüber (2017), Dapi (2020), Grigsby, Hurst, and Yildirmaz (2021), Hazell and Taska (2021), Choi, Figueroa, and Villena-Roldán (2020)

They interpret high job switcher cyclicality as an artifact of cyclical movements in match quality rather than true wage flexibility. My paper differs in two aspects. First, I compare cyclicality across jobs rather than workers, which reinterprets differences in wage rigidity as firm wage practices rather than match upgrading bias or workers leveraging their outside options during bargaining. To argue for this interpretation, in Figure 2 I distininguish all workers based on their previous employment and find that the increment for the worker being poached is insignificant at almost every job bracket level. First, I observe this heterogeneity for both new hires and incumbents. Thus, unlike Haefke, Sonntag, and Van Rens (2013) and Gertler, Huckfeldt, and Trigari (2020), who focus on previously unemployed workers as a way to deal with match upgrading bias, I treat this distinction at the job level as a show of heterogeneous wage cyclicality and, as a corollary, find match upgrading bias to not be of concern.

Theoretically, this paper adds to the wage rigidity literature by analyzing the heterogeneous effects of rigidity depending on the labor market structure. Hall (2005) and Pissarides (2009) consider a standard DMP framework with bargained wages to discuss effects of wage rigidity. Morales-Jiménez (2022) and Fukui (2020) use random search with wage posting to endogenously model wage rigidity with applications to unemployment. However, random search cannot account heterogeneous hiring pools as all jobs will have the same probability of hiring an unemployed worker. Recently, Balke and Lamadon (2022), Souchier (2022), and Rudanko (2023) incorporated wage rigidity into a directed search framework. The former two use a dynamic contracting model[2] between a risk-neutral firm and a risk-averse worker where risk-aversion incentivized firms to smooth wages. This, however, does not have any implications for unemployment. Rudanko (2023) instead models wage rigidity via within-firm wage equity constraints, which amplifies unemployment fluctuations. In contrast to these papers, I forego endogenizing wage rigidity and instead focus on its differential effects across the job ladder, by building a model with heterogeneity in both cyclicality and hiring pools.

The rest of the paper is organized as follows. Section 2 presents the procedure of estimating wage cyclicality across jobs based on their hiring pools. Section 3 describes the model and its theoretical properties. Section 4 explains the calibration of the model and gives the simulation results. Section 5 concludes.

[2]Lagakos and Ordonez (2011) use a similar contracting framework, with the focus on explaining heterogeneity in wage passthrough across different industries. Their theoretical framework does not incorporate any search, so it cannot speak on unemployment, but their empirical result interestingly goes in contrast to mine, likely due to them estimating passthrough rather than cyclicality.

2 Estimating wage cyclicality

This section presents novel evidence on the heterogeneity of wage rigidity across different jobs. I distinguish jobs based on the proportion of workers they poach. The estimation reveals that jobs poaching the fewest workers exhibit significantly more rigid wages. I find this heterogeneity for both incumbents and new hires. Lastly, I show that the result cannot be explained by procyclical match upgrading, suggesting actual differences in job-side wage rigidity.

2.1 Data

Data from this study come from a French matched employer-employee dataset - Déclarations Annuelles de Données Sociales (DADS), built by the French Statistical Institute (INSEE) from the social contributions declarations of firms. The dataset covers about 85% of all French workers and spans the years 1976-2019. On an annual basis, it provides employment information (salaries, hours worked, occupation, and, importantly, precise start and end dates of every employment spell), worker information (age, experience), and firm information (sector, industry, size). The dataset is available in a panel form for a subsample (1/12th) of workers. The key advantage of the dataset is the precise information on workers' employment spells combined with its matched nature. The former allows tracking workers' histories to determine whether each time they find a new job they transitioned to that job from employment or unemployment. The latter then allows relating that information to jobs, thus giving information on the kinds of workers that each job hires.

2.2 Identifying job hiring pool

To classify jobs based on who they hire, I first need to classify workers. An observation (worker·firm·year) is classified as a new hire if the worker is not observed at the same firm the year prior. A newly hired worker is considered a job-to-job transitioner if she is observed at a full-time job at most 4 weeks prior to having started this one. Thus, a worker is allowed to have a 4 week-long break between jobs before being considered an out-of-unemployment hire. Finally, for each job (firm·occupation·region) I calculate the share of new hires that are job-to-job transitioners and then pool jobs into equally sized brackets based on this share. These brackets are calculated on a regional level to focus on the job ladder effects within the region and control for the composition effect of different regions. For calculating this share and all further computations I restrict attention to the years 2003-2019, jobs lasting at least a month, with weekly hours between 10 and 100, and 25-55yo workers in the private sector. Appendix 1 provides more information on sampling choices. The majority of jobs poach about 35% of their workers from other jobs, but with significant heterogeneity: for the case of 10 brackets, the jobs in the highest bracket on average hire more than 10 times as many job-to-job transitioners as jobs in the lowest bracket. Those jobs also pay higher wages and hire more educated workers.

2.3 Estimation strategy

The empirical strategy is based on the approach initially suggested by Abowd, Kramarz, and Margolis (1999) and used extensively in matched employer-employee datasets since then (e.g. Carneiro, Guimarães, and Portugal (2012), Stüber (2017), Dapi (2020)). It tests for real wage cyclicality using a level wage equation with controls for worker observed and unobserved (constant) heterogeneity, unobserved (constant) job heterogeneity, and business cycle conditions.

The baseline specification is

$$ln(w_{ijt}) = \mu(t) + \alpha U_{rt} + new_{ijt} + new_{ijt} \cdot U_t + \gamma x_{it} + FE_i + FE_j + \epsilon_{ijt}$$

where w_{ijt} is the real hourly wage of worker i, in a job j, in the year t; U_{rt}, unemployment in region r at time t, acts as a business cycle indicator; $\mu(t) = \mu_0 + \mu_1 t + \mu_2 t^2$ is a quadratic time trend, x_{it} is a vector of time-varying worker characteristics such as age and experience; FE_i, FE_j are worker and job fixed effects. To compare the behavior of wages over the business cycle between incumbents and new hires, these regressions include a dummy variable new_{ijt} for whether a worker is a new hire, as well as the interaction term between the dummy and the cycle indicator.

Job fixed effects allow controlling for job up- and down-grading, which would have resulted in a procyclical bias. Worker fixed effects help control for worker heterogeneity, which, as shown by other studies (e.g. Keane, Moffitt, and Runkle 1988), leads to a countercyclical bias.

To estimate wage rigidity separately for jobs based on the proportion of job-to-job transitioners they hire, I add the corresponding brackets as an additional dimension of heterogeneity into the regression:

$$ln(w_{ijt}) = \mu(t) + \alpha U_{rt} + new_{ijt} + new_{ijt} \cdot \tilde{\alpha}^{new} U_{rt} + \gamma x_{it} + FE_i + FE_j + \epsilon_{ijt}$$

$$+ EE_j \cdot \tilde{\alpha}^{EE} U_t + new_{ijt} EE_j \cdot \tilde{\alpha}^{new \cdot EE} U_{rt} + EE_j \cdot \tilde{\mu}^{EE}(t)$$

where EE_j is a dummy variable corresponding to a particular job bracket. I add job bracket-specific time trend $\tilde{\mu}^{EE}(t)$ to ensure occupation- or industry-specific long-run changes over

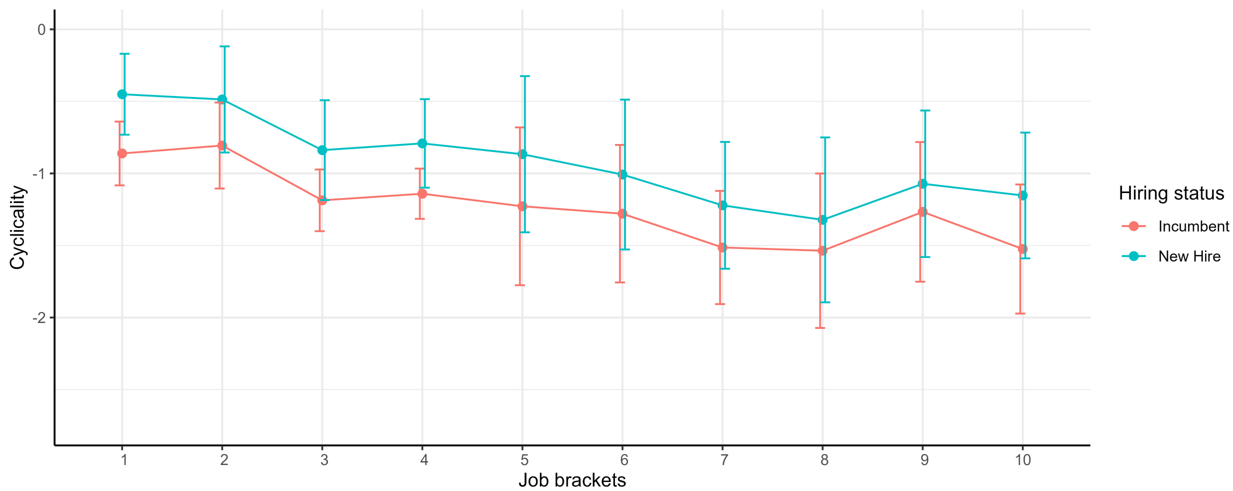

Figure 1: Wage cyclicality across jobs. The x-axis denotes the wage bracket of the job, the y-axis denotes wage cyclicality at that bracket. Cyclicality of new hires and incumbents are considered separately.

the 2 decades do not affect the cyclicality coefficient[3]. The coefficients of interest are α and $\tilde{\alpha}^{EE}$. Used as a wage cyclicality measure, α measures the semi-elasticity of real wages with respect to the unemployment rate for incumbents in the jobs hiring the lowest share of job-to-job transitioners. The coefficient vector $\tilde{\alpha}^{EE}$ then measures the differentials in semi-elasticity of wages of incumbents between jobs of the lowest bracket and the others. For example, in the case of 3 brackets, $\tilde{\alpha}^{EE}$ would be 2-dimensional, with the first dimension corresponding to cyclicality differences between the lowest and the middle bracket, and the second dimension measuring the differential between the lowest and the highest bracket.

2.4 Main result and robustness

Running the regression reveals strong cyclicality differences across jobs. Figure 1 plots wage cyclicality for both incumbent workers and new hires for each job, with the cyclicality values for incumbents ranging from -0.8 in bracket 2 to above 1.5 in brackets 7,8, and 10. Overall the pattern, though nonmonotonic, clearly suggests that wages are more cyclical in jobs that higher fewer unemployed workers, for both incumbents and new hires. Curiously, I find that new hires tend to have less cyclical wages than incumbents. This seems to be a particular case for France as other papers using 2-way fixed effects regressions in matched employer-employee data (e.g. Carneiro, Guimarães, and Portugal (2012), Stüber (2017), Dapi (2020))

[3]Table 6 shows the same regression, but with industry-specific time trends. Results do not seem to be sensitive to the choice of particular time trends.

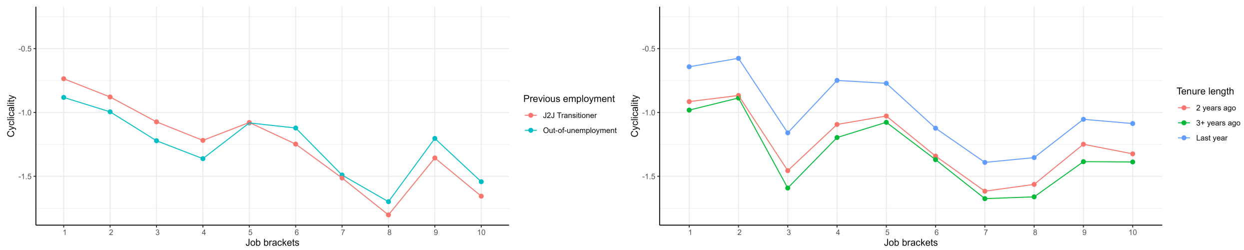

Figure 2: Wage cyclicality across employment histories and tenure length. The first graph distinguishes incumbent workers based on their prior employment, the second - based on how long they have been employed at the current firm.

all find new hires to have at least as cyclical wages as new hires. The key question is whether this result is susceptible to procyclical match upgrading bias.

Procyclical match upgrading bias comes from a hypothesis that not only do workers find better jobs during booms, but they also find better matches, resulting in higher productivity. This brings about a wage increase that may appear even in jobs where wages are completely unresponsive to aggregate conditions, thus leading econometricians to mischaracterize the wages as cyclical. Since this bias relates not just to the job, but to the match upgrading, controlling for the distribution of jobs is unlikely to help. This bias affects the wages for workers across jobs, rather than within jobs, thus primarily relating to the new hires. Moreover, as Gertler, Huckfeldt, and Trigari (2020) suggest, the bias works mainly through job-to-job transitioners who are more likely to upgrade their matches in booms than in recessions.

There are two points to consider in regard to this bias: the overall effect of it and, crucially, the differential effect on job-to-job transitioners. Overall, both incumbent and new hire wage cyclicalities are likely over-estimated. Incumbent estimations are naturally less affected by the bias, but it may still be there nonetheless: if workers upgrade their matches during the boom in 2017, in 2018 they will be considered incumbents with higher wages. I address this potential issue in two ways: differentiate workers based on their previous employment, and consider long-term incumbents.

Controlling for the worker's previous employment allows us to directly compare cyclicality heterogeneity between out-of-unemployment workers and job-to-job transitioners. The first plot of Figure 2 presents the wage cyclicality of incumbent workers across employment histories. At each bracket level, the difference across estimates is not statistically significant, thus the level effect of procyclical match upgrading does not seem to be an issue. For both UE and EE workers, I find more cyclical wages in higher brackets. This suggests that the observed heterogeneity is not caused by procyclical match upgrading as only the estimates of the UE workers would be affected by it. The results of this regression also suggest that a worker's outside option plays little role in determining wage cyclicality: once employed, past employment history no longer seems to matter. This rules out differences in bargaining power as a potential explanation for the observed heterogeneity.

As an alternative approach, I differentiate incumbent workers based on their tenure at the current job. The second plot of Figure 2 shows wage cyclicality for workers hired one, two, or at least three years ago. Some level differences in cyclicality can be seen, though in an unexpected direction: recent incumbents, seemingly the most likely to be affected by the procyclical match upgrading bias, have the least cyclical wages. Though persistent, these level differences are also insignificant in most cases. Thus, even if procyclical upgrading does play a role, that role is quite minor. In terms of heterogeneity, the slopes across the three incumbent types are close to the same, suggesting no differential effect of the bias.

3 Model

I develop a variant of a directed search model to explore how wage rigidity's impacts vary by job hiring pool. An economy consists of workers and firms. Workers, both unemployed and employed, search for jobs, while firms post vacancies. The model partitions the economy into M distinct submarkets, each exogenously defined by unique wage levels and rigidity. I begin by outlining the economic environment, then detail the decision-making processes of workers and firms, including the free-entry condition.

To highlight the differential effects of wage rigidity, I then analyze a simplified model featuring just two submarkets: one hires exclusively the unemployed, and the other solely poaches workers. The examination reveals that rigidity in the former submarket amplifies unemployment fluctuations as standard, whereas rigidity in the second submarket has the completely opposite effect of dampening fluctuations. This signifies the need for controlling for each submarket's hiring pool and wage cyclicality.

3.1 Labor Market

The economy is populated by a continuum of workers with measure 1 and a continuum of firms with positive measure, distributed across M submarkets. Each worker is endowed with an indivisible unit of labor and maximizes the expected sum of per-period consumption discounted at the factor $\beta \in (0, 1)$. Each firm operates a technology that turns one unit of labor into y units of output, common to all firms. Output values y lie in a set $Y = \{y_1, y_2, ..., y_{N(y)}\}$, where $N(y) \geq 2$ is an integer. Each firm maximizes the expected sum of profits discounted at the rate β.

Time is discrete and infinite. At the beginning of each period, the state of the economy can be summarized by the tuple $\psi = (y, u)$, where y denotes aggregate productivity and $u \in [0, 1]$ denotes the proportion of unemployed workers.

Each period is divided into four stages: separation, search, matching, and production. At the separation stage, each match is destroyed with probability $\delta \in (0, 1)$.

At the search stage, workers and firms search for matches across different submarkets. Specifically, a firm chooses how many vacancies to open in each submarket, and a worker chooses which submarket to visit if she has an opportunity to search. The cost of maintaining a vacancy for one period is $k > 0$. The worker has the opportunity to search with a probability that depends on her employment status. If the worker was unemployed at the beginning of the period, she can search in a submarket $m' \in M$ with probability $\lambda_u(m') : M \to [0, 1]$. If the worker was employed at the beginning of the period and did not lose her job during the separation stage, she can search with probability $\lambda_e(m') : M \times M \to [0, 1]$. Finally, if the worker lost her job during the separation stage, she cannot search.

The introduction of search probability, and its heterogeneity across submarkets is crucial for the quantitative stage. It allows to calibrate for heterogeneous hiring pools across different submarkets, letting, for example, submarkets that tend to hire the most unemployed have the largest λ_u. There is another important feature that need to be captured: each job bracket in the data features hiring from both unemployment and every other bracket. This suggests that unemployed and employed workers do not search completely separately: some unemployed workers search for the highest paying jobs, and employed workers do often move horizontally or even down. To account for that, I introduce search taste shocks into workers' preferences. I denote the taste shock ϵ_{imt} and let it be *iid* across workers, submarkets, and time. It is only meant to augment the search decisions, allowing workers to search in submarkets that, without these shocks, they would never pick.

At the matching stage, the workers and the vacancies that are searching in the same location are brought into contact by a meeting technology with constant returns to scale that can be described in terms of the vacancy-to-worker ratio θ (i.e., the tightness). Specifically, the probability that a worker meets a vacancy is $p(\theta)$, where $p : R_+ \to [0, 1]$ is a twice continuously differentiable, strictly increasing, and strictly concave function that satisfies the boundary conditions $p(0) = 0$ and $p(\infty) = 1$.

At the production stage, an unemployed worker produces $b > 0$ units of output. A worker employed in a match produces y units of output. At the end of this stage, nature draws the next period's aggregate component of productivity, $\hat{y}$, from the probability distribution $\phi(\hat{y}|y), \phi : Y \times Y \to [0, 1]$.

Submarkets take interpretation of job ladder rungs, and are ex-ante heterogeneous only in their wages. I assume exogenous wage rigidity in the form of Blanchard and Galı (2010):

$$w^k_{m,t} = \bar{w}_m \cdot y_t^{1-\alpha_m}$$

where $\bar{w}_m$ is the wage level at submarket k. Without loss of generality I assume that $\bar{w}_m$ increases with m, thus jobs higher up the ladder pay more. Rigidity in wages is modeled as elasticity of wages to aggregate productivity, $\alpha_m \in [0,1]$ serves as a measure of wage rigidity. This specification allows submarkets to be different in both wage flexibility and wage level. The exact formula is not crucial as long as it implies that wage rigidity indeed affects hiring incentives. For example, endogenizing rigidity via wage-equity constraints as in Rudanko (2023) would apply, but differences in rigidity stemming from heterogeneous Nash Bargaining weights, following Hagedorn and Manovskii (2013), would not. This latter example can luckily be ruled out as empirically we found that workers' outside options (whether they come from employment or unemployment) have a significantly smaller impact on wage cyclicality than the firm's overall hiring (see Table 2). I stick to the reduced-form wages as they most clearly show what kind of mechanism I am after.

I introduce the wage vector w_m alongside the distribution of employed labor $g : M \to [0,1]$ into an aggregate description of the economy $\psi(y,u,g,w)$. I denote double (u,g) as the labor distribution of the economy. The vacancy-to-worker ratio of submarket m is denoted as $\theta(m,\psi)$. In equilibrium, $\theta(m,\psi)$ will be consistent with the firms' and workers' search decisions.

3.2 Worker and Firm problems

Consider an unemployed worker at the beginning of the production stage and denote $U(\psi)$ as her lifetime utility. In the current period, she produces and consumes b. In the next period, she may be able to search with probability λ_u and match with a firm in a submarket m' with probability $p(\theta(m,\psi))$. If the worker indeed matches, her continuation utility is $W(\psi',m')$, where W is the value of being employed in a submarket m'. $\epsilon_{im't}$ is the *iid* preference shock for that submarket. Thus,

$$U(\psi) = b + \beta E_{\psi'|\psi,\epsilon_{m'}} \max_{m'} \Big[U(\psi') + \lambda_u(m')p(\theta(m',\psi'))(W(\psi',m') - U(\psi')) + \epsilon_{m'}\Big] \tag{1}$$

Now, consider a worker at the beginning of the production stage. In the current period, worker consumes the entire wage w. Next period, the match may separate with probability d, in which case his continuation utility is $U(\psi')$. If not fired, worker may match with another firm in submarket m' with probability $\lambda_e(m,m') \cdot p(\theta(m',\psi'))$, resulting in new continuation value $W(m',\psi')$. With probability $(1-d)(1-\lambda_e(m,m')\cdot p(\theta(m',\psi'))$ worker stay at the same jobs until the next production stage. Thus, the value of being employed is

$$\begin{aligned} W(m,\psi) =& w_m + \beta E_{\psi'|\psi,\epsilon'_m} \max_{m'} \Big[dU(\psi') + \\ & (1-d)[W(m,\psi') + \lambda_e(m,m')p(\theta(m',\psi'))(W(m',\psi') - W(m,\psi')) + \epsilon_{m'}]\Big] \end{aligned} \tag{2}$$

In the current period, firm produces y and pays w to the worker. If the worker leaves for any reason, the continuation profit is zero. For each future state of the economy ψ', denote worker's optimal on-the-job search decision (accounting for the realized preference shock) as m^*. Then the value of filled job is:

$$J(m,\psi) = y - w_m + \beta E_{\psi'|\psi,\epsilon_{m'}} \Big[(1-d)(1-\lambda_e(m,m^*)p(\theta(m^*,\psi')) \cdot J(m,\psi')\Big] \tag{3}$$

At the search stage, a firm chooses how many vacancies to create and where to locate them. The firm's cost of creating a vacancy in submarket m is κ. The firm's benefit from creating a vacancy in submarket m is

$$q(\theta(m,\psi))[J(m,\psi)] \tag{4}$$

When the cost of the vacancy is strictly larger than the benefit, the firm creates no vacancies. Vice-versa, when the cost is strictly smaller, infinitely many vacancies are created. And when the cost and the benefit are equal, the firm's profit is independent of the number of created vacancies in submarket m.

In any market visited by a positive number of workers, the tightness is consistent with the firm's incentives to create vacancies if and only if

$$\kappa \geq q(\theta(m,\psi))[J(m,\psi)] \tag{5}$$

and $\theta(i,\psi) \geq 0$ with complementary slackness.
Since w_m increases with m, J decreases with m, and thus workers face a trade-off when choosing a submarket: it is easier to find a job in lower submarkets, while higher submarkets pay more. This trade-off is what ultimately leads workers in different positions to search in different locations.

3.3 Heterogeneous effects of wage rigidity

Job ladder chain

To illustrate how effects of wage rigidity depend on the hiring pool of the job, consider a simplified version of the above model: no productivity shocks, constant wages, search decisions are completely exogenous (assume large enough variance of preference shocks). There are two submarkets: the first hires only unemployed workers, while the second only poaches workers from the first. We achieve this by setting $\lambda_u(2) = \lambda_e(1,1) = \lambda_e(2,2) = 0$ and $\lambda_u(1) = \lambda_e(1,2) = 1$. Consider the economy already in the steady-state so that the aggregate description of the economy ψ stays constant.

The value of a job then takes the following form:

$$J(m) = y - w_m + \beta(1 - \lambda_e(m,2)p(\theta(2)))J(m) = \frac{y - w_m}{1 - \beta(1 - \lambda_e(m,2)p(\theta(2)))}$$

where y is productivity of a match, w_m is submarket-specific wage, and $\lambda_e(m,2)p(\theta(2))$ is a probability that the worker will be poached into the second submarket, only positive for $m > 0$.

Proposition 1. *Starting from a steady-state, consider a perturbation to wage w in submarket k. The wages in the two submarkets have the opposite effects on unemployment.*

For $k = 1$, $\frac{\partial u}{\partial w_1} > 0$.For $k = 2$, $\frac{\partial u}{\partial w_2} < 0$

Sketch of the proof: First, note that the standard free-entry condition still applies for each submarket. Tightness $\theta(m)$ determines job-finding probabilities at each of these submarkets. Since only the first submarket hires the unemployed, $\theta(1)$ is the sufficient statistic for the unemployment rate.

Submarket 1 has a standard effect on unemployment: w_1 only affects $J(1)$, which in turn determines the tightness $\theta(1)$. Increase in the wage lowers lowers hiring incentives in the first submarket, thus the tightness goes down, raising the unemployment rate. This follow standard intuition of how wage rigidity affects unemployment, the same as in Hall (2005).

The second submarket can affect unemployment only indirectly, through a chain effect: $\frac{\partial \theta(1)}{\partial w_2} = \frac{\partial \theta(1)}{\partial J(1)} \frac{\partial J(1)}{\partial w_2}$. First, just like for submarket 1, increase in w_2 lowers hiring incentives in that submarket and thus the tightness. The firms in the first submarket are now less worried about poaching, so they are incentivized to hire more, lowering the unemployment rate.

Although this is a result for permanent wage changes in a non-stochastic economy, it can easily be extended to a model with cyclical productivity and rigid wages: during recessions, wage rigidity implies wages being relatively high, thus, as we just found, lowering the job-finding probability for the unemployed. Thus, wage rigidity in the first submarket would amplify unemployment fluctuations, and, similarly, rigidity in the second submarket would dampen them.

Effects of heterogeneous unemployment hiring

Consider a different extreme case: the two submarkets hire from unemployment only, at different rates $\lambda_u(1) > \lambda_u(2)$. Assume, prior to any perturbations, $w_1 = w_2$. Value a job in both submarkets is then

$$J = y - w + \beta J = \frac{y - w}{1 - \beta}$$

Proposition 2. [4] *Starting from a steady-state, consider a perturbation to wage w in submarket k. The effect of such perturbation on unemployment is proportional to ratio of unemployed workers hired.*

$$\frac{\partial u}{\partial w_k} \propto \lambda_u(k)$$

Moreover, the relative effect of wage changes across submarkets is equal to the ratio of unemployed hires.

$$\frac{\partial u / \partial w_1}{\partial u / \partial w_2} = \frac{\lambda_u(1)}{\lambda_u(2)}$$

This example tackles another facet of the job ladder structure: different hiring rates from unemployment. The implication is immediate: the direct effect of wage rigidity in a particular submarket on unemployment depends on how many unemployed workers that submarket hires. The second result of this proposition allows us to compare the direct effects across submarkets: a submarket hiring twice as many unemployed workers will have twice as large an effect on unemployment.

Both these forces: the unemployment hiring rate and the poaching rate matter for how wage rigidity at a particular submarket may impact unemployment.

4 Quantitative model

I calibrate and simulate the model to asses the impact of heterogeneous wage rigidity on unemployment volatility. I calibrate the model to the moments generated from the French data, with the focus on capturing heterogeneous wage cyclicality and hiring pools across submarkets. Lastly, I conduct comparative statics analyses: evaluate wage rigidity's impact across submarkets, and compare the unemployment volatility between the calibrated model and one with uniform wage rigidity.

[4] Model appendix proves both propositions in a generalized case of M submarkets.

4.1 From analytical to quantitative

I focus on the case of three submarkets, the lowest primarily occupied by the unemployed and the highest by the employed workers. Connecting to the empirical section, the submarkets should be interpreted as the hiring pool brackets $EE_j = 1, EE_j = 2, EE_j = 3$ from the Section 2.

I simulate the stochastic economy version of the model, with aggregate productivity as the only exogenously time changing variable, for 10068 periods and drop the first 10000 from the main analysis. The number of the remaining periods has been chosen to match the number of quarters in the data (68 from 2003 to 2019). I track unemployment over the simulation and use the ratio of the standard deviation of unemployment to the standard deviation of productivity (both log HP-filtered with the parameter 10^5) as the key statistic of the simulation.

4.2 Calibration

I calibrate the model to the quarterly frequency and take the standard literature values for the time discounting rate β and the flow utility of the unemployed workers b. I calibrate the cost of posting a vacancy κ to match the average French unemployment over the years 2003-2019.

β	Time discounting	Standard quarterly value	0.988
b	Flow utility of unemployment	Standard lower bound	0.4
y_ρ	Productivity persistence	Taken from M-R	0.938
y_σ	Volatility of productivity	Taken from M-R	0.02
δ	Separation rate	Taken from M-R	0.023
ϕ	Matching function constant	Taken from M-R	1.268
γ	Matching function elasticity	Taken from M-R	0.5
$\bar{w}$	Wage level	Ratio from the data	[0.57,0.73,0.95]
$\bar{y}_m$	Submarket productivity	Set profitability to 0.05	[0.62,0.78,1.0]
λ	Search efficiency	Match distribution of UE and EE	
α	Wage rigidity	Match regression estimates	[0.60,0.41,0.44]
κ	Cost of posting a vacancy	Match average unemployment	3.2

In many ways, this model is still comparable to the standard DMP model, in that each particular submarket does employ random search with the classic free-entry condition. This results in many of the parameters of the model being comparable to the parameters of the

standard DMP models. I take the productivity y law of motion, the job-finding probability function $p(\theta) = \phi\theta^{\gamma}$, and the separation rate δ from Murtin and Robin (2018), who used the OECD data applied to France to estimate these parameters.
Past this, there are several significant departures from the literature that my model takes, with no parameters easily comparable to the literature. Summarizing these departures:

1. Several submarkets: need wage-related parameters for each submarket
2. Mixed search: need to account for the mixed search properties of the data
3. Wage rigidity: need to match the cyclicality estimates of Section 2

Several submarkets: it is necessary to establish both the general wage level $\bar{w}_1$ and the differences between the wage levels $\bar{w}_2/\bar{w}_1$ and $\bar{w}_3/\bar{w}_1$. These values matter in that they define the relative (time-independent) profitability of the job to the firm, compared to the worker and also across submarkets. The heterogeneous profitability across submarkets would imply heterogeneous sensitivity of the firms themselves to wage rigidity. As I have no measure of how differently firms across the job ladder benefit from their workers, I shut down this channel and assume homogeneous profitability. For that, to keep heterogeneity in wages, I introduce submarket-specific productivity scale $\bar{y}_m$. Thus, the productivity of a job at time t in submarket m is $\bar{y}_m y_t$. I set the profitability $\bar{y}_m - \bar{w}_m = 0.05$, which is the conservative upper bound: Hall (2005) has 0.035, Shimer (2005) has ≈ 0.02, Hagedorn and Manovskii (2008) have it lower. I normalize $\bar{y}_m$ to 1 and set $\bar{w}_2/\bar{w}_1$ and $\bar{w}_3/\bar{w}_1$ to match ratios of average wages across the job brackets. For example, wages at the top bracket are about 62% higher than in the bottom bracker, so I set $\bar{w}_3/\bar{w}_1 \approx 1.62$. This results in submarket-specific productivity levels being equal to [0.62,0.78,1.0] and wage levels equal to [0.57,0.73,0.95].

Mixed search: I adjust the probability to search matrices $\lambda_u(m'), \lambda_e(m, m')$ to match the complete transition matrix across unemployment and all the submarkets observed in the data. Propositions 1 and 2 highlight the importance of this exercise: both the number of unemployment hirings and the submarket's position on the job ladder are crucial for correctly assessing the effect of its wage rigidity.

The left matrix denotes average transition probabilities observed in the data, the right - λ, which includes λ_u and λ_e, calibrated to match the same moments in the model. The first term of λ is normalized to 1, and all the other entries are allowed to be of any value.

Wage rigidity: the only remaining parameters are the rigidity parameters α_m, determining the wage rigidity in each of the submarkets. I calibrate these parameters to match the estimates from Table 2. More precisely, in the simulation, I track wages in each submarket

$$\text{Transition probabilities} = \begin{array}{c} \\ U \\ 1 \\ 2 \\ 3 \end{array} \begin{array}{c} \begin{array}{ccc} 1 & 2 & 3 \end{array} \\ \begin{pmatrix} 0.37 & 0.22 & 0.07 \\ 0.04 & 0.05 & 0.05 \\ 0.02 & 0.05 & 0.05 \\ 0.01 & 0.02 & 0.05 \end{pmatrix} \end{array} \qquad \lambda = \begin{array}{c} \\ U \\ 1 \\ 2 \\ 3 \end{array} \begin{array}{c} \begin{array}{ccc} 1 & 2 & 3 \end{array} \\ \begin{pmatrix} 1.0 & 0.87 & 0.51 \\ 0.03 & 0.04 & 0.03 \\ 0.02 & 0.06 & 0.05 \\ 0.01 & 0.03 & 0.09 \end{pmatrix} \end{array}$$

across time, aggregate them to the annual frequency, and regress log wages on unemployment. That is, for each submarket, I run the following regression:

$$ln(w^a_{m,t} + 1) = \beta_m u^a_t + \epsilon,$$

with the 1 being added to the logarithm in order to keep the percentage change interpretation. I calibrate the theoretical rigidity parameters α_m so that these regression estimates $\hat{\beta}_m, m \in M$ match the empirical estimates of incumbent wage cyclicality in Table 3. Targeting only incumbent wage cyclicality provides lower computational time at little cost as empirically I find new hire and incumbent wage cyclicalities to be similar, both in values and in their heterogeneity across job types.

4.3 Results

Under this calibration, the model achieves the ratio $std(u)/std(y)$ of 1.45, notably below 4.5 in the data. This may be explained by the conservatively high job profitability. I focus on two comparisons: the relative importance of wage cyclicality between the submarkets, and the change in unemployment volatility from using heterogeneous wage rigidity estimates rather than homogeneous ones (from Table 2). For each of these comparisons I consider 2 calibrations: the one described above and the same calibration, but with no on-the-job search. This allows me to separately consider the direct effect of heterogeneous hiring pools on cyclicality, arising simply from jobs hiring a different number of unemployed workers, and and indirect effect, which also includes jobs affecting each others' incentives through poaching. Interestingly, the case with no on-the-job search produces lower cyclicality. This is due to firms having stronger incentives to hire workers in the absence of risk of having those workers leave. To compensate, the calibration with no on-the-job search has higher cost of vacancy posting κ, which, as a side effect, also lowers unemployment volatility.

	No OJS	With OJS
Homogeneous cyclicality	1.258	1.202
Heterogeneous cyclicality	1.280 (1.7%Δ)	1.448 (20%Δ)
Increase in the 1st submarket	1.30 (1.5%Δ)	1.482 (2.3%Δ)
Increase in the 2nd submarket	1.293 (1.0%Δ)	1.468 (1.3%Δ)
Increase in the 3rd submarket	1.284 (0.3%Δ)	1.453 (0.3%Δ)

Table 1: Unemployment volatility

Relative importance of submarkets

To confirm and quantify the intuition that jobs hiring more unemployed workers have a larger impact on unemployment volatility, I consider a policy experiment of changing wage cyclicality in each of the submarkets and comparing their effects. For each of the two calibration cases, without recalibrating the model, I increase the wage rigidity parameter α by 0.1 in one of the submarkets. I then compare the increase in volatility of unemployment achieved by this change across different submarkets. For the case of no OJS, the relative importance of each submarket is proportional to the ratio of the unemployed workers they hire: the first submarket hires 67% more unemployed workers than the 2nd submarket and 5 times more than the 3rd submarket. This is similar to the relative effects on the unemployment volatility: the 1st submarket has 50% larger effect the 2nd submarket and 5 times larger the 3rd. The complete calibration, with on-the-job search inculded, amplifies these differences: the first submarket is now 76% more impactful than the second more than 7 times more impactful than the third. For each of these cases, the relative importance of submarkets is scale independent: doubling any rigidity increase to 0.2 also doubles the effect on unemployment volatility.

Value of heterogeneous wage rigidity

I recalibrate the model using the homogeneous wage cyclicality estimates by applying the classic regression used commonly in the literature. Moving from the homogeneous wage rigidity calibration to the heterogeneous one increases the volatility of unemployment by 20%. These percentage changes persist even for the lower profitability values, where the unemployment volatility of the homogeneous model is notably larger. Thus, taking into account the heterogeneity of wage rigidity across different jobs significantly increases the effect of rigidity on the volatility of unemployment.

4.4 Robustness

Can try: different profitability, equal wage?, maybe put no J2J transitions in here? Different matching function?

5 Conclusion

I estimate wage cyclicality separately for different jobs, based on their hiring pools. I use the matched employer-employee data to find that wages, both for new and incumbent workers, are significantly more rigid in jobs hiring from unemployment than in jobs poaching workers. I then simulate a model incorporating the separation of search and heterogeneous wage rigidity across different submarkets to find that wage rigidity in the entry-level submarket matters significantly more for the volatility of unemployment than in the higher submarkets. Together, the empirical and the theoretical results imply that, for unemployment volatility purposes, wages are highly rigid. I confirm this by comparing the heterogeneous wage cyclicality calibration of the model to the homogeneous one and find that accounting for the heterogeneity across jobs increases the unemployment volatility by 20%.

Potential interesting application of the empirical result could be explaining some of the business cycle-related job ladder facts. As one example, Moscarini and Postel-Vinay (2018) find that the job-to-job transition rate is procyclical, and especially so at the bottom of the job ladder. This might be because wages at the bottom of the ladder are too high during recessions, thus disincentivizing workers from transitioning to a different job. It would also be interesting to understand where the observed heterogeneity in wage cyclicality stems from.

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A Data appendix

A.1 Sample selection

I restrict attention to years 2002-2019 for tracking workers’ histories due to the sample size of workers being doubled in 2002. Once each worker’s history is accounted for (new hires and job-to-job transitioners are identified), I drop the year 2002. For computational reasons I take a subsample of the panel: I keep 1/3 of all the workers in the population, and then further drop workers who had on average more than 4 different jobs a year. For the remaining workers, I only keep observations for the ages 25-55 in order to avoid misidentifying young workers getting education as an unemployment spell. On the job side, I restrict attention to private sector jobs lasting at least a month, with weekly hours between 10 and 100. For each job I calculate the number of new hires that were successfully identified as either previously unemployed or job-to-job transitioners, and, if there are fewer than 5 of those for a given job, I do not calculate the ratio of job-to-job transitioners for that job. Once each appropriate job has its ratio of job-to-job transitioners determined, I pool jobs into brackets based on the number of observations in each bracket. For example, for the case of just two brackets, I would pick the ratio of job-to-job transitioners such that half of the observations have jobs with fewer job-to-job transitioners and half the observations have jobs with more. Once each job is assigned to a bracket, I add additional restrictions on observations for all the regressions: wages have to be above national minimum wage for that year and below 1000000.

A.2 Classic results

	Total cyclicality	New hire	Distinguishing UE and EE
U	-1.19^{***}	-1.29^{***}	-1.18^{***}
	(0.15)	(0.17)	(0.15)
$U + U \cdot new_{ijt}$		-1.02^{***}	-0.91^{***}
		(0.16)	(0.16)
$U + U \cdot new_{ijt} \cdot EE_{ijt}$			-0.89^{***}
			(0.18)
Num. obs.	4498096	4484887	402322
Adj. R^2 (full model)	0.91	0.91	0.91
Adj. R^2 (proj model)	-0.15	-0.10	-0.10

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2: Baseline regression: comparing incumbent and new hire cyclicality

A.3 Main result

	2 brackets	3 brackets	5 brackets	10 brackets
Incumbents				
$EE_j = 1$	-1.13^{***}	-0.98^{***}	-0.96^{***}	-0.86^{***}
	(0.13)	(0.09)	(0.09)	(0.10)
$EE_j = 2$	-1.40^{***}	-1.44^{***}	-1.22^{***}	-0.81^{***}
	(0.2)	(0.19)	(0.14)	(0.14)
$EE_j = 3$		-1.37^{***}	-1.32^{***}	-1.18^{***}
		(0.19)	(0.18)	(0.10)
$EE_j = 4$			-1.49^{***}	-1.14^{***}
			(0.24)	(0.08)
$EE_j = 5$			-1.34^{***}	-1.22^{***}
			(0.18)	(0.26)
$EE_j = 6$				-1.28^{***}
				(0.22)
$EE_j = 7$				-1.51^{***}
				(0.18)
$EE_j = 8$				-1.53^{***}
				(0.25)
$EE_j = 9$				-1.27^{***}
				(0.23)
$EE_j = 10$				-1.52^{***}
				(0.21)
New Hires				
$EE_j = 1$	-0.76^{***}	-0.58^{***}	-0.55^{***}	-0.45^{**}
	(0.16)	(0.13)	(0.13)	(0.13)
$EE_j = 2$	-1.05^{***}	-1.08^{***}	-0.85^{***}	-0.48
	(0.20)	(0.21)	(0.15)	(0.17)
$EE_j = 3$		-1.06^{**}	-0.95^{***}	-0.83^{***}
		(0.21)	(0.21)	(0.16)
$EE_j = 4$			-1.23^{***}	-0.79^{***}
			(0.25)	(0.14)
$EE_j = 5$			-0.99^{***}	-0.87^{**}
			(0.19)	(0.25)
$EE_j = 6$				-1.001^{***}
				(0.24)
$EE_j = 7$				-1.22^{***}
				(0.21)
$EE_j = 8$				-1.32^{***}
				(0.27)
$EE_j = 9$				-1.07^{***}
				(0.24)
$EE_j = 10$				-1.15^{***}
				(0.20)
Num. obs.	511026	511026	511026	511026
R^2 (full model)	0.93	0.93	0.94	0.94
R^2 (proj model)	0.22	0.22	0.22	0.22
Adj. R^2 (full model)	0.92	0.92	0.92	0.92
Adj. R^2 (proj model)	0.01	0.01	0.01	0.01

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3: Main regression: all the bracket distinctions

A.4 Robustness

	2 brackets	3 brackets	5 brackets	10 brackets
Incumbents from Unemployment				
$EE_j = 1$	-1.14^{***}	-1.07^{***}	-0.96^{***}	-0.88^{***}
	(0.13)	(0.14)	(0.15)	(0.15)
$EE_j = 2$	-1.43^{***}	-1.39^{***}	-1.35^{***}	-0.99^{***}
	(0.20)	(0.15)	(0.14)	(0.18)
$EE_j = 3$		-1.46^{***}	-1.26^{***}	-1.22^{***}
		(0.29)	(0.17)	(0.23)
$EE_j = 4$			-1.53^{***}	-1.36^{***}
			(0.29)	(0.21)
$EE_j = 5$			-1.40^{***}	-1.08^{***}
			(0.28)	(0.20)
$EE_j = 6$				-1.12^{***}
				(0.22)
$EE_j = 7$				-1.49^{***}
				(0.21)
$EE_j = 8$				-1.69^{***}
				(0.34)
$EE_j = 9$				-1.20^{***}
				(0.36)
$EE_j = 10$				-1.54^{***}
				(0.34)
Incumbents from Employment				
$EE_j = 1$	-1.02^{***}	-0.92^{***}	-0.79^{***}	-0.74^{***}
	(0.16)	(0.16)	(0.18)	(0.21)
$EE_j = 2$	-1.45^{***}	-1.33^{***}	-1.18^{***}	-0.88^{***}
	(0.20)	(0.14)	(0.14)	(0.19)
$EE_j = 3$		-1.56^{**}	-1.19^{***}	-1.07^{***}
		(0.32)	(0.17)	(0.25)
$EE_j = 4$			-1.59^{***}	-1.22^{***}
			(0.32)	(0.19)
$EE_j = 5$			-1.54^{***}	-1.08^{***}
			(0.30)	(0.19)
$EE_j = 6$				-1.25^{***}
				(0.20)
$EE_j = 7$				-1.51^{***}
				(0.21)
$EE_j = 8$				-1.80^{***}
				(0.37)
$EE_j = 9$				-1.36^{***}
				(0.37)
$EE_j = 10$				-1.66^{***}
				(0.36)
Num. obs.	511026	511026	511026	511026
R^2 (full model)	0.93	0.93	0.94	0.94
R^2 (proj model)	0.22	0.22	0.22	0.22
Adj. R^2 (full model)	0.92	0.92	0.92	0.92
Adj. R^2 (proj model)	0.01	0.01	0.01	0.01

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4: Heterogeneous cyclicality across employment histories (continued on the next page)

	2 brackets	3 brackets	5 brackets	10 brackets
New Hires from Unemployment				
$EE_j = 1$	-0.74^{***}	-0.59^{**}	-0.47^{*}	-0.41^{**}
	(0.18)	(0.22)	(0.24)	(0.18)
$EE_j = 2$	-1.11^{***}	-0.98^{***}	-0.92^{***}	-0.59^{**}
	(0.20)	(0.19)	(0.19)	(0.25)
$EE_j = 3$		-1.18^{***}	-0.85^{**}	-0.83^{**}
		(0.25)	(0.21)	(0.29)
$EE_j = 4$			-1.22^{***}	-0.98^{***}
			(0.27)	(0.26)
$EE_j = 5$			-1.16^{***}	-0.70^{***}
			(0.23)	(0.17)
$EE_j = 6$				-0.95^{***}
				(0.21)
$EE_j = 7$				-1.14^{***}
				(0.20)
$EE_j = 8$				-1.48^{***}
				(0.29)
$EE_j = 9$				-1.06^{***}
				(0.32)
$EE_j = 10$				-1.46^{*}
				(0.29)
New Hires from Employment				
$EE_j = 1$	-1.02^{***}	-0.39	-0.31	-0.30^{**}
	(0.16)	(0.23)	(0.25)	(0.25)
$EE_j = 2$	-1.45^{***}	-0.82^{***}	-0.67^{***}	-0.39
	(0.20)	(0.24)	(0.21)	(0.26)
$EE_j = 3$		-0.93^{**}	-0.69^{**}	-0.57^{*}
		(0.33)	(0.26)	(0.31)
$EE_j = 4$			-1.05^{***}	-0.72^{**}
			(0.35)	(0.29)
$EE_j = 5$			-0.88^{**}	-0.55^{*}
			(0.30)	(0.27)
$EE_j = 6$				-0.71^{**}
				(0.28)
$EE_j = 7$				-0.94^{***}
				(0.28)
$EE_j = 8$				-1.23^{***}
				(0.39)
$EE_j = 9$				-0.79^{*}
				(0.41)
$EE_j = 10$				-0.94^{***}
				(0.32)
Num. obs.	511026	511026	511026	511026
R^2 (full model)	0.93	0.93	0.94	0.94
R^2 (proj model)	0.22	0.22	0.22	0.22
Adj. R^2 (full model)	0.92	0.92	0.92	0.92
Adj. R^2 (proj model)	0.01	0.01	0.01	0.01

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5: Heterogeneous cyclicality across employment histories

	Job bracket time trends	Industry time trends
Incumbents		
$EE_j = 1$	-0.86^{***}	-0.85^{***}
	(0.10)	(0.16)
$EE_j = 2$	-0.81^{***}	-0.94^{***}
	(0.14)	(0.21)
$EE_j = 3$	-1.18^{***}	-1.27^{***}
	(0.10)	(0.19)
$EE_j = 4$	-1.14^{***}	-1.15^{***}
	(0.08)	(0.17)
$EE_j = 5$	-1.22^{***}	-1.05^{***}
	(0.26)	(0.16)
$EE_j = 6$	-1.28^{***}	-1.35^{***}
	(0.22)	(0.21)
$EE_j = 7$	-1.51^{***}	-1.39^{***}
	(0.18)	(0.23)
$EE_j = 8$	-1.53^{***}	-1.69^{***}
	(0.25)	(0.27)
$EE_j = 9$	-1.27^{***}	-1.28^{***}
	(0.23)	(0.19)
$EE_j = 10$	-1.52^{***}	-1.58^{***}
	(0.21)	(0.21)
New Hires		
$EE_j = 1$	-0.45^{**}	-0.48^{**}
	(0.13)	(0.19)
$EE_j = 2$	-0.48	-0.65^{**}
	(0.17)	(0.27)
$EE_j = 3$	-0.83^{***}	-0.96^{***}
	(0.16)	(0.24)
$EE_j = 4$	-0.79^{***}	-0.84^{***}
	(0.14)	(0.22)
$EE_j = 5$	-0.87^{**}	-0.74^{***}
	(0.25)	(0.19)
$EE_j = 6$	-1.001^{***}	-1.14^{***}
	(0.24)	(0.19)
$EE_j = 7$	-1.22^{***}	-1.18^{***}
	(0.21)	(0.19)
$EE_j = 8$	-1.32^{***}	-1.57^{***}
	(0.27)	(0.22)
$EE_j = 9$	-1.07^{***}	-1.16^{***}
	(0.24)	(0.20)
$EE_j = 10$	-1.15^{***}	-1.29^{***}
	(0.20)	(0.20)
Num. obs.	4498096	4484887
Adj. R^2 (full model)	0.91	0.91
Adj. R^2 (proj model)	-0.15	-0.10

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 6: Heterogeneous cyclicality with different time trends

	2 brackets	3 brackets	5 brackets	10 brackets
U	-1.35^{***}	-1.20^{***}	-1.17^{***}	-1.01^{***}
	(0.27)	(0.28)	(0.28)	(0.32)
$U \cdot (EE_j = 2)$	-0.64^{**}	-0.81^{***}	-0.28	-0.29
	(0.27)	(0.23)	(0.27)	(0.28)
$U \cdot (EE_j = 3)$		-0.70^{*}	-0.47^{***}	-0.33
		(0.38)	(0.16)	(0.38)
$U \cdot (EE_j = 4)$			-1.22^{***}	-0.56^{*}
			(0.24)	(0.33)
$U \cdot (EE_j = 5)$			-0.53	-0.48^{*}
			(0.46)	(0.27)
$U \cdot (EE_j = 6)$				-0.73^{***}
				(0.22)
$U \cdot (EE_j = 7)$				-1.42^{***}
				(0.38)
$U \cdot (EE_j = 8)$				-1.34^{***}
				(0.18)
$U \cdot (EE_j = 9)$				-0.71^{*}
				(0.41)
$U \cdot (EE_j = 10)$				-0.69
				(0.46)
Num. obs.	441694	441694	441694	441694
R^2 (full model)	0.94	0.94	0.94	0.94
R^2 (proj model)	0.20	0.20	0.20	0.20
Adj. R^2 (full model)	0.92	0.92	0.92	0.92
Adj. R^2 (proj model)	-0.02	-0.02	-0.02	-0.02

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 7: Focus on long incumbents (observed in the same firm 2 years ago)

B Model appendix

B.1 Proof of propositions from Section 3.3

For each of the three cases, I extend the model to an abstract number of submarkets M. Denote by $p(\theta(m))$ the probability of finding a match in submarket m.

Case 1 (Chain-poaching)

Consider k submarkets. The first submarket hires from unemployment. Then submarket $k > 1$ poaches from submarket $k-1$.

Proposition 3. *Starting from a steady-state, consider a perturbation to wage w in submarket k. The wages in the two submarkets have the opposite effects on unemployment. If k is odd,* $\frac{\partial u}{\partial w_k} > 0$*.If k is even,* $\frac{\partial u}{\partial w_k} < 0$

Proof. The proof is by induction. Base: $\frac{\partial u}{\partial w_1} > 0$. Unemployment in this model takes the standard form: $u_{t+1} = u_t(1 - \lambda_u(1)p(\theta(1))) + (1-u)d$ In a steady-state, $u = \frac{d}{\lambda_u(1)p(\theta(1))+d}$. Taking a derivative wrt w_1: $\frac{\partial u}{\partial w_1} = \frac{\partial u}{\partial p(\theta(1))}\frac{\partial p(\theta(1))}{\partial w_1}$. Relating this to the value of the job J(1): $\frac{\partial p(\theta(1))}{\partial w_1} = \frac{\partial p(\theta(1))}{\partial \theta(1)}\frac{\partial \theta(1)}{\partial J(1)}\frac{\partial J(1)}{\partial w_1}$ Assuming a CRS matching function, $\frac{\partial p(\theta(1))}{\partial \theta(1)} > 0$ and $\frac{\partial q(\theta(1))}{\partial \theta(1)} < 0$, and thus $\frac{\partial \theta(1)}{\partial J(1)} > 0$. Lastly, since $J(m) = \frac{y-w_m}{1-\beta(1-p(\theta(m+1)))}$, $\frac{\partial J(1)}{\partial w_1} = -1/(1-\beta(1-p(\theta(2)))) < 0$ Therefore, as all the other partial derivatives besides $\frac{\partial J(1)}{\partial w_1}$ are positive, $\frac{\partial u}{\partial w_1} < 0$.

Step: for $k > 1$, $\frac{\partial u}{\partial w_k}/\frac{\partial u}{\partial w_{k-1}} < 0$.
$\frac{\partial u}{\partial w_k} = \frac{\partial u}{\partial p(\theta(k-1))}\frac{\partial p(\theta(k-1))}{\partial \theta(k-1)}\frac{\partial \theta(k-1)}{\partial J(k-1)}\frac{\partial J(k-1)}{\partial p(\theta(k))}\frac{\partial p(\theta(k))}{\partial \theta(k)}\frac{\partial \theta(k)}{\partial J(k)}\frac{\partial J(k)}{\partial w_k}$
There are two clearly negative terms in this expression: $\frac{\partial J(k-1)}{\partial p(\theta(k))}$ and $\frac{\partial J(k)}{\partial w_k}$, the rest, besides the very first term, are positive.

To compare this to $\frac{\partial u}{\partial w_{k-1}}$, note that $\frac{\partial u}{\partial w_{k-1}} = \frac{\partial u}{\partial p(\theta(k-1))}\frac{\partial p(\theta(k-1))}{\partial w_{k-1}}$. The second term is negative, thus $\frac{\partial u}{\partial w_k}/\frac{\partial u}{\partial w_{k-1}} < 0$. □

Case 2: Heterogeneous unemployment hiring rates

Consider M submarkets. All hire from unemployment, but at different rates $\lambda_u(k)$. There is no poaching and wages are equal.

Proposition 4. *Starting from a steady-state, consider a perturbation to wage w in submarket k. The effect of such perturbation on unemployment is proportional to ratio of unemployed workers hired.*

$$\frac{\partial u}{\partial w_k} \propto \lambda_u(k)$$

Moreover, the relative effect of wage changes across submarkets is equal to the ratio of unemployed hires.

$$\frac{\partial u/\partial w_k}{\partial u/\partial w_{k'}} = \frac{\lambda_u(k)}{\lambda_u(k')}$$

Proof. In the steady-state, $u = \frac{\delta}{\sum_{k=1}^{M} \lambda_u(k)p(\theta(k))+\delta}$.
Then $\frac{\partial u}{\partial w_k} = -\delta(\frac{1}{\sum_{k=1}^{M} \lambda_u(k)p(\theta(k))+\delta})^2 \lambda_u(k)\frac{\partial p(\theta(k))}{\partial w_k} \propto \lambda_u(k)$. Taking the ratio across different submarkets, $\frac{\partial u/\partial w_k}{\partial u/\partial w_k'} = \frac{\lambda_u(k)\frac{\partial p(\theta(k))}{\partial w_k}}{\lambda_u(k')\frac{\partial p(\theta(k'))}{\partial w_{k'}}} = \frac{\lambda_u(k)}{\lambda_u(k')}$ since $w_k = w_{k'}$ and thus $J(k) = J(k')$. $\square$

C Quantitative appendix