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), which is not always the case. I differentiate jobs based on their hiring pool: whether they hire mostly unemployed or employed workers - and separately estimate their wage cyclicality. I find that wages in jobs hiring from unemployment are significantly less cyclical than in other jobs, both for incumbent workers and new hires. 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. I find that wage rigidity in jobs hiring unemployed workers has a 3 times larger effect than the rigidity of other jobs, thus confirming the original intuition. Moreover, moving from homogeneous wage rigidity estimates to heterogeneous ones increases the unemployment volatility by 20%. Therefore, accounting for the heterogeneity of wage cyclicality raises the value of wage rigidity as an amplification mechanism.

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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: if wages are rigid, during a recession, wages are stuck at high levels, thus firms are disincentivized from searching for workers, increasing unemployment. But what type of rigidity matters for the volatility of unemployment? This paper proposes the job hiring pool as the key source of heterogeneity.

Jobs do not all hire the same workers, nor do all the jobs hire the same number of unemployed workers. Data shows that jobs are heterogeneous in their pools. Ranking jobs based on the ratio of unemployed workers they hire, I find that jobs above the 5th quantile hire eight times as many unemployed workers as jobs below the 1st quantile. Intuitively, this heterogeneity is of primary importance for the volatility of unemployment. Jobs hiring mainly unemployed workers have a fundamentally different connection to the unemployment pool than jobs poaching workers. If wages are rigid in a job hiring unemployed workers, then the standard intuition follows: during recessions, wages will be high, thus the job will hire fewer workers, increasing the unemployment level. On the other hand, jobs that poach workers can only impact unemployment indirectly, by affecting hiring incentives of the jobs actually looking for unemployed workers.

I use the French matched employer-employee panel data DADS to separately estimate the wage cyclicality of jobs hiring from unemployment and employment. The matched nature of the data is crucial for measuring hiring pools. The employee side of the data allows tracking the history of each worker, allowing one to identify, each time a worker finds a new job, whether she was previously employed (employment-to-employment, or EE) or unemployed (unemployment-to-employment, or UE). Matching that with the employer side, I calculate how many UE and EE workers each job hires, providing information on each job's hiring pool. I classify jobs based on their proportion of UE workers and then estimate wage rigidity separately for each of the brackets. The first finding of the paper is that wages in jobs that poach workers are significantly more cyclical that in jobs that hire unemployed workers. These cyclicality differences are found for both incumbent workers and new hires.

Focus on job-level heterogeneity, rather than match- or worker-level is important for two reasons. First, it is job-side wage rigidity that primarily matters for the volatility of unemployment, rather than the worker side, as the jobs are the ones making hiring decisions. Second, rather than interpreting the results as differences in workers' abilities to leverage their outside options, the job-level nature of the result implies that heterogeneity occurs at the level of jobs' hiring practices. To argue for this interpretation, I add the worker dimension (whether a worker is a job-to-job transitioner) and find that it does not affect cyclicality. More precisely, the increment for the worker being a job-to-job transitioner is insignificant at almost every job bracket level. This does not come as a surprise though as, past the initial stage of hiring, workers' previous outside options usually have little effect on their wages (Di Addario et al. (2023)).

I then develop a labor search model to measure the relative importance of wage cyclicality across jobs of different hiring pools. The approach is built around a simple intuition that jobs hiring the unemployed and jobs poaching workers have mechanically different ways of affecting unemployment. If a job hires only unemployed workers, just hiring more is enough to affect unemployment. On the other extreme, a job exclusively poaching workers from other firms cannot affect unemployment directly. Instead, it can only affect it via the threat of poaching workers from jobs that do hire from unemployment. To incorporate this intuition and compare the two effects, I develop a labor search model with on-the-job search and separation of search: workers search in different locations depending on their current employment status, with locations following a job ladder structure. This is closely related to directed search models, with the key difference being the discrete and finite number of submarkets. More precisely, each submarket has a set of jobs tied to it, meaning that these jobs can only post vacancies in that submarket. Workers choose in which location 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. I let each location have its own wage determination mechanism, defined by its wage level and wage cyclicality. 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 differences in wage cyclicalities across submarkets

In the quantitative exercise, I restrict attention to two submarkets, differentiated by both the wage level and wage rigidity. One of the submarkets has a higher wage level, and the employed workers (optimally) search in that submarket, while the unemployed workers mostly search in the other location. The second finding of the paper, and the first of the model, is that rigid wages in jobs that hire employed workers have a 3 times smaller effect on the standard deviation of unemployment than rigidity in jobs that hire unemployed workers. 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 value of accounting for wage rigidity heterogeneity across different submarkets, I compare my calibration with the case where wages are equally cyclical in all the jobs. The third finding of the paper is that the volatility of unemployment is 20% higher in the calibration accounting for the heterogeneity in wage cyclicality.

This dimension of heterogeneity is new to the literature. Random search models usually used to study the effect of wage rigidity on unemployment volatility are unable to account for heterogeneous hiring pools, as all jobs successfully hire unemployed workers. Balke and Lamadon (2022) and Souchier (2022) endogenize wage rigidity in models of directed search via the dynamic contracting framework but do not take into account implications for unemployment volatility. Rudanko (2023) incorporates a within-firm equity constraint on wages, resulting in amplified responses of firms to shocks. However, these papers do not incorporate potential heterogeneity in wage rigidity. The closest empirical work is Teramoto (2023), who looks at heterogeneous wage cyclicality across workers of different incomes in the US, but within a random search framework, thus not accounting for firms' heterogeneous hiring pools. In contrast, I make this distinction explicit in both theoretical and empirical settings by exploring the differences in levels of cyclicality across these jobs and their effects on unemployment volatility.

Related Literature

This paper contributes to the empirical wage cyclicality literature by looking at the job-side heterogeneity in the cyclicality. The majority of the literature focused on distinguishing new hire and incumbent wage cyclicality literature [1], with the main point of contention being job composition and procyclical match upgrading biases. Unlike these papers, focusing on the comparison between the new hire and incumbent wages, my paper is less interested in controlling for these biases as they primarily affect new hire estimation, while this paper's empirical result holds for both new hires and incumbents. Instead, this paper is one of the first (alongside Cervini-Plá, López-Villavicencio, and Silva (2018) and Teramoto (2023)) to estimate heterogeneous wage cyclicality, with the key point of difference between my paper and those above is that I focus on job-side heterogeneity, while their works document worker-side heterogeneity.

[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)

Within the incumbent versus new hire wage cyclicality literature, the papers closest in their empirical methodology to mine are those by Haefke, Sonntag, and Van Rens (2013) and Gertler, Huckfeldt, and Trigari (2020), which both directly estimate the wage cyclicality of new hires from unemployment to control for the procyclical match upgrading bias. Both use employee-side data: CPS and SIPP, respectively. Haefke, Sonntag, and Van Rens (2013) find strong procyclicality in UE new hire wages, while Gertler, Huckfeldt, and Trigari (2020) find that UE new hire wages are as rigid as wages of incumbent workers and indicate that the observed new hire wage procyclicality in other papers is entirely due to high cyclicality in EE new hire wages. They interpret high new hire EE cyclicality as an artifact of cyclical movements in match quality rather than true wage flexibility. My paper differs in two aspects. First, I compare wage rigidity across jobs for both new hires and incumbents and find that, even for incumbents, wages are more rigid in jobs hiring from unemployment. This supports the focus on cross-firm rather than cross-worker heterogeneity and also implies that disaggregating only at the new hire level is not enough. Second, rather than comparing cyclicality across workers, I compare it across jobs, which reinterprets differences in wage rigidity as heterogeneous firm wage practices rather than match upgrading bias or workers leveraging their outside options in the bargaining stage. To argue for this interpretation, in Figure 2 I add the worker dimension (whether a worker is UE or EE) to my main regression and find that the increment for the worker being a job-to-job transitioner is insignificant at almost every job bracket level. 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 rigidity.

Another notable comparison is a paper by Lagakos and Ordonez (2011), who compare wage rigidity, measured as the responsiveness of wages to the marginal productivity of labor, across the sectors of the US economy based on the education level of their workers. They find that sectors with higher educated workers have more rigid wages, and suggest that the result comes from firms having higher displacement costs of higher educated workers: these workers are harder to substitute, so firms insure them more in order to keep them. It is not easy to reconcile their finding with mine, as firms that poach workers tend to have more a educated workforce. I confirm this in my data. However, I fail to replicate their result using my data. Instead, I find the opposite of their result in that higher educated sectors have less rigid wages. I suspect that the difference comes from our measures of wage rigidity, as my measure of unemployment and their measure of marginal productivity of labor may not co-move.

Theoretically, this paper relates to the labor search and job ladder literature. There are several approaches to modeling on-the-job search in the literature. The first approach assumes random search with either wage bargaining (Lise and Robin (2017), Moscarini and Postel-Vinay (2018)) or wage posting (Moscarini and Postel-Vinay (2013), Morales-Jiménez (2022), Fukui (2020)). All workers search in the same job pool and, over time, find better and better jobs, moving up the job ladder. Notably, Morales-Jiménez (2022) and Fukui (2020) model wage rigidity in their papers with applications to unemployment fluctuations. However, as is the case with the entire random search literature, these papers cannot account for the separation of search: in random search, all workers search in the same pool, and thus all jobs have the same probability of hiring an unemployed worker. Instead, I require heterogeneity of jobs' hiring pools not just in the relative sense, but also in the absolute one: jobs at the top should be less likely to hire unemployed workers.

For this purpose, directed search (Moen (1997), Menzio and Shi (2011), Schaal (2017)) is a more appropriate framework as separation of search is embedded into it. Recently, Balke and Lamadon (2022), Souchier (2022), and Rudanko (2023) attempted to incorporate wage rigidity into a directed search framework. The former two use a dynamic contracting model 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 fluctuations. Rudanko (2023) instead models wage rigidity via within-firm wage equity constraints. My paper takes the effect of wage rigidity on unemployment fluctuations as given and instead focuses on modeling the implications of heterogeneous wage cyclicality.

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 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 job-to-job transitioners that they hire. I then proceed to show that wages are significantly more rigid in the jobs that hire the fewest job-to-job transitioners. This heterogeneity is there 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 $\widetilde{\mu(t)}$ to ensure occupation- or industry-specific long-run changes over the 2 decades do not affect the cyclicality coefficient[2]. 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

[2] 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.

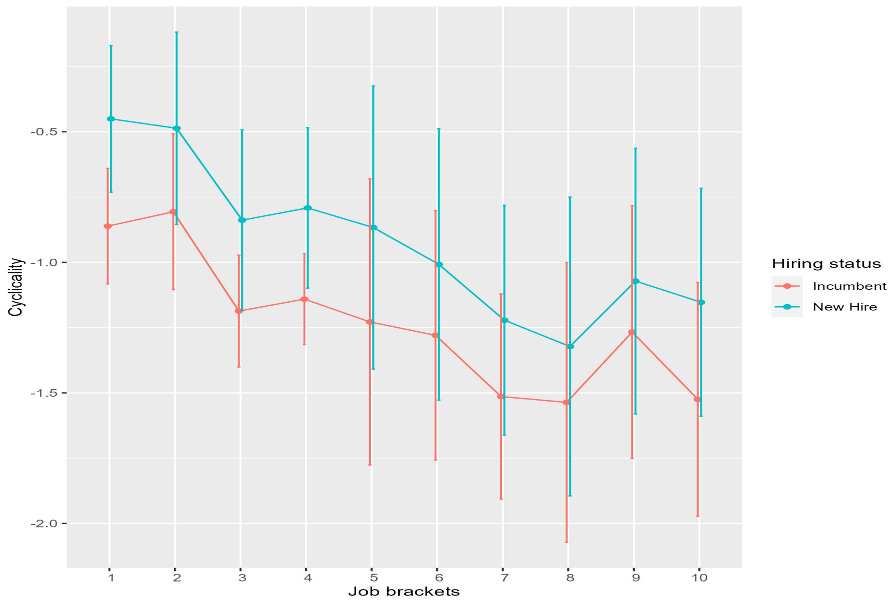

Figure 1: Wage cyclicality across jobs

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)) 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

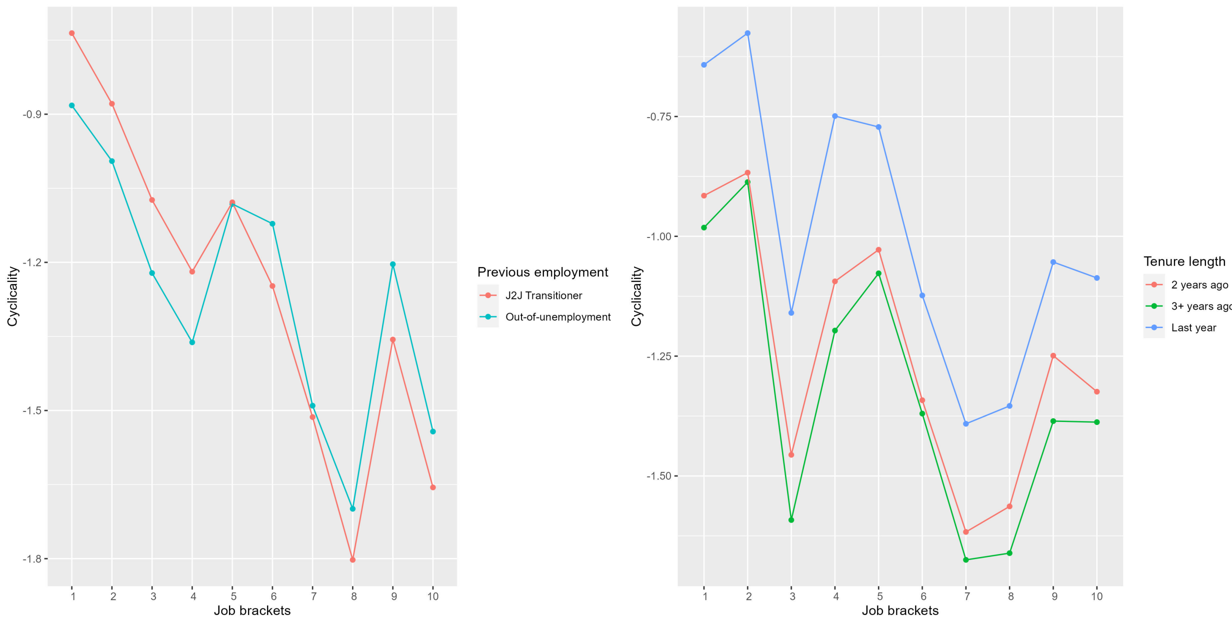

Figure 2: Wage cyclicality across employment histories and tenure length

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 consider a labor search model with a new notion of search - separation of search: workers choose a location to search in, with each location having its own wage determination mechanism. Unlike random search, different workers may search in different locations, and, unlike directed search, wages in these locations are not tied to the location itself. It offers the same benefits as directed search in allowing workers in different positions to search in different submarkets, while also letting wages in different locations be chosen differently. Both of these conditions are necessary for my paper, as I am interested in the heterogeneous effects of wage rigidity across different steps of the job ladder.

3.1 Physical Environment

The economy is populated by a continuum of workers with measure 1 and a continuum of firms with positive measure. Each worker is endowed with an indivisible unit of labor and maximizes the expected sum of periodical 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 continues forever. 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, match is destroyed with probability $\delta \in (0, 1)$.

At the search stage, workers and firms search for matches across different locations. Specifically, a firm chooses how many vacancies to open in each location, and a worker chooses which location 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 with probability $\lambda_u(m) : M \to [0, 1]$, where M, $||M|| \geq 2$, is the set of locations workers can search in. 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 $\lambda_e(m) : M \to [0, 1]$. Finally, if the worker lost her job during the separation stage, she cannot search.

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 $\phi(\hat{y}|y), \phi : Y \times Y \to [0, 1]$.

3.2 Labor Market

The market consists of M submarkets. They take interpretation of job ladder rungs, and are ex-ante heterogeneous only in their wages. Within each submarket, matches are either new hires or incumbents. A match is a new hire in period t, if this is its first period of existence. Otherwise, the match is an incumbent. I take a reduced-form approach to wage determination:

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

, and $\bar{w}_m$ 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 degree of comovement between wages and aggregate productivity, $\alpha \in [0, 1]$ serves as a measure of wage rigidity.

This specification allows submarkets to be different in levels of both wage flexibility and worker bargaining power, and new hire and incumbent wages to be different in terms of wage flexibility. The exact formula for the determination mechanism is not crucial, as long as it exhibits comovement between wages and aggregate productivity, the comovement is dampened in more rigid submarkets, and the comovement is separate from the wage level. For example, Nash Bargaining wages with submarkets being heterogeneous only in their bargaining power would not work, since, though wages comove with productivity more under higher bargaining power, bargaining power also affects the average wages, and thus on its own the bargaining power has no effect on volatility of unemployment (Hagedorn and Manovskii (2008))). Instead, if we also introduce a degree of wage rigidity into Nash Bargaining mechanism (say, wages are a convex combination of bargained wages and some fixed value, with rigidity parameter determining the weights), all the conditions are satisfied, and wage rigidity actually has an impact on unemployment volatility. This is arguably not a strong as assumption as empirically we find 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.

At the separation stage, an employed worker moves into unemployment with probability $\delta \in (0, 1)$. At the search stage, each firm chooses how many vacancies to create and in which submarkets to locate them. On the other side of the market, each worker who has the opportunity to search chooses which submarket to visit. At the matching stage, each worker searching in submarket m meets a vacancy with probability $p(\theta(m, \psi))$. Similarly, each vacancy located in submarket m meets a worker with probability $q(\theta(m, \psi))$. At the production stage, an unemployed worker produces b units of output, and an employed worker produces y units of output.

3.3 Worker and Firm problems

Consider an unemployed worker at the beginning of the production stage and denote $V_u(\psi)$ 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

$V_e(\psi, m) - V_{ef}(\psi, m)$, where V_e, V^{ef} are the total value of a match and the firm's share of the value of a new match (both specific to submarket m), respectively. Thus,

$$V_u(\psi) = b + \beta E_{\hat{\psi}|\psi} \max_m \Big[V_u(\hat{\psi}) + \lambda_u(m) D(m, V_u(\hat{\psi}), \hat{\psi}) \Big], \tag{1}$$

where D represents the (net) value of search in the submarket m:

$$D(m, V_u(\hat{\psi}), \hat{\psi}) = p(\theta(m, \hat{\psi}))(V_e(\hat{\psi}, m) - V_{ef}(\hat{\psi}, m) - V_u(\hat{\psi})) \tag{2}$$

Now, consider a worker-firm match at the beginning of the production stage. In the current period sum of worker's utility and firm's profit is the productivity of the match y. Next period, pair may separate with probability d, or worker match with another firm (if not fired) in submarket m with probability $\lambda_e(m) \cdot p(\theta(m, \hat{\psi}))$, and in both cases firm's continuation profit is zero. With probability $(1-d)(1-\lambda_e(m) \cdot p(\theta(m, \hat{\psi}))$ worker and firm stay together until the next production stage. Thus, the value of the match is

$$V_e(\psi, m) = y + \beta E_{\hat{\psi}|\psi} \Big[dV_u(\hat{\psi}) + (1-d)[V_e(\hat{\psi}, m) + \lambda_e(m^*) D(m^*, V_e(\hat{\psi}), \hat{\psi})] \Big], \tag{3}$$

where

$$m^* = arg \max_{m'} E_{\hat{\psi}|\psi} \Big[V_e(\hat{\psi}) - V^{(}_{ef}\hat{\psi}) + \lambda_e(m') D(m', V_e(\hat{\psi}, m) - V^{(}_{ef}\hat{\psi}, m), \hat{\psi}) \Big] \tag{4}$$

is the submarket, where worker currently employed in submarket m chooses to search, maximizing own expected utility.

Firm's share of the value depends on whether the match is new or incumbent ($k = \{new, inc\}$):

$$V^k_{ef}(\psi, m) = y - w^k_m + \beta E_{\hat{\psi}|\psi} \Big[(1-d)(1-\lambda_e(m^*) p(\theta(m^*, \hat{\psi}))) \cdot V_{ef}(\hat{\psi}, m) \Big] \tag{5}$$

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 k. The firm's benefit from creating a vacancy in submarket m is

$$q(\theta(m, \psi))[\tilde{V}^{(}_{ef}\psi, m)] \tag{6}$$

Where $\tilde{V}_{ef}(\psi, m) = \tilde{p}(m, \psi) \cdot V^{(}_{ef}\psi, m)$ is the benefit of finding a worker, which is equal to (probability worker accepts the job offer)·(firm's share of a match value)[3] 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

[3]Note that I calibrate the model so that worker always accepts the job.

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

$$k \geq q(\theta(m,\psi))[\tilde{V}_{ef}(\psi,m)] \tag{7}$$

and $\theta(i,\psi) \geq 0$ with complementary slackness.
Since $\eta(m)$ increases with m, V_{ef} 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.

4 Quantitative model

I calibrate and simulate the model in order to assess the importance of introducing heterogeneous wage rigidity on unemployment volatility. More precisely, I intend to capture the search separation and wage rigidity properties of different jobs found in the data and see just how much is gained by introducing the heterogeneity in wage rigidity into the model. I start by explaining the basics of the simulation, along with the extra ingredients specific to the quantitative version. I then explain the calibration procedure and, lastly, do several comparative statics exercises: compare the importance of wage rigidity across the different submarkets, and compare the volatility of unemployment of the model with heterogeneous wage rigidity to the one with the same level of rigidity across all 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. Unlike in the theoretical model, in a real economy 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. To account for that, I introduce taste shocks into the workers' search preferences. Essentially, each worker's net value of search $D(m, V_u(\hat{\psi}), \hat{\psi}) = p(\theta(m, \hat{\psi}))(V_e(\hat{\psi}, m) - V_{ef}^{new}(\hat{\psi}, m) - V_u(\hat{\psi})) + \epsilon_{imt}$ now has the shock variable ϵ_{imt} augmenting it. That way, even if on average unemployed workers prefer the lowest submarket, some unemployed workers will still be incentivized to search in better submarkets. I let the taste shock ϵ_{imt} be extreme value distributed, with location 0, scale 1 and shape 0, iid across workers, submarkets, and time. That way, the probability that, say, an unemployed worker decides to search in submarket m' given the aggregate conditions $\hat{\psi}$ is equal to $\frac{V_u(\hat{\psi})+\lambda_u(m')D(m',V_u(\hat{\psi}),\hat{\psi})}{\sum_{m\in M} V_u(\hat{\psi})+\lambda_u(m)D(m,V_u(\hat{\psi}),\hat{\psi})}$. Since we have a continuous measure of workers, this personal probability translates into the ratio of unemployed workers searching in the submarket m.

Since the model is Block Recursive, it is easily numerically solvable as both the value functions and the allocations do not depend on the distribution of labor. Once solved, 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 low 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 separation of search properties of the data

3. Wage rigidity: need to match the rigidity 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 even 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. Important of relative transition probabilities from unemployment to each of the submarkets is clear: a submarket hiring a lot of unemployed workers will have a larger effect on unemployment. However, transition probabilities across submarkets also matter: even a submarket that never hires unemployed may have an impact by poaching workers from the submarkets that do.

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

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 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, which 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.

5 Conclusion

I estimate wage rigidity 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 twice as 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 rigidity 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^{***}	-1.28^{***}	-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 Block Recursivity

In this section, I define Block Recursive equilibrium and prove that every equilibrium of this model is Block Recursive. Intuitively, equilibrium is considered Block Recursive if none of the value and policy functions depend on the distribution of labor. Thus, if all the equilibria are Block Recursive, as I prove below for the case of equal new hire and incumbent wages, the model can be solved outside of the steady-state. The proof extends to the case of unequal new hire and incumbent wages if workers still always search with an intent to accept the job. This can be achieved either by making sure that new hire wages are always higher than incumbent, or by allowing workers uninterested in searching to not search.

Definition 1. *A Block Recursive Equilibrium (BRE) consists of the market tightness function $\theta : M \times W \times Y \to R_+$,value function of the unemployed worker $V_u : W \times Y \to R$, policy function for the unemployed worker $m_u : W \times Y \to M$, a joint value function for a firm-worker match $V_e : M \times Y \to R$, policy function for the worker-firm match $m^* : M \times W \times Y \to M$, and firm's share of the match value $V_{ef} : M \times W \times Y \to R$. These functions satisfy the following conditions: (i) $\theta(m, w, y)$ satisfies condition (7) for all $(m, w, y) \in M \times W \times Y$; (ii) $V_u(w, y)$ satisfies (1) for all $(w, y) \in W \times Y$ and $m_u(w, y)$ is the associated policy function; (iii) $V_e(m, w, y)$ satisfies (3) for all $(m, w, y) \in M \times W \times Y$, and $m^*(m, w, y)$ and $d(m, w, y)$ are the associated policy functions; (iv) $V_{ef}(m, w, y)$ satisfies condition (5) for all $(m, w, y) \in M \times W \times Y$.*

Proposition 1. *All equilibria are Block Recursive*

Proof. Let $\alpha_m^{new} = \alpha_m \ \forall m$ so that $V_{ef} = V_{ef}$. Let $(\theta, V_u, V_e, V_{ef}, m_u, m^*)$ be an equilibrium. I take 4 steps to show that it is Block Recursive.

1. Show that workers searching optimally are at worst indifferent between the new job offer and the current position and,hence, may always search with an intent to accept the new job offer. By definition of m^*, $E\{V_e(\hat{\psi}, m^*) - V_{ef}(\hat{\psi}, m^*) + \lambda_e(m^*)D(m^*, V_e(\hat{\psi}, m^*) - V_{ef}(\hat{\psi}, m^*), \hat{\psi})\} \geq$
   $E\{V_e(\hat{\psi}, m') - V_{ef}(\hat{\psi}, m') + \lambda_e(m')D(m', V_e(\hat{\psi}, m') - V_{ef}(\hat{\psi}, m'), \hat{\psi})\}$
   $\forall m' \in M$
   Letting $m' = m$ we get that $E\{V_e(\hat{\psi}, m^*) - V_{ef}(\hat{\psi}, m^*) + \lambda_e(m^*)D(m^*, V_e(\hat{\psi}, m^*) - V_{ef}(\hat{\psi}, m^*), \hat{\psi})\} \geq 0$
   For unemployed workers, it is assumed that $\forall \psi \in \Psi, \exists m \in M s.t. V_e(m, \psi) - V_{ef}(m, \psi) \geq$

$V_u(\psi)$, since otherwise Nash Bargaining formulation would break down (it would require either $y < b$ or $\eta < 0$).

Thus, workers always accept new job offers and, hence, $\tilde{V}_{ef} = V_{ef}$.

2. Express number of a submarket m as function of market tightness θ and aggregate economy ψ using market clearing condition (7): $m = [q(\theta) * V_{ef}(\psi)]^{-1}/k$. If m is not an integer, set m=0, and $\lambda_u(0) = \lambda_e(0) = 0$

3. Now worker's search problem can be expressed not as choosing m, but as choosing θ. This allows us to reexpress value functions (substitute m with $m(\theta,\psi)$ and $\theta(m,\psi)$ with θ). Thus, employed workers choose
$\theta^*(\theta) = argmax_{\theta'} E\{V_e(\hat{\psi}) - V_{ef}(\hat{\psi}) + \lambda_e(m(\theta,\hat{\psi}))p(\theta')(V_e(\hat{\psi}, m(\theta',\hat{\psi})) - V_{ef}(\hat{\psi}, m(\theta',\hat{\psi})) - (V_e(\hat{\psi}, m(\theta,\hat{\psi})) - V_{ef}(\hat{\psi}, m(\theta',\hat{\psi})))\}$
Then
$V_{ef}(\theta,\psi) = y - w_m + \beta E\{(1-d)(1-\lambda_e(m(\theta^*(\theta),\hat{\psi}))p(\theta^*(\theta))) * V_{ef}(\hat{\psi},\theta)\}$
Once $m(\theta,\psi)$ is substituted into the equation, one can notice that, if $V_{ef}(\hat{\psi},\theta)$ is independent of (u,g), then $V_{ef}(\psi,\theta)$ is independent of labor distribution as well. Thus, the fixed point of the value function is independent of (u,g) and,hence,V_{ef} is indeed independent of the labor distribution and, given this result and using similar arguments, V_e and V_u become independent as well.

4. Finally, all the policy functions are independent of (u, g) as well.

Market tightness θ is pinned down by condition (7) and, since V_{ef} is independent of labor distribution, θ is as well. Since both θ and all the value functions are independent of (u,g), all the other policy functions are independent, too, for the same reasons as above: if next period's policy functions are independent of (u,g), then current period's policy functions are independent as well.

$\square$