Posted Wage Rigidity

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We introduce a new dataset of establishment-level posted wages with job titles. We document three new facts implying that nominal new hire wages are rigid, and especially rigid downwards. First, posted wages rarely change between successive vacancies. Second, posted wages are weakly procyclical. Third, nominal posted wages are more rigid downwards than upwards. We plug our estimate of new hire wage rigidity into a standard labour search model. The estimated rigidity generates large and asymmetric unemployment fluctuations.

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1 Introduction

Why does unemployment rise during recessions? One explanation is wage rigidity (Hall, 2005). With rigid wages, incentives to hire fluctuate as labour demand shifts. If wages are especially rigid downwards, unemployment rises sharply during recessions. In the benchmark theory, it is wage rigidity for *new hires*—as opposed to incumbent workers—that matters. In the United States, fluctuations in hours worked are largely due to hiring (Shimer, 2012). The new hire wage is relevant on this margin. Incumbent wages may not be allocative. Even with incumbent wage rigidity, the present value of wages can still vary if new hire wages are flexible (Barro, 1977; Pissarides, 2009).

We know relatively little about the empirics of new hire wages. Using survey data on new hires, some papers find strong procyclicality (Haefke, Sonntag, and Van Rens, 2013), and others find weak procyclicality (Gertler, Huckfeldt, and Trigari, 2016). There is limited evidence on whether new hire wages are especially rigid downwards.

We introduce a new online dataset to study new hire wages. Our dataset contains establishment level posted wages with job titles and hours, covering 10% of total US vacancies since 2010. Posted wages closely comove with measures of the new hire wage from survey data. We can track this measure of the new hire wage across successive vacancies posted by the same job or establishment.[1] Our data has wide coverage and contains precise measures of posted wages with hours worked, and bonus or overtime pay where applicable.

Our measure of the nominal new hire wage is rigid, and especially rigid downwards. We present three new facts about posted wages to support this finding.

In our first new fact, nominal posted wages rarely change between successive vacancies posted for the same job. A measure of the new hire wage therefore adjusts infrequently. For the typical job, posted wages remain unchanged for 5 quarters, across multiple vacancies. Our estimated duration is similar to prior estimates for incumbent wage spells (e.g. Barattieri, Basu, and Gottschalk, 2014), suggesting that new hire and incumbent wages are similarly rigid.

In our second new fact, posted wages are weakly procyclical. We study the comovement of posted wages and regional unemployment in a state-quarter panel. Posted wages comove little with regional unemployment, implying wage rigidity for new hires.[2] Compared to existing work using US survey data, there are two advantages.[3] First, we focus on wage variation of new vacancies for the same job, to hold fixed the composition of jobs. Without this precaution, one

[1]An establishment is a physical location of a firm, for example, a given physical branch of Starbucks. A job is a job title at that establishment, such as a barista at Starbucks.

[2]We study nominal posted wages in our regressions. However time fixed effects sweep away variation in the national price level. Our estimates therefore suggest that one measure of the real new hire wage is also rigid.

[3]See Pissarides (2009) for a review of papers that use survey data to study new hire wage cyclicality.

might estimate a procyclical new hire wage due to changes in job composition, and overlook job level wage rigidity. However, it is job-level wage rigidity that captures firms' incentives to hire new workers into the job. If vacancy creation is more cyclical for high wage jobs, then wages for newly hired workers are procyclical—even if wages do not vary within jobs (Gertler and Trigari, 2009; Hagedorn and Manovskii, 2013). With our job level vacancy data, we can isolate job-level fluctuations in the new hire wage. In a second advantage, our estimated wage cyclicality is precise, exploiting wage variation at state-quarter level. We rule out strong procyclicality. Past work, from survey data, often cannot rule out strong or weak cyclicality.

In our third new fact, nominal posted wages are more rigid downwards than upwards. We present several pieces of evidence. First, the probability of a posted wage decrease is much lower than the probability of increase between successive vacancies. Second, the probability of a posted wage increase is strongly procyclical; the probability of a posted wage decrease is acyclical. Third, the comovement between posted wages and unemployment is asymmetric—when unemployment falls, posted wages rise; when unemployment rises, posted wages do *not* fall. Collectively, this evidence implies that new hire wages are more rigid downwards than upwards. Previous evidence that wages are especially rigid downwards comes from incumbent workers. Yet even if incumbent wages are rigid downwards, new hire wages may not be. Implicit contracting models (Beaudry and DiNardo, 1991) predict that incumbent wages are rigid downwards, but that new hire wages are *flexible* downwards. Nevertheless, we document that a measure of new hire wages are especially rigid downwards.

Finally, we turn to a standard Diamond-Mortensen-Pissarides model to understand the quantitative importance of our results. We plug in our estimate of new hire wage rigidity, and find that large and asymmetric unemployment fluctuations result. The model confirms the canonical importance of new hire wage rigidity, and the secondary role of incumbent wages.

Related literature. Our paper contributes to the literature that measures new hire wage rigidity. The prior literature for the United States largely uses survey data. Key papers include Bils (1985), Shin (1994), Hagedorn and Manovskii (2013), Haefke et al. (2013), Kudlyak (2014), Gertler et al. (2016) and Basu and House (2016). In the prior literature, views differ on new hire wage cyclicality. For example, Haefke et al. (2013) find strong procylicality and Gertler et al. (2016) find weak procyclicality. An important recent paper, Grigsby, Hurst, and Yildirmaz (2018), studies worker-level administrative payroll data on new hires.

Prior work on new hires typically tracks workers, and not jobs. Workers are only hired once into a given job. Thus surveys cannot study how the wage adjusts between successive new hires. Our dataset studies posted wages across successive vacancies for the same job. We can study the probability that a measure of the new hire wage changes at the job level.

A key challenge for survey estimates is job composition (Gertler and Trigari, 2009; Hagedorn and Manovskii, 2013). Survey estimates of new hire wage cyclicality study the wages for newly hired workers, either workers switching jobs, or entering work from unemployment. This wage variation pools two sources of variation—first, wage rigidity at the new job into which the worker is hired; and second, wage variation due to cyclical changes in job composition. Conceptually, wage rigidity at the job level governs firms' incentives to create vacancies for that job. Cyclical changes in job composition might generate an overall procyclical wage, even if wages are rigid within jobs or establishments. For example, workers may be more likely to switch into high paying jobs during booms, generating procyclical wages due to job composition. We isolate within-job wage variation when we study wage cyclicality, removing the confounding effect of job composition.

From survey data, there is limited evidence that new hire wages are more rigid downwards than upwards. Precision is a challenge. Survey data has measurement error in hourly wages, and small sample sizes. It is difficult to precisely estimate nonlinearities in the wage adjustment process. Our dataset contains well measured wages with posted hours worked, as well as substantial variation at state-quarter frequency. The data yields precise estimates, letting us detect nonlinear wage adjustment.

A literature argues that new hire wage rigidity can rationalise large and asymmetric unemployment fluctuations. Given limited evidence on new hires, this literature often calibrates to incumbent wage rigidity. We provide a direct estimate of new hire wage rigidity, of a similar magnitude to previous calibrations. Key papers rationalising unemployment fluctuations with wage rigidity include Hall (2005), Hall and Milgrom (2008), Hagedorn and Manovskii (2008) and Gertler and Trigari (2009). Many papers argue that if wages are more rigid downwards than upwards, unemployment may be particularly volatile during recessions (e.g. Tobin, 1972; Akerlof, Dickens, and Perry, 1996; Dupraz, Nakamura, and Steinsson, 2016; Chodorow-Reich and Wieland, 2017). Pissarides (2009) emphasises that new hire wages are key for unemployment fluctuations. Incumbent wage rigidity may not be allocative (Barro, 1977).[4]

Our paper relates to the literature on incumbent wage rigidity (Card and Hyslop, 1997; Le Bihan et al., 2012; Barattieri et al., 2014; Daly and Hobijn, 2014; Sigurdsson and Sigurdardottir, 2016; Grigsby et al., 2018). This literature finds that wages for incumbent workers remain unchanged for long periods, and are especially rigid downwards. We document similar properties for a measure of the wage for new hires. We therefore match a conjecture of Gertler and Trigari (2009), that new hire and incumbent wages are similarly rigid. In theory, new hire and incumbent wages might be similarly rigid due to internal equity concerns (Bewley, 2002). How-

[4] Incumbent wage rigidity may still be relevant for unemployment fluctuations in some models. Theories of financial frictions (Schoefer, 2015), endogenous separations (Mortensen and Pissarides, 1994) or variable effort (Bils, Chang, and Kim, 2014) rely on incumbent wage rigidity to generate unemployment fluctuations.

ever, implicit contracting models suggest incumbent wages should be more rigid than new hire wages (Harris and Holmstrom, 1982; Beaudry and DiNardo, 1991).

Finally, we contribute to the literature on online vacancy posting, by studying the cyclicality of online posted wages. Hershbein and Kahn (2016), Modestino et al. (2015), Modestino et al. (2016) and Deming and Kahn (2018) study variation in skill requirements of job postings. Marinescu and Wolthoff (2016) examine the impact of wage posting on worker-firm matching. Azar et al. (2017) and Azar et al. (2018) study monopsony power in labour markets.

2 Dataset

Our main resource is a proprietary dataset of online posted wages, provided by Burning Glass Technologies. Burning Glass extracts vacancy data from online job boards, and company websites. The vacancy data contains posted salaries, for 2010-2016. The vacancy data contains industry and occupation information. Occupation information is at the 2- 4- or 6-digit SOC code level.[5] The industry information is at the 2- 4- and 6-digit NAICS code level.

The posted salaries contain a measure of hours worked. Posted salaries are classified as hourly, weekly, monthly or annual.[6] The salary includes bonus, commission or shift pay where applicable. Roughly half of the data posts a range of salaries. The rest posts a point salary. For jobs that post a range, we use the mean of the range as the posted wage of the job. Appendix Section C explores in detail alternative ways of treating jobs that post a range.

The wage posting data reports establishment and job title. Each physical location at which a firm employs workers is an establishment. An establishment is therefore a location identifier, measured at the zipcode level. Job titles are cleaned using Burning Glass' algorithm. Throughout the paper, we will use the term "job" to refer to a job-title within an establishment whose wages are quoted at a given frequency (e.g. annual or daily).

Figure 1 presents an example of a job that posts wages for multiple vacancies. The firm is Progressive Car Insurance. The establishment is the branch of the firm in Pasadena, California. The job title is claims adjuster. The salary is a posted annual wage, base pay. Then according to our definition, a job is a claims adjuster at the Pasadena establishment of Progressive Car Insurance.

The data on wage postings covers around 10% of total vacancies posted in the United States during 2010-2016, according to (Carnevale et al., 2014). Burning Glass attempts to collect the near-universe of job vacancy postings, from 40,000 distinct online sources. Burning Glass tracks

[5]These occupation codings are granular—a 6 digit SOC code is at the detail of, for example, a high school Spanish teacher.

[6]The measure of hours is an important advantage. In the United States, administrative data often does not contain measures of hours worked. Survey data tends to have recall error in hours worked and salary payments.

vacancies from both online job boards, and also directly from the company websites that post vacancies online, and then applies a deduplication algorithm. Vacancies in Burning Glass are unlikely to be "stale". Vacancy posting on job boards is costly, and most inactive vacancies are deleted after one month. Meanwhile, 92% vacancies on company websites are taken down within a quarter.

Table 2 presents summary statistics for the Burning Glass data. There are many vacancies within each state-quarter. There is coverage across almost all 6-digit SOC occupations. A large fraction of jobs contain establishment and job title identifiers.

In many specifications, we study regional business cycle variation. We use regional unemployment from the Local Area Unemployment Statistics (LAUS) and regional employment from the Quarterly Census of Employment and Wages (QCEW). We also study occupational data from the 2014-2016 Occupational Employment Statistics (OES).

2.1 Posted Wages Track Other New Hire Wage Measures

This subsection studies the relationship between posted wages and other measures of the new hire wage from survey data. Specifically, we use the CPS to construct a quarterly measure of the new hire wage. We also compare posted wages against occupation and regional wages. We find that the posted wage captures variation in these other measures, showing that posted wages are a valid measure of the new hire wage. In following sections, we can then exploit the new features of the Burning Glass data to study the wage for new hires.

The posted wage on new vacancies is the wage firms advertise will be paid at the start of a job. Therefore one expects that the posted wage reflects the wage for new hires. Hall and Krueger (2012) survey 1300 workers who had recently searched for jobs, and their findings largely confirm this intuition. Hall & Krueger find that 1/3 of workers bargain over their wages with employers, and the remaining 2/3 receive the wage dictated by their employer at the start of the match. Therefore for vacancies that post a wage, most workers are likely to receive this wage at the start of the match. The posted wage should then capture variation in the wage for new hires.

Posted wages from our dataset capture variation in an alternative measure of the new hire wage, constructed from the CPS. We construct a measure of the aggregate quarterly new hire wage for 2010-2016. The CPS has a rotating panel strucure. By linking workers across consecutive monthly waves of the CPS, one can identify workers who were previously unemployed, and calculate the new hire wage averaging across these workers. We follow the procedure in Haefke et al. (2013) to construct this measure. The measure of the new hire wage is quarterly.

We regress log quarterly posted wages in Burning Glass on log quarterly wages for new hires from the CPS. The two wage measures comove closely. The results are in Table 1. We calculate the quarterly log median salary for hourly base pay workers, and hourly total pay workers in Burning Glass. We compare these series to the quarterly log mean wage for newly hired hourly workers in the CPS. We study hourly workers in Burning Glass and the CPS because these series should be comparable—it is less clear how to compare the wages of non-hourly workers in each dataset. We use two measures of the new hire wage in the CPS, either weighting by hours or by the CPS sample weights. For base pay workers the regression coefficient is near 1, with or without a time trend. Posted wages in Burning Glass and CPS new hire wages comove closely. For total pay workers, the regression coefficient is more unstable depending on whether we include a time trend. Therefore posted wages capture variation in another measure of the new hire wage at quarterly frequency. Figure 3 plots annual wages from Burning Glass, and the CPS New Hires series. The figure confirms the findings from regressions—posted wages in Burning Glass capture variation in other measures of the new hire wage.

The posted wage data matches variation in wages by occupation. We study occupation at the six-digit SOC level[7]. We take the median posted wage within each occupation for Burning Glass for 2010-2016; and the median hourly wage within occupation from the 2014-2016 Occupational Employment Statistics (OES), the establishment-level survey of occupational wages in the US. We regress OES wages on Burning Glass wages, by occupation. The results are in Table 3 and Figure 4. Wages by occupation in Burning Glass closely match the OES. When occupational wages in the OES rise by one percent, occupational wages rise in Burning Glass by a similar amount.

We also compare wages by region. Again, posted wages track other sources of wages. We study regions at the core-based statistical area[8] (CBSA) level. We take the median posted wage within each CBSA for Burning Glass for 2010-2016; and compare to the 2010-2016 Quarterly Census of Employment and Wages (QCEW), the regional census of wages in the United States. We regress QCEW earnings on Burning Glass wages, by CBSA. Since hours worked are not reported in the QCEW, we use weekly earnings instead. The results are in Table 4 and Figure 5. Wages by CBSA in Burning Glass closely match the QCEW.

Posted wages capture variation in other measures of the new hire wage, as expected given the survey results of Hall and Krueger (2012). We can then document new facts about new hire wages, using the posted wages dataset.

[7]These occupations are granular, at the level of, for example, a high school Spanish teacher.

[8]A CBSA is an urban area, either a micropolitan or metropolitan statistical area. It is defined by commuting ties, to accurately capture the local labour market.

2.2 Representativeness

We study the representativeness of our dataset. Figure 2 plots the relative share of Burning Glass occupations, at the 2-digit SOC level, versus the 2014-2016 Occupational Employment Statistics. Burning Glass overweights transportation, healthcare, computation, and finance; and underweights construction, education, and food preparation. Where important for robustness, we reweight to target the distribution of employment across 6 digit SOC occupations in the United States, to deal with issues of data representation.

Hershbein and Kahn (2016) document similar patterns in Burning Glass data, and also show that Burning Glass matches industry shares of vacancy posting in the BLS's JOLTS survey well. Moreover, Hershbein and Kahn (2016) show that the representativeness of Burning Glass is stable over time. They compare the Burning Glass occupation shares with the occupation shares for new hires in the CPS. Changes in representativeness for 2007-2015 are small, in their extract of Burning Glass. The accuracy of other popular data sources on online vacancy postings is declining over time (Cajner and Ratner, 2016).

3 Fact 1: Posted Wages Rarely Change Between Vacancies

This section studies how wages change between successive vacancies posted for a given job or establishment. We find that posted wages rarely change—the duration of the typical wage posting spell is 5 quarters. Thus a measure of the new hire wage adjusts infrequently at the job level.

Figure 1 presents the example job, and shows the helpful new feature of our dataset. The job is a claims adjuster working for Progressive Car Insurance in Pasadena, California. We can observe the posted wage across multiple vacancies posted for the job. We can therefore study how a measure of the new hire wage adjusts across successive vacancies.

In the example job, the posted wage changes three times, even as the job creates eleven vacancies over three years. For the job, posted wages change infrequently. We next show that this pattern holds generally—posted wages adjust infrequently at the job level.

3.1 Measuring The Duration of Posted Wage Spells

Now, we study the probability of nominal wage change and the duration of nominal posted wage spells. As before, we define a job as a job-title by establishment by pay category[9] unit. We aim to study wages across successive vacancies for the same job, and so restrict to jobs with multiple wage postings. We take the mean posted wage within each job-quarter. After these

[9]A pay category is a salary type (e.g. base pay or bonus) by work hours (e.g. annual or hourly) cell.

steps, there are roughly 1.6 million observations. Table 5 presents summary statistics for this subsample. There remains a large number of jobs for which we observe repeat postings. These jobs cover 99% of 6-digit SOC occupations in the US economy by employment share, and are well represented in all states. We can reweight at a granular level to target the occupational or geographic distribution of jobs in the US.

Not all jobs post wages in all quarters. Rather, the posted wage is "missing" in some quarters. We cannot directly observe the quarterly probability of posted wage change, nor the duration of posted wage spells. We adapt a standard approach from the price letting literature to overcome this problem. When researchers calculate the frequency with which goods prices change, the regular price is often missing, due to stockouts, sales or substitutions. The standard approach (Nakamura and Steinsson, 2008; Klenow and Kryvtsov, 2008) is to treat the regular goods price as a latent variable, that evolves stochastically when it is unobserved, and treat the observed goods price as draws from the latent process. One then estimates the stochastic process for the latent goods price, and can calculate the probability that goods prices change, even when the price is not always observed.

We adapt this standard procedure to estimate the quarterly probability of posted wage change. We assume that within each occupation, there is a latent posted wage. The hazard rate of the latent posted wage change is constant across time and common across all jobs within 2 digit SOC occupation. We estimate the hazard rate for each occupation and then take the median across occupations. This process infers changes in the latent wage, by treating observed wages as draws from the latent process. If the observed wage does not change between successive vacancies, the latent wage also does not change. If the observed posted wage does change, the latent posted wage also changes. The latent wage can change multiple times if the observed wage changes once, and is more likely to change if the gap between successive vacancies is longer.[10]

We use implied durations to measure the length of posted wage spells, as in the price setting literature. Other simple procedures for calculating duration may be downwards-biased in the presence of censoring (Heckman and Singer, 1984).

One can imagine other plausible procedures for calculating the probability of posted wage change. In practice, we found that other natural alternatives made little difference to our findings.

[10]Formally, let $\{w_{it}\}$ be the sequence of log posted wages for job i and quarter t. Let γ_{it} be the gap in quarters between the posted wage at t and the previous posted wage. Let I_{it} be an indicator for whether the posted wage changed, where $I_{it} = 1$ if $w_{it} \neq w_{i,t-\gamma_{it}}$. The quarterly hazard rate of posted wage change, assumed to be time-invariant, is given by λ, which we estimate by maximum likelihood. The likelihood function is $L = \prod_i \prod_t \left(1 - e^{-\lambda\gamma_{it}}\right)^{I_{it}} \left(e^{-\lambda\gamma_{it}}\right)^{1-I_{it}}$. The probability of a posted wage change for each occupation is $f = 1 - e^{-\lambda}$. The implied duration of a posted wage spell is $d = 1/\lambda$. We take the weighted median across occupations.

3.2 Estimates of Posted Wage Spells

We find that nominal posted wages change infrequently, leading to long posted wage setting spells. Table 6 reports the results. Across all columns, the probability of wage change is similar, and low—the corresponding implied durations are around 5 quarters. Column (1) estimates the quarterly probability of posted wage change according to our method. Column (2) reweights vacancies at a granular level, to target the distribution of jobs from the OES, the nationally representative establishment survey of occupational employment. Column (3) reweights to target the regional distribution of jobs from the QCEW. Column (4) drops jobs from the bottom quartile of the wage distribution. Minimum wages might be driving the infrequent changes. Column (4) dismisses this concern, by showing infrequent changes across the top of the wage distribution. Results are similar in all cases, confirming that posted wages change infrequently. Table 7 documents the same statistics at annual frequency. The results are similar, again showing infrequent changes.

3.3 Comparing Posted and Incumbent Wage Spells

We now compare our finding to incumbent wage spells. Our estimated posted wage spells are similar to prior estimates for incumbents. Figure 6 presents a range of estimates of the duration of incumbent wage spells, from survey data. The estimated duration of Barattieri et al. (2014), which correct for measurement error in reported wages, is close to ours.[11] Previous work, especially Gertler and Trigari (2009), conjectured that new hire and incumbent wages were similarly rigid—we provide evidence in support. The wage for new hires may be especially important for unemployment fluctuations. Indeed, in the model of Gertler and Trigari (2009), infrequent adjustment in the new hire wage leads to large unemployment fluctuations.

Survey datasets of new hire wages, used in prior work, cannot study the frequency of new hire wage adjustment. Surveys typically track workers and not jobs. Workers are hired into job only once. Therefore survey datasets cannot track the new hire wage across multiple hires into the same job or establishment over time. We can track the posted wage for the same job across multiple vacancies, letting us document infrequent adjustment in a measure of the new hire wage.

[11] Other estimates do not correct for measurement error, which biases the estimated probability of wage change upwards.

4 Fact 2: Posted Wages Are Weakly Procyclical

This section finds that posted wages are weakly procyclical. Our estimates imply wage rigidity for new hires. We highlight a key threat from cyclical changes in job composition. Using our job-level wage data, we hold composition constant by focussing on within-job wage variation. We estimate posted wage cyclicality by regressing posted wages on quarterly state level unemployment. Our dataset allows precise estimates, and we reject meaningful cyclicality.

4.1 Cyclical Changes in Composition and Wage Rigidity

Before outlining our benchmark regression, we explain a key threat—cyclical changes in job composition—and how we plan to surmount it.[12] Consider an economy where wages are rigid for all jobs. An unemployed worker can get hired as a barista during a recession, but as a banker during a boom. Though wages are rigid within each job, the overall wage for the newly hired worker is procyclical. Thus overall wage cyclicality does not imply flexible wages at the job level. It is job-level wage rigidity that determines firms' incentives to hire new workers into the job. More generally, overall variation in the wage for new hires pools two sources of variation—within job wage rigidity and changes in composition between jobs. If high wage vacancy creation is relatively procyclical, overall wages will be procyclical even if job level wages are rigid.

Our dataset is well suited to controlling for cyclical changes in composition. We observe a measure of the wage for new hires across successive vacancies within the same job or establishment. We can study wage cyclicality within jobs and establishments, disentangling job level rigidity from changes in composition.

4.2 Using Regional Unemployment Variation

In our benchmark regression, we study wage cyclicality in regional labour markets. By studying regional data, we surmount the relatively short time series in our data.

State level unemployment is measured with noise due to small surveys. We project unemployment onto an administrative measure of employment, from the QCEW.[13] We then avoid attenuation bias from noisy measures of unemployment.

States are a natural definition of a regional labour market. Since 2010, interstate migration has been relatively low, and mostly unrelated to cyclical considerations (Yagan, 2016; Beraja et al., 2016). Moreover there is substantial regional business cycle variation during this period.

[12] (Gertler and Trigari, 2009) and Hagedorn and Manovskii (2013) also highlight this difficulty.

[13] This step is equivalent to instrumenting for state level unemployment with log employment, to deal with measurement error.

Various states (e.g. the District of Columbia and New York) saw rising unemployment during 2010-2012 due to the prolonged impact of the Great Recession. Other states saw rising unemployment due to the faltering labour market recovery in 2013 (e.g. Illinois, Oklahoma, Massachusetts and Ohio). A third group of states suffered in 2015-6 due to falling oil prices (e.g. North Dakota, Texas, Wyoming, New Mexico, Alaska and Oklahoma). In section 6, we use a model to understand the aggregate implications of our regional estimates.

4.3 Our Specification

Our benchmark regression for measuring posted wage cyclicality is

$$\Delta \log w_{jst} = \alpha + \text{controls}_{jst} + \beta \Delta U_{st} + \varepsilon_{jst}. \tag{1}$$

β is a measure of new hire wage cyclicality, coming from posted wages. A more negative number indicates greater cyclicality. w_{jst} is the nominal posted wage in job j in quarter t. U_{st} is the change in quarterly state level unemployment. Posted wages are differenced at the job level. We project ΔU_{st} onto $\Delta \log(\text{Employment}_{st})$, which is state-quarter employment growth from the QCEW—thereby avoiding bias from measurement error.[14] This regression uses our dataset to focus on within job variation, thereby eliminating the confounding effect of job composition. By running the regression in first differences, we avoid issues of nonstationarity or a persistent error process.

In our benchmark regression, we study nominal wages. However, we add time fixed effects, which sweep away variation in the national price level. Therefore our results also measure real wage rigidity, when real wages deflated by national prices. In Section 6, we show that this measure of the real wage is relevant for standard labour search models.

For comparison, consider the canonical regression for estimating new hire wage cyclicality, as in e.g. Bils (1985). The regression is

$$\Delta \log w_{ht} = \alpha + \beta \Delta U_t + \text{controls}_{ht} + \varepsilon_{ht}$$

Then w_{ht} is the new hire wage in household h, measured from survey data. Therefore $\Delta \log w_{ht}$ is the growth in the wage for a worker who *switches jobs* between the previous and the current quarter, and the new hire wage is the wage for job switchers.[15] U_t is quarterly unemployment measured at the national level. In this regression, wages are differenced at the *household* level.

[14] Table 8 reports the first stage regression projecting quarterly state unemployment changes onto employment growth. As expected, the two series are closely correlated.

[15] In notable exceptions, Haefke et al. (2013) and Gertler et al. (2016) develop methods to study new hire wages for workers entering jobs from unemployment.

There are two key differences between our regression (1) and the standard regression. First, our regression differences a measure of new hire wages at the job level, thereby holding constant job composition. Standard regressions study new hire wages at the household level. The job into which the household is newly hired may depend on the business cycle. Hence the standard regression pools two sources of variation: wage cyclicality in the new job, and cyclical variation in the composition of jobs. Therefore the standard regression conflates within-job wage rigidity—the relevant variation for firms' hiring incentives—with composition. Our approach hones in on job-level wage rigidity, and avoids this concern.

In a second difference versus the standard approach, our regression harnesses state-quarter variation. In Section 6, we use a model to relate our estimates to past aggregate estimates.

4.4 Estimates of Posted Wage Cyclicality

Table 9 presents estimates of regression (1). Across all specifications, posted wage cyclicality is low—our measure of new hire wages comoves weakly with regional business cycles. In our main specification, after a percentage point quarterly fall in regional unemployment, wages within a typical job grow by only 0.2%. Posted wages are procyclical, but the degree of procyclicality is small. In column (1), we run regression (1), with time fixed effects. In column (2), we add a state specific trend. In column (3) we reweight to target the occupation distribution from the 2014-2016 Occupational Employment Statistics, the nationally representative establishment survey.[16] In column (4) we reweight to target the regional distribution of jobs from the 2010-2016 QCEW. Across all specifications, estimated posted wage cyclicality is similar and low. Annual estimates of wage cyclicality, in Table 10, are higher, but are still relatively low. In unreported estimates, we find that posted wages are similarly procyclical with other definitions of the local labour market, such as Metropolitan or Combined Statistical Areas. Overall, the infrequent changes documented in section 3 mean a measure of new hire wages are weakly procyclical.

In Table 11, we project annual unemployment changes on a measure of labour demand growth measured as in Bartik (1991).[17] The estimates are similar to those of Table 10. This step isolates cyclical fluctuations in wages and unemployment arising from labour demand shocks. One might worry that regional business cycle variation is partly driven by labour supply shocks during 2010-2016, which would complicate the interpretation of our estimates. However, con-

[16] One might worry that occupations with high turnover are over-represented in our dataset relative to the distribution of jobs, which could bias the estimates. By reweighting to the national occupation distribution and showing similar results, we overcome this concern.

[17] Table 12 reports the first stage regression of unemployment changes on the growth in Bartik-predicted labour demand. The first stage is strong only at annual frequency. It is weaker than the first stage regression in which we simply project unemployment changes on employment growth, which is our baseline specification.

ditional cyclicality with respect to labour demand is similar to the estimate of unconditional cyclicality. Distinguishing between labour demand and supply shocks does not seem to be important for our analysis.

Posted wages are weakly procyclical across *all* jobs for which an establishment hires. We rerun regression equation (1), but now average wages by establishment-quarter, instead of by job-quarter. Table 13 reports the results. As within jobs, establishment-level posted wages are weakly procyclical. After a percentage point fall in quarterly state level unemployment, posted wages rise by 0.35%. Again, the benchmark figure is robust to reweighting to target the regional distribution of jobs in the US economy, or adding state specific trends. Thus establishment level posted wages are weakly procyclical.

Roughly half of the wages in our dataset post a range of wages, instead of a point wage. In the previous regressions, we take the mean value of the range, for jobs that post a range of wages. In Appendix Section C, we explore various robustness tests to this assumption, and find that our substantive conclusion is unaltered—posted wages are weakly procyclical regardless of how one treats jobs posting a range of wages.

4.5 Giving Context To Our Estimates

We find weak cyclicality in a measure of the new hire wage. In section 6, a model shows that our estimate of new hire wage cyclicality leads to large hiring fluctuations. The model also interprets the aggregate implications of our regional cyclicality estimates.

Here, we compare our estimates with past estimates on time series data. Our estimates are lower than previous. Our cyclicality estimate is regional and previous estimates are aggregate. The previous literature estimates new hire wages from household-level survey data, which may partly reflect cyclical changes in job composition. Nevertheless the raw comparison is helpful. Figure 7 and Table 14 compare our estimate of new hire wage rigidity with six leading estimates of new hire wage cyclicality from time series data.

Our estimate is lower all of the time series estimates. This low estimate suggests substantial new hire wage rigidity. Of course, the comparison is not exact, since previous estimates are from the aggregate quarterly time series, and ours are from a state-quarter panel. However, the model in section 6 confirms that we measure weakly procyclical wages.

Figure 7 highlights a second benefit of our dataset. Our estimates are precise. Our standard errors are clustered by state, and so are robust to arbitrary residual correlation within each state.[18] Given large standard errors, previous work may not be able to reject strong or weak

[18] Abadie, Athey, Imbens, and Wooldridge (2017) emphasise that standard errors should be clustered across units assigned the same treatment. In time series regressions of wage cyclicality, standard errors should at least be clustered within each time period as in the specification of Hagedorn and Manovskii (2013), or the wage data

cyclicality, contributing to the differing views. We obtain precision for four reasons. First, we harness extra variation from regional business cycles. Second, we only study within-job or -establishment variation, which eliminates extraneous variation in wages. Third, our dataset is large. The CPS, the largest survey dataset with quarterly new hire wage information, has 2000-3000 new hires per quarter—our dataset has close to 1 million wage postings in each quarter. Fourth, our posted wages are measured precisely, avoiding the recall error that plagues survey data on wages.

Why do we estimate lower cyclicality than previous papers? Posted wages track other quarterly measures of the new hire wage during 2010-2016, as in Figure 3 and Table 1. Measurement is unlikely to explain the difference between our results and previous.

Cyclical changes in composition cannot explain the difference between our estimates and previous. Table 15 studies regional new hire wage cyclicality for job switchers, using regional CPS survey data on new hire wages. Since these regressions study wage cyclicality for workers switching jobs, the composition of jobs into which workers are hired can potentially change with the business cycle. The estimates are noisy, given the small sample sizes in survey data\. However the CPS survey data does not suggest greater wage cyclicality. Therefore composition cannot reconcile our results with previous findings.

Our estimated new hire wage cyclicality is most likely lower than others due to downwards wage rigidity. Suppose that wages are more rigid downwards than upwards. Then during periods of low labour demand, average wage cyclicality will fall. In section 5 we confirm that our measure of new hire wages is more rigid downwards than upwards. The sample period for the posted wages data, from 2010 to 2016, is a period of low labour demand—implying that downwards rigidity should lower average wage cyclicality.

Survey datasets are too noisy to assess with precision whether new hire wages are especially rigid downwards. Nevertheless, Table 16 presents imprecise evidence from survey data in favour of downwards rigidity. New hire wages from the CPS, for 1984-2006, seem more rigid downwards than upwards. We regress growth in the quarterly composition adjusted measure of the new hire wage, from Haefke et al. (2013), on the change on unemployment. We study the response of wages separately for positive and negative changes in unemployment. When unemployment falls, new hire wages seem to rise strongly—and do not seem to fall when unemployment rises.

In section 3, we documented infrequent adjustment in a measure of the new hire wage. In this section, we find that the infrequent adjustment leads to weakly procyclical wages. In some scenarios, infrequent wage changes at the job level could have few aggregate consequences. Suppose that firms optimally time their wage changes, in a state-dependent fashion. Then

should be grouped within the time period as in the specification of Haefke et al. (2013).

infrequent changes might generate minimal overall wage rigidity (Caplin and Spulber, 1987; Golosov and Lucas Jr, 2007). By studying wage cyclicality directly, we link wage rigidity to infrequent wage adjustments.

5 Fact 3: Posted Wages Are Especially Rigid Downwards

This section shows our measure of new hire wages is more rigid downwards than upwards. We present an array of evidence. First, posted wages are much more likely to rise than to fall across successive vacancies. Second, the probability of posted wage increase is procyclical, while the probability of wage decrease is acyclical. Third, unemployment and posted wages comove asymmetrically. When unemployment rises, posted wages do not fall—though wages rise as unemployment falls.

Each finding suggests a constraint on cutting posted wages between successive vacancies. We document, to our knowledge for the first time, that a measure of new hire wages is more rigid downwards than upwards. It is well known that incumbent wages are rigid downwards, but wage rigidity for new hires may be more important unemployment fluctuations. We confirm in Section 6 that our estimated downwards rigidity for new hires implies asymmetric unemployment fluctuations.

5.1 The Probability of Posted Wage Increase Is Higher Than The Probability of Decrease

Posted wages are more likely to rise than to fall. This finding is consistent with a constraint on cutting new hire wages, i.e. downwards rigidity. The unique features of our dataset—where we observe wages on successive vacancies posted for the same job—let us document this new finding.

Figure 8 plots the distribution of nonzero wage growth. There are two clear points. First, posted wages rise more often than they fall. Secondly, posted wages "pile up" against the constraint—there are many small positive wage increases, but far fewer small wage decreases. Both points suggest downwards rigidity for wages on new vacancies for a given job. We take the distribution of posted wage growth between two consecutive vacancies posted for the same job, and then exclude observations with zero wage growth. As before, we average wages within each job-quarter, meaning wage growth is quarterly. However, not all jobs post in consecutive quarters. We truncate the plot at $\pm 10\%$ wage growth.

Next, in Figure 9 we plot the distribution of non-zero wage growth separately for states with rapid and gradual falls in unemployment for 2010-2016. In the states with gradual falls in unemployment, the distribution of wage changes "bunches up" against the zero constraint. In the states with rapid falls in unemployment, and so a tightening labour market, the distribution of wage increase is more spread out. Nevertheless in states with either rapid or gradual falls, the probability of wage rises is much larger than wage falls. Again, the plot suggests a constraint on cutting a measure of new hire wages within a job. In states with a tightening labour market, the constraint at zero is binding for a smaller proportion of jobs.

We next calculate the probability of posted wage increases and decreases. The results are in Table 17. As expected, the probability of wage increase is much higher than the probability of posted wage decrease. As mentioned in Section 3, not all jobs posted wages in all quarters. One cannot directly observe the quarterly probability of posted wage change for all jobs. We adapt the procedure of Section 3, to estimate the probability quarterly of posted wage increase and decrease separately. In Section 3, we used a hazard model to estimate the probability of wage change. In this exercise, we apply the same hazard model to separately estimate the probability of wage increase and decrease. Posted wages are more likely to rise than to fall. Table 17 shows that the finding is robust across several specifications, including after reweighting to target the occupational or regional distribution of jobs, or excluding low wage jobs—in order to strip out the effect of minimum wages. Table 18 repeats the analysis at annual frequency, with similar results. This evidence is the first, to our knowledge, showing that a measure of the new hire wage rarely falls between successive vacancies. Other datasets, from surveys, track workers and not jobs, and cannot detect how wages change between successive hires or vacancies.

5.2 The Probability of Wage Increase Is Procyclical, Decrease Is Acyclical

The probability of wage increase is sensitive to labour market slack, the probability of wage decrease is not. Again, this finding suggests a constraint on cutting wages between vacancies. Firms let wages respond to cyclical conditions by varying whether wages increase—while rarely lowering wages irrespective of labour market tightness.

Table 19 shows that the probability of increase is more cyclical than the probability of decrease. We calculate the probability of wage increase and decrease within each state-quarter[19]. We regress the probabilities on the change in unemployment for each state-quarter, projecting unemployment on employment growth as before. When unemployment falls rapidly, wages should grow faster. Table 19 shows that wages adjust mainly through increases, and not decreases, given the constraint on cutting wages. The results are robust to reweighting to target

[19]For this exercise, we do not estimate the probability of wage increase and decrease using a hazard model. Instead, we calculate the probability of wage increase (decrease) as the share of vacancies for which the wage increases (decreases), in a given quarter. This procedure avoids estimating a hazard model on relatively small sample sizes within state-quarters, which might be inconsistent.

the regional distribution of jobs, or calculating the analogous measures at annual frequency, as in Table 20.

5.3 Posted Wages Comove Asymmetrically With Unemployment

Wage cyclicality displays an asymmetric pattern. When unemployment rises, posted wages do not fall—though wages do rise as unemployment falls. Meanwhile posted wages become progressively more cyclical as regional labour markets tighten during 2010-2016. These findings again imply downwards wage rigidity.

Table 21 regresses posted wage growth on state level unemployment changes. Wages are much more sensitive to unemployment falls than unemployment rises. The wage cyclicality regression is similar to Section 4, on the state-quarter panel. We regress quarterly wage growth, differenced by job, on the change in unemployment, differenced by state, and project unemployment changes on employment growth from the QCEW. However, we do this regression separately for positive and negative unemployment changes. In the table, wages are much less cyclical with respect to increases in unemployment. The difference is statistically significant in the benchmark specification, and economically large. The results confirm that wages are less rigid upwards than downwards. The results are robust across several specificaitons, including reweighting to target the regional or occupational distribution of jobs, or adding in state-specific trends.

Table 21 also reports a quadratic specification, and finds similar nonlinearities. We regress posted wage growth, differenced by job, on the change in unemployment, and also the unemployment change squared. The squared coefficient is significant and positive. Again, posted wages are more sensitive to falls in unemployment than to increases. Again, the result is robust to reweighting to the occupational or regional job distribution, or adding in state-specific trends.

The size of this asymmetry is large. Consider the top specification in column (1) of Table 21. Posted wages are completely insensitive to rises in unemployment, though wages rise as unemployment falls. In Section 6, a model confirms that unemployment responds much more to contractionary labour demand shocks due to downwards wage rigidity. Though previous work also argues for important effects from downwards wage rigidity, it appeals to evidence from incumbent workers. We find downwards wage rigidity for new hires, which may be most relevant for unemployment fluctuations.

Our dataset lets us document the new fact. Given the large dataset of well measured wages, we are able to precisely estimate nonlinearities—which eludes noisier data from surveys.[20]

[20]Table 16 attempts to uncover downwards wage rigidity for new hires using survey data. Table 16 regresses the

Downwards wage rigidity for new hires implies that wages became progressively more flexible during 2010-2016, as regional labour markets tightened. We confirm this prediction. In a tighter labour market, a greater share of wage changes should be increases, to which downwards rigidity considerations need not apply. Thus overall wage flexibility should increase as labour markets tighten. We repeat the wage cyclicality regression from Section 4. That is, we regress quarterly wage growth, differenced by job, on the change in unemployment, differenced by state, and project unemployment changes on employment growth from the QCEW. We estimate cyclicality coefficients separately for every year, by interacting quarterly state level unemployment with year dummies.

Figure 10 and Table 22 report the results. During the early part of the sample period, posted wages are insensitive to unemployment. Labour markets are slack and downwards constraints presumably bind for a greater share of jobs, reducing wage flexibility. At the end of the sample period, posted wages become more sensitive to unemployment. Labour markets are slack, suggesting downwards constraints on wage setting matter less, again consistent with downwards rigidity. Our finding is robust across several specifications, e.g. with state-specific trends, or reweighting to the occupational or regional distribution. This rich variation underscores the benefit of our dataset. We can precisely estimate wage cyclicality regressions on a state-quarter panel, separately for every year in our panel.

A common conjecture (Gertler and Trigari, 2009; Chodorow-Reich and Wieland, 2017) supposes that new hire wages inherit the properties of incumbent wages, including their downwards rigidity. One motivation is internal equity, which implies similar rigidity of new hire and incumbent wages (Bewley, 2002). Other forces may cause the rigidity of new hires and incumbents to differ. Implicit contracting models predict that incumbent wages should be rigid downwards, while new hire wages are flexible (Harris and Holmstrom, 1982; Beaudry and DiNardo, 1991).[21] We provide new evidence that new hire and incumbent wages are similarly rigid, in line with the conjecture.

growth in the new hire wage on changes in unemployment, separately for positive and negative changes. The new hire wage measure is from Haefke et al. (2013), quarterly for 1984-2006 and composition-adjusted, from the CPS. In this regression, the new hire wage appears to be more sensitive to unemployment falls than to unemployment increases, consistent with downwards rigidity. However, the results are prohibitively noisy, underscoring the importance of our precise estimates.

[21]Within jobs, risk neutral firms insure risk averse workers, by offering them downwards rigid contracts. The wage for new hires, as firms and workers enter a new implicit contract, is not constrained by the insurance motive. Beaudry and DiNardo (1991) present evidence that incumbents have more rigid wages than new hires, though their interpretation of the data is disputed (Hagedorn and Manovskii, 2013).

6 Model: Estimated Rigidity Implies Large And Asymmetric Hiring Fluctuations

This section turns to a standard Diamond-Mortensen-Pissarides model, to understand the quantitative importance of our estimated wage rigidity and compare it to previous findings. We derive a simple formula linking new hire wage rigidity to fluctuations in unemployment. The formula affirms the canonical importance of the new hire wage. We calibrate to our estimate of wage rigidity. Large and asymmetric unemployment fluctuations result—as expected, given our estimate of weakly procyclical wages for new hires. Previous papers calibrate to incumbent wage rigidity, whereas we calibrate to a measure of new hire rigidity, the more relevant measure. Our model underscores the main takeaway of the paper: new hire wages are rigid, especially downwards.

6.1 Model Overview

The model is in discrete time. Workers and firms engage in search and matching, in a standard frictional labour market. Firms create vacancies V_t, and there are U_t unemployed workers searching for jobs in each period. Each vacancy costs γ to create, and there is free entry in vacancy creation. Unemployed workers match with vacancies, to initiate jobs. The number of matches is $m_t = AU_t^{\alpha} V_t^{1-\alpha}$. $\theta_t \equiv V_t / U_t$ is market tightness, the ratio of vacancies to unemployment. Unemployed workers each find jobs with probability $f(\theta_t) = \frac{m_t}{U_t} = A\theta_t^{1-\alpha}$. Each vacancy is filled with probability $q(\theta_t) = \frac{m_t}{V_t} = A\theta_t^{-\alpha}$.

Firms are risk neutral, and discount profits with discount factor β. In period $t+j$, a job that starts in period t produces output $y_{t,t+j}$. A job that starts in period t pays wage w_t to the worker every period, throughout the match. Each job ends with exogenous probability s in every period. y_t measures labour demand, and is the cyclical indicator in this model. In this model, y_t is labour productivity—i.e. output per worker.[22] We assume that y_t is a random walk.

We have presented a standard DMP model, which we will use to understand the quantitative importance of our estimated wage rigidity. Importantly, we do not impose any particular process for wage determination. Wages could be determined by Nash bargaining (Shimer, 2005; Hagedorn and Manovskii, 2008), wage norms (Hall, 2005), alternate offer bargaining (Hall and Milgrom, 2008), or wage posting (Moen, 1997; Chodorow-Reich and Karabarbounis, 2016). For our purposes, the precise details of the wage determination process are of secondary importance.

[22] In this model, labour demand shocks come from productivity shocks. Realistic extensions of the basic DMP model include nominal rigidities, allowing aggregate demand shocks to also affect labour demand (e.g. Gertler, Sala, and Trigari, 2008; Blanchard and Gali, 2010; Christiano, Eichenbaum, and Trabandt, 2016).

w_t is the wage for *new hires*. It is the wage paid to a new hire made in period t, during every period of the match. The wage paid to the worker is then constant throughout the match, so that incumbent wages are perfectly rigid—though new hire wages can be flexible.

For simplicity, we made two assumptions. Firstly, labour demand y_t is a random walk. Secondly, wages are constant throughout the match. These assumptions are standard, and generate a simple formula mapping from wage rigidity to unemployment fluctuations. Shimer (2005) shows that these assumptions closely approximate a more general economy with autoregressive labour demand shocks, and wages which can change over the match. Since wages are constant throughout the match, we are assuming that incumbent wages are completely rigid. Given the large rigidity documented for incumbent wages, this assumption is sensible.

In Appendix Section D.1, we extend the model to autoregressive labour demand and wages which vary during the match. We also extend the model to account for fixed costs of matching, as in Pissarides (2009). The quantitative results are unchanged in either case.

6.2 Formula: From New Hire Wage Rigidity to Tightness Fluctuations

We next derive a formula that links the wage rigidity for new hires to fluctuations in labour market tightness. Labour market tightness fluctuations determine unemployment fluctuations in DMP models. We plug our estimated wage rigidity into this formula. We can then understand whether our estimated wage rigidity generates large unemployment fluctuations.

We have:

$$\frac{d\log\theta_t}{d\log y_t} = \frac{1}{\alpha}\left(1 - \frac{dw_t}{dy_t}\right)\frac{y_t}{y_t - w_t}. \tag{2}$$

The middle term in equation (2) captures new hire wage rigidity. Ljungqvist and Sargent (2017) derive a similar formula.

w_t is the new hire wage. When new hire wages are flexible, so $\frac{dw_t}{dy_t}$ is close to 1, fluctuations in labour demand lead to small fluctuations in tightness and unemployment, so that $\frac{d\log\theta_t}{d\log y_t}$ is small. When new hire wages are rigid, $\frac{dw_t}{dy_t}$ is low and $\frac{d\log\theta_t}{d\log y_t}$ is large.

In this formula, it is *new hire* wage rigidity that affects unemployment fluctuations. Incumbent wages are fixed throughout the match, and so completely rigid. However, if new hire wages are flexible, than unemployment fluctuations are small. As emphasised by Pissarides (2009), incumbent wage rigidity has limited allocative implications. It is the present value of wage payments that matters for firms and workers. Since wages do not change within matches, the present value of wages comoves with the wage for new hires.

The first term in equation (2) relates to the matching function parameter α. It mediates how firm level hiring decisions translate into market tightness. The third term is the inverse of firms' profit share on matches. A small profit share also raises the sensitivity of tightness to labour demand. When profits are small, they are also elastic. Profits become sensitive to labour demand, meaning that firms' incentives to hire are also cyclically sensitive (Hagedorn and Manovskii, 2008; Ljungqvist and Sargent, 2017). When we calibrate formula (2), we choose a low value for the inverse profit share—thereby isolating the role of wage rigidity for hiring fluctuations.

The model does not impose any particular wage posting or bargaining process. Rather, we will calibrate equation (2) using our estimates of wage rigidity.

6.3 Calibrating New Hire Wage Rigidity Using Regional Data

The next step is to calibrate formula (2), using an estimate of $\frac{dw_t}{dy_t}$. Then we can understand the impact of our estimated new hire wage rigidity for hiring fluctuations. Our estimates of wage cyclicality come from state level data. We adapt previous methods to derive a value of $\frac{dw_t}{dy_t}$ from our state level estimates.

The standard method proxies for labour demand y_t using labour productivity (e.g. Gertler and Trigari, 2009; Pissarides, 2009; Chodorow-Reich and Karabarbounis, 2016).[23] We follow the standard method. Labour productivity is GDP per worker, or a close equivalent. One obtains $\frac{dw_t}{dy_t}$ from a time series regression of new hire wages on a measure of labour productivity.

We adapt the standard procedure to regional data. We previously obtained $\frac{dw_t}{dU_t}$ from a quarterly panel of state level data, in Section 4. We use state level labour productivity as a proxy for regional labour demand y_t. We uncover an estimate of $\frac{dy_t}{dU_t}$ from state level data. We use quarterly state level employment from the QCEW, and quarterly state GDP from the BEA, to construct a measure of quarterly state level labour productivity. We regress our measure of labour productivity on unemployment to obtain $\frac{dy_t}{dU_t}$. Table 23 reports the results. Given our estimates of $\frac{dw_t}{dU_t}$ and $\frac{dy_t}{dU_t}$, we can immediately obtain an estimate $\frac{dw_t}{dy_t}$, to plug into equation (2). We find $\frac{dw_t}{dy_t} = 0.32$ on quarterly data. The equivalent calculation for annual data is similar.

In Appendix Section D.2, we show that this calibration strategy remains correct after we embed the standard DMP mechanism in a monetary union model. Hence our calibration strategy lets us understand the implications of our regional wage cyclicality estimates for aggregate unemployment fluctuations. In sections 4 and 5, we study nominal wages. Since we use aggregate time effects in our regressions, we also estimate real wage cyclicality, where the real wage is deflated by national prices. Appendix Section D.2 confirms that this is the correct measure of real wage cyclicality.

We calibrate the other variables in formula (2). The consensus value of α, the matching parameter, is 0.5 (Petrongolo and Pissarides, 2001; Şahin, Song, Topa, and Violante, 2014). For-

[23] In general, labour demand shocks also arise due to aggregate demand and nominal rigidities. The standard approach ignores these shocks, though they may be important for unemployment fluctuations.

mula (2) shows that labour market tightness, and hence unemployment, is more sensitive to labour demand when the inverse profit share is high. To isolate the role of wage rigidity, we conservatively calibrate a large value of the profit share. We use the upper bound on the profit share from Karabarbounis and Neiman (2018), setting $\frac{y_t - w_t}{y_t} = 0.2$.[24]

6.4 Estimated New Hire Wage Rigidity Implies Large Unemployment Fluctuations

When we calibrate formula (2), we find $\frac{d\log\theta_t}{d\log y_t} = 6.3$. Wage rigidity implies large fluctuations in labour market tightness. For context, the sensitivity of labour market tightness to labour productivity in the time series is $\frac{d\log\theta_t}{d\log y_t} = 7.6$. Therefore the sensitivity of tightness to labour demand, given our estimated wage rigidity, accounts for the fluctuations in the time series data. Wage rigidity can generate substantial market tightness fluctuations, and provides a solution to the unemployment volatility puzzle first documented in Shimer (2005).

In matching models, fluctuations in labour market tightness determine fluctuations in unemployment. Thus our estimated wage rigidity implies large fluctuations in unemployment. In the standard DMP model we have $\frac{d\log u}{d\log\theta} = -(1-\alpha)(1-u)$. Thus log unemployment and log tightness are proportionate.[25]

Hall (2005), Hagedorn and Manovskii (2008), Hall and Milgrom (2008) and Gertler and Trigari (2009) invoke wage rigidity to rationalise the high sensitivity of tightness to labour demand documented in Shimer (2005). Our exercise confirms that wage rigidity generates large unemployment fluctuations. Hagedorn and Manovskii (2008) and Gertler and Trigari (2009) calibrate to an estimate of incumbent wage rigidity, whereas we calibrate to new hire wage rigidity. The similar findings emphasise the main message of the paper: that new hire wages are rigid.

6.5 Estimated Downwards Wage Rigidity Implies Asymmetric Unemployment Fluctuations

Finally we provide a simple calculation to quantify the effects of our estimated downwards wage rigidity on the asymmetry of unemployment fluctuations. We find that labour market tightness—and hence unemployment—is roughly twice as sensitive to negative labour demand shocks than positive labour demand shocks of equal size.

[24] As in Pissarides (2000), we deduct payments to capital before calculating labour productivity and the profit share.

[25] Ths formula holds exactly at the steady state. However Shimer (2005) shows that in the basic DMP model, steady state elasticities closely approximate model elasticities outside the steady state, since transitional dynamics are limited.

We calibrate formula (2), using our estimates of asymmetric wage cyclicality from section 5. In section 5, we estimated $\frac{dw_t}{dU_t}^{+} = 0.124$ and $\frac{dw_t}{dU_t}^{-} = -0.408$. We leave all other parameters in the calibration unchanged. When we plug the estimated asymmetry of wage cyclicality into formula (2), we find $\frac{d\log\theta_t}{d\log y_t}^{+} = 3.5$ and $\frac{d\log\theta_t}{d\log y_t}^{-} = 7.7$

In this simple calculation, log labour market tightness is twice as sensitive to a negative labour demand shock than a positive labour demand shock of the same size. Log unemployment and log tightness are roughly proportionate. Therefore unemployment is also roughly twice as sensitive to negative than positive labour demand shocks of the same size. Unemployment responds asymmetrically to labour demand—implying quantitatively important effects from downwards wage rigidity.

Previous papers emphasise asymmetric fluctuations in unemployment due to downwards wage rigidity (Chodorow-Reich and Wieland, 2017). In the DMP model, the wage for new hires is crucial. We support previous arguments by showing that the degree of asymmetry in unemployment fluctuations is substantial, when calibrated to a measure of downwards rigidity for new hires.

7 Conclusion

We present new evidence that the nominal new hire wage is rigid, and especially rigid downwards. First, we introduce a new dataset of posted wages. We then present three new facts about posted wages to support the overall finding of downwards wage rigidity for new hires.

Our dataset contains establishment level posted wages with job titles and hours, covering 10% of total US vacancies since 2010. Posted wages closely comove with measures of the new hire wage from survey data. We can track this measure of the new hire wage across successive vacancies posted by the same job or establishment. Our data has wide coverage and contains precise measures of posted wages with hours worked, and bonus or overtime pay where applicable.

In our first new fact, nominal posted wages rarely change between successive vacancies posted for the same job. A measure of the new hire wage therefore adjusts infrequently. For the typical job, posted wages remain unchanged for 5 quarters, across multiple vacancies.

In our second new fact, posted wages are weakly procyclical. We study the comovement of posted wages and regional unemployment in a state-quarter panel. Posted wages comove little with regional unemployment, implying wage rigidity for new hires.

In our third new fact, nominal posted wages are more rigid downwards than upwards. We present several pieces of evidence. First, the probability of a posted wage decrease is much lower than the probability of increase between successive vacancies. Second, the probability of a posted wage increase is strongly procyclical; the probability of a posted wage decrease is acyclical. Third, the comovement between posted wages and unemployment is asymmetric—when unemployment falls, posted wages rise; when unemployment rises, posted wages do *not* fall. Collectively, this evidence implies that new hire wages are more rigid downwards than upwards.

Finally, we turn to a standard Diamond-Mortensen-Pissarides model to understand the quantitative importance of our results. We plug in our estimate of new hire wage rigidity, and find that large and asymmetric unemployment fluctuations result. The model confirms the canonical importance of new hire wage rigidity, and the secondary role of incumbent wages.

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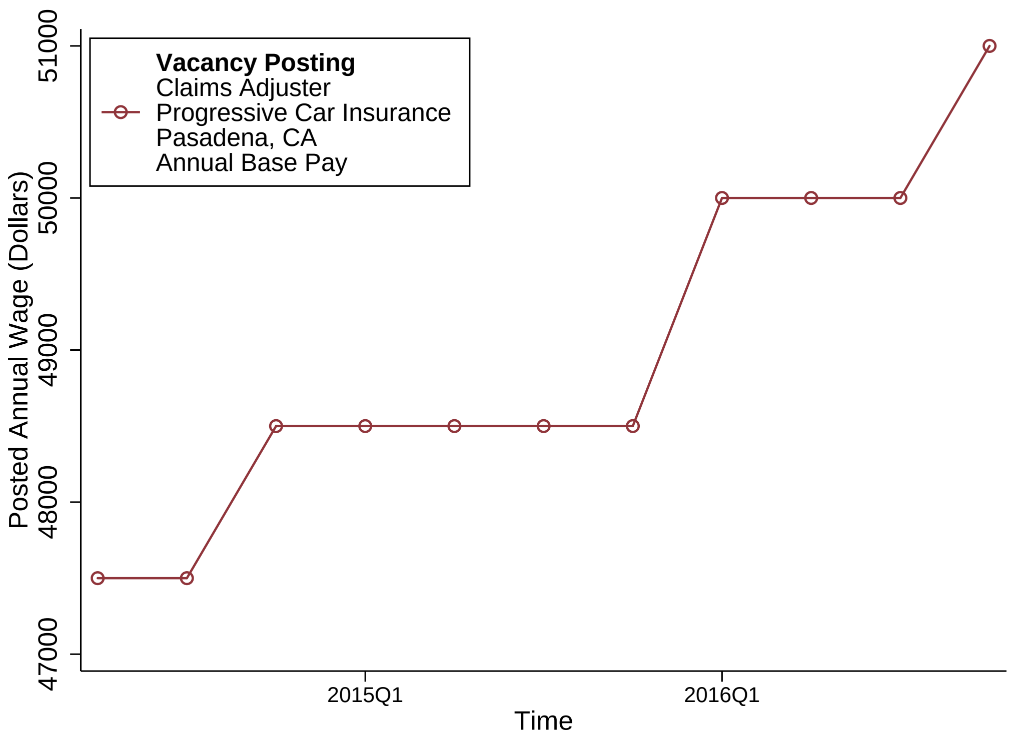
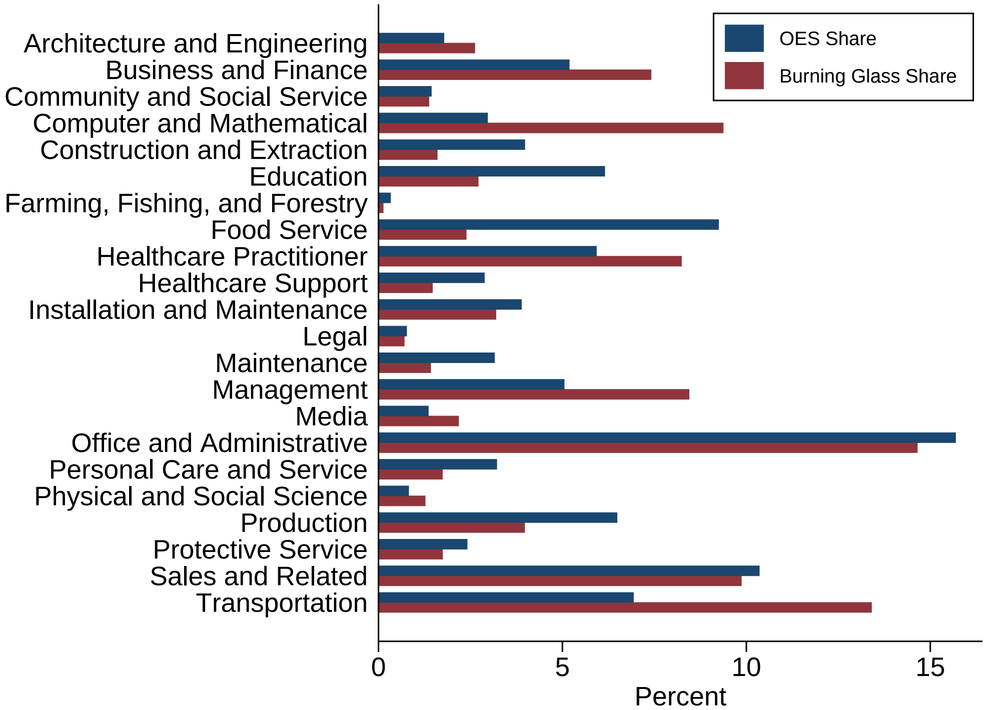
A Figures

Figure 1: Job Vacancy Posting—An Example



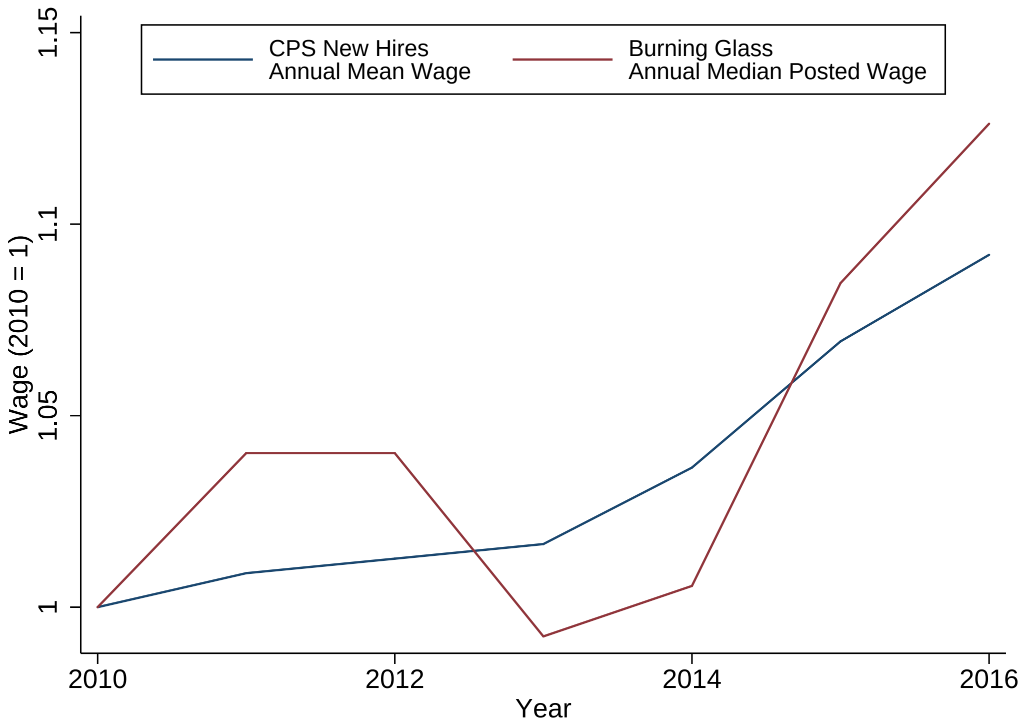
Notes: A job is a job-title by establishment by salary type by pay frequency unit. Claims Adjuster is a job title, for a vacancy posted by an establishment of Progressive Car Insurance, in Pasadena, California, for an annual base pay salary.

Figure 2: Comparison of Employment Shares by Occupation, in Burning Glass and the OES



Notes: In Burning Glass, the data is 2010-2016; in the OES, the data is 2014-2016. In both datasets, the comparison is at the 2 digit SOC level, and excludes military.

Figure 3: Aggregate Wages in CPS New Hires and Burning Glass Since 2010

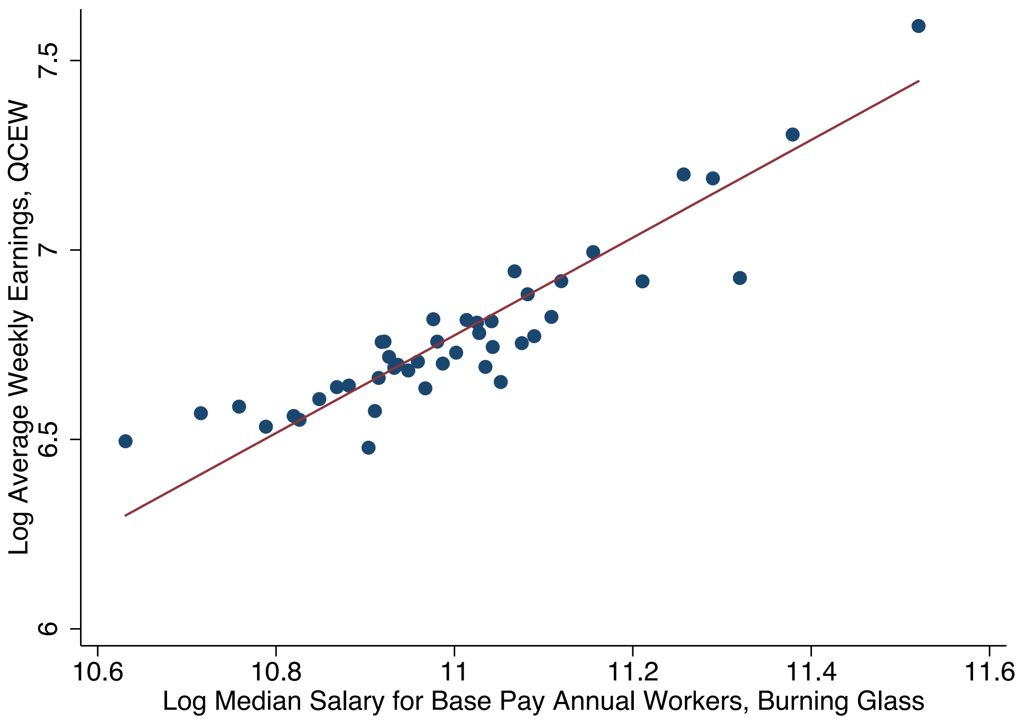


Notes: In Burning Glass, the wage measure is the annual median for hourly base pay workers. In the CPS, the wage measure is annual mean wage for new hires, weighted by the CPS weights. New hire wages in the CPS are taken from the Outgoing Rotation Group wages. New hires are identified by linking workers to their employment status in the previous four months. These series do not adjust for composition.

Figure 4: Burning Glass Salaries Match OES Hourly Wages

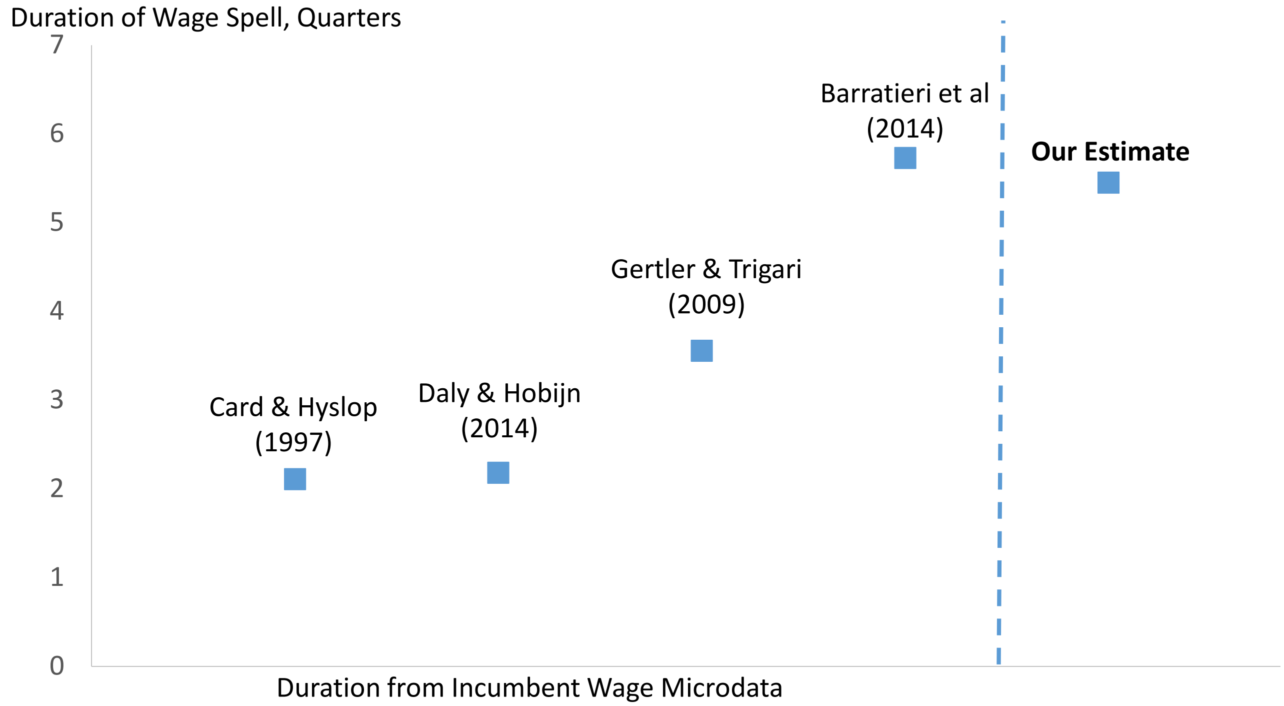
Notes: In both Burning Glass and the OES, the variable is the log of the median salary for hourly base pay workers, by 6-digit SOC cells. Burning Glass data is 2010-2016. The OES data is 2014-2016. The data are binned into percentiles of the regressor, and weighted by employment shares in the OES at the 6-digit level. The regression slope, estimated from the underlying data, is 1.139.

Figure 5: Burning Glass Salaries Match QCEW Weekly Earnings



Notes: In Burning Glass, the variable is the log of the median salary for hourly base pay workers, by CBSA. In the QCEW, the variable is the log of average weekly earnings, by CBSA. Burning Glass and QCEW data are both 2010-2016. The data are binned into percentiles of the regressor, and weighted by employment shares in the QCEW at the CBSA level. The regression slope, estimated from the underlying data, is 1.30.

Figure 6: Comparison of Probability of Posted Wage Change with Incumbent and Time Series Estimates

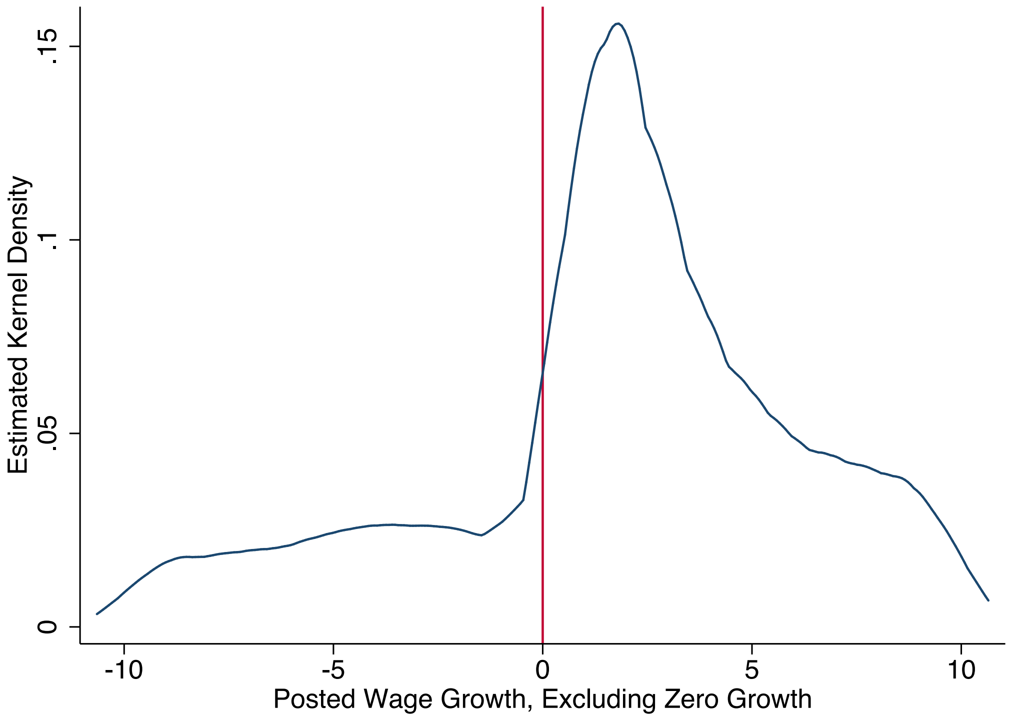


This graph reports the implied duration of wage spells based on microdata. We contrast the implied duration of posted wage spells, with previous estimates of the implied duration of incumbent wage spells from microdata.

Figure 7: Our Estimates of the New Hire Wage Cyclicality Compared With Other US Estimates

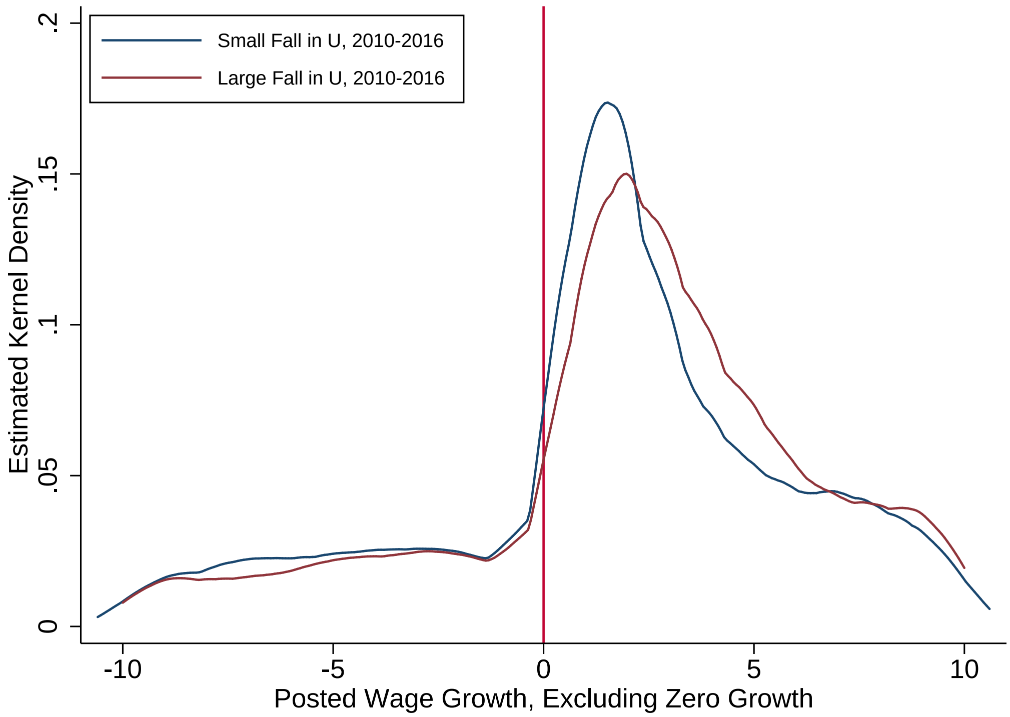
Notes: squares are the median point estimates of the unemployment semi-elasticity of new hires in each paper, and lines are the corresponding 95% confidence intervals. Details of construction are in Table 14.

Figure 8: Distribution of Non-Zero Wage Growth



Notes: this graph is the distribution in the growth of posted wages, excluding zeros. A job is an establishment by job-title by salary type by pay frequency unit. Posted wages are averaged by job-quarter. Wage growth is the growth in posted wages between two consecutive postings by the same job. The wage growth distribution is truncated at ±10%. Kernel density estimation uses an Epanechnikov kernel with a bandwidth of 0.65.

Figure 9: Distribution of Non-Zero Wage Growth for States with Large and Small Unemployment Declines



Notes: this graph is the distribution in the growth of posted wages, excluding zeros. A job is an establishment by job-title by salary type by pay frequency unit. Posted wages are averaged by job-quarter. Wage growth is the growth in posted wages between two consecutive postings by the same job. The wage growth distribution is truncated at ±10%. Kernel density estimation uses an Epanechnikov kernel with a bandwidth of 0.65. The distribution is shown separately for jobs in the top and bottom quartile of state unemployment declines between 2010 and 2016.

Figure 10: Time Varying Estimates of Quarterly Wage Rigidity

Note: squares denote point estimates and bars denote 95% confidence intervals, where standard errors are clustered by states. See Table 22 for details on the regression.

B Tables

Table 1: Comparison of New Hire Wages in the CPS and Burning Glass

Dependent Variable:	Quarterly Log Median Salary Hourly Workers, Burning Glass	
	Base Pay Workers	
Independent Variable:		
Quarterly Log Mean New Hire	1.002***	1.007*
Wage, CPS ORG Weight	(0.143)	(0.428)
Quarterly Log Mean New Hire	0.937***	0.707
Wage, CPS Hours Weight	(0.157)	(0.389)
	Total Pay Workers	
Independent Variable:		
Quarterly Log Mean New Hire	1.811***	0.164
Wage, CPS ORG Weight	(0.342)	(0.695)
Quarterly Log Mean New Hire	1.752***	0.255
Wage, CPS Hours Weight	(0.317)	(0.579)
Time trend	N	Y
Number of Observations	28	28

Notes: In Burning Glass, the dependent variable is the quarterly log median salary, for hourly workers, and either total pay or base pay. In the CPS, the dependent variable is the wage for new hires. The wage is usual hourly earnings, including overtime, for hourly and non-hourly workers, for new hires, which we construct following the "wage 4" series from CEPR. New hire wages in the CPS are taken from the Outgoing Rotation Group wages. New hires are identified by linking workers to their employment status in the previous four months. One, two and three asterisks denote significance at the 5, 1 and 0.1 percent levels, respectively. The CPS hours weight is by usual hours worked multiplied by the sample weights from the ORG.

Table 2: Summary Statistics

	Min	Max	Average
Posts Per State	4799	3012689	421412
Posts Per Quarter	279252	1278327	782622
Posts Per State-Quarter	49	190582	15050
Posts Per 6 Digit SOC Code	1	1925439	25500
Total Posts	21913422		
Share Missing Job Title	.57		
Share Missing Establishment Code	.57		
Share of 6 digit SOC occupations covered in the OES	.99		

Pay Categories:

	Base Pay	Bonus	Commission	Total Pay	Shift Premium	Short Term Incentive	Total
Annual	3962172	530169	93827	3648138	39	27	8234372
Daily	330899	306405	25329	857674	7	75	1520389
Hourly	6067618	376666	32355	3918815	1887	18	10397359
Monthly	380414	438023	15650	743509	49	5	1577650
Weekly	80038	22368	12843	68401	2	0	183652
Total	10821141	1673631	180004	9236537	1984	125	21913422

Table 3: Comparison of OES and Burning Glass Wages, by 6-digit SOC Occupation

Dependent Variable:	Log Median Hourly Wage by Occupation (OES)			
	(1)	(2)	(3)	(4)
Independent Variable:				
Log Median Salary	1.139***	1.174***	0.779***	1.001***
by Occupation (BG)	(0.0945)	(0.0678)	(0.0883)	(0.0899)
BG Salary Type	Base Pay, Annual	Base Pay, Hourly	Total Pay, Annual	Total Pay, Hourly
Observations	742	751	742	754

Notes: the dependent variable is the log median hourly wage, by 6-digit SOC occupation in the 2014-2016 Occupational Employment Statistics. The independent variable is the log median salary, by 6-digit SOC occupation in Burning Glass, for each salary type and pay frequency, for 2010-2016. The regression is weighted least squares, weighted by 6-digit SOC occupation employment share in the OES. Robust standard errors are in parentheses. One, two and three asterisks denote significance at the 10, 5 and 1 percent levels, respectively.

Table 4: Comparison of QCEW and Burning Glass Wages, by CBSA

Dependent Variable:	Log Average Weekly Earnings by CBSA (QCEW)			
	(1)	(2)	(3)	(4)
Independent Variable:				
Log Median Salary	1.295***	1.390***	1.069***	0.900***
by CBSA (BG)	(0.0754)	(0.127)	(0.100)	(0.149)
BG Salary Type	Base Pay, Annual	Base Pay, Hourly	Total Pay, Annual	Total Pay, Hourly
Observations	928	928	927	928

Notes: the dependent variable is average weekly earnings by CBSA, from the 2010-2016 QCEW. The independent variable is the median salary by CBSA, pay frequency and salary type, from the 2010-2016 Burning Glass data. The regression is weighted least squares, weighted by CBSA employment in the QCEW. Robust standard errors are in parentheses. One, two and three asterisks denote significance at the 5, 1 and 0.1 percent levels, respectively.

Table 5: Summary Statistics, for Data Differenced by Job

	Min	Max	Average	Total
Total Vacancy Posts				1598505
Share of employment in OES by 6 digit SOC occupation				.99
Posts Per Job	2	23	2.5	
Jobs per 6 digit SOC occupation	1	176081	1247.2	
Jobs per State	264	118076	19909	
Jobs per Quarter	7519	117566	38343	

Notes: a job is an employer by location by pay frequency by salary type by job title unit. We take the quarterly average wage by job, and then difference by the job.

Table 6: Quarterly Posted Wage Setting Statistics

	Unweighted (1)	OES Weights (2)	QCEW Weights (3)	High Wage Jobs (4)
Median Quarterly Probability of Posted Wage Change for Job	0.167	0.159	0.16	0.161
Median Implied Duration of Posted Wage Spell (Quarters)	5.454	5.769	5.531	5.459

Notes: a job is an establishment by region by job title by salary type by pay frequency observation. Posted wages are averaged within each job-quarter. The sample is the 2010-2016 Burning Glass data. We estimate the probability of posted wage change for each job using a similar method to Klenow & Kryvtsvov (2008) and Nakamura & Steinsson (2008). We assume that the hazard rate of job change is constant and identical for all jobs in the same 2 digit SOC code occupation. We then estimate the hazard rate of job change by maximum likelihood. We then calculate the implied duration and probability of change for each occupation, and then take the median across occupations, weighted by the number of vacancies. In column (2), we reweight to target the distribution of jobs at the 6 digit SOC level from the 2014-2016 OES. In column (3) we reweight to target the distribution of employment across states from the 2010 QCEW. In column (4) we drop jobs in the bottom quartile of the wage distribution.

Table 7: Annual Posted Wage Setting Statistics

	Unweighted	OES Weights	QCEW Weights	High Wage Jobs
Median Annual Probability of Posted Wage Change for Job	0.405	0.418	0.402	0.418
Median Implied Duration of Posted Wage Spell (Years)	1.841	1.836	1.875	1.841

Notes: a job is an establishment by region by job title by salary type by pay frequency observation. Posted wages are averaged within each job-year. The sample is the 2010-2016 Burning Glass data. We estimate the probability of posted wage change for each job using a similar method to Klenow & Kryvtsvov (2008) and Nakamura & Steinsson (2008). We assume that the hazard rate of job change is constant and identical for all jobs in the same 2 digit SOC code occupation. We then estimate the hazard rate of job change by maximum likelihood. We then calculate the implied duration and probability of change for each occupation, and then take the median across occupations, weighted by the number of vacancies. In column (2), we reweight to target the distribution of jobs at the 6 digit SOC level from the 2014-2016 OES. In column (3) we reweight to target the distribution of employment across states from the 2010 QCEW. In column (4) we drop jobs in the bottom quartile of the wage distribution.

Table 8: First Stage of Quarterly State Unemployment Change on Employment Growth

Dependent Variable:	Quarterly Unemployment Change			
	(1)	(2)	(3)	(4)
Independent Variable:				
Quarterly Employment Growth	-0.215***	-0.216***	-0.262***	-0.263***
	(0.0265)	(0.0262)	(0.0157)	(0.0157)
Time Effect	Y	Y	Y	Y
State Effect	N	Y	N	Y
QCEW Weight	N	N	Y	Y
Number of Observations	1404	1404	1404	1404
R^2	0.599	0.631	0.637	0.663
F Statistic	66.14	67.78	277.8	282.1
State Clusters	52	52	52	52

Notes: the dependent variable is the quarterly change in state level unemployment, from the 2010-2016 LAUS. The independent variable is the quarterly growth in state level employment from the 2010-2016 QCEW. In columns (3) and (4), the regression is weighted least squares, reweighted to target average state level employment in the QCEW. Standard errors are in parentheses, clustered by state. One, two and three asterisks denote significance at the 5, 1 and 0.1 percent levels, respectively. The sample is vacancies in the 50 states, plus the District of Columbia and Puerto Rico.

Table 9: Quarterly Posted Wage Cyclicality, Differenced by Job

Dependent Variable:	Quarterly Posted Wage Growth, by Job			
	(1)	(2)	(3)	(4)
Independent Variable:				
Quarterly Unemployment Change	-0.221*	-0.0886**	-0.243*	-0.250**
	(0.0831)	(0.0330)	(0.0962)	(0.0844)
Time Effects	Y	Y	Y	Y
State Effects	N	Y	N	N
OES Weights	N	N	Y	N
QCEW Weights	N	N	N	Y
Number of Observations	1566535	1566414	1511901	1566535
State Clusters	52	52	52	52

Notes: the dependent variable is quarterly percentage posted wage growth, from the 2010-2016 Burning Glass data. Posted wages are averaged within each job-quarter. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS. We project unemployment changes onto state-quarter employment growth from the 2010-2016 QCEW. Posted wage growth is trimmed at the 1st and 99th percentiles. A job is an employer by location by pay frequency by salary type by job title unit. Standard errors are in parentheses, clustered by state. One, two and three asterisks denote significance at the 5, 1 and 0.1 percent levels, respectively. We also add in a set of dummy variables for the length between two consecutive vacancy postings. The sample is vacancies in the 50 states, plus the District of Columbia and Puerto Rico. In some specifications, we reweight either to target the regional employment distribution from the 2010-2016 QCEW or the occupation employment distribution at the 6 digit SOC level from the 2014-2016 OES.

Table 10: Annual Posted Wage Cyclicality, Differenced by Job

Dependent Variable:	Annual Posted Wage Growth, by Job			
	(1)	(2)	(3)	(4)
Independent Variable:				
Annual Unemployment Change	-1.380***	-1.422***	-1.427***	-1.447***
	(0.126)	(0.0963)	(0.127)	(0.130)
Time Effects	Y	Y	Y	Y
State Effects	N	Y	N	N
OES Weights	N	N	Y	N
QCEW Weights	N	N	N	Y
Number of Observations	523041	523041	518296	523041
State Clusters	52	52	52	52

Notes: the dependent variable is annual percentage posted wage growth, from the 2010-2016 Burning Glass data. Posted wages are averaged within each job-year. The independent variable is the change in state-year unemployment from the 2010-2016 LAUS. We project unemployment changes onto state-year employment growth from the 2010-2016 QCEW. Posted wage growth is trimmed at the 1st and 99th percentiles. A job is an employer by location by pay frequency by salary type by job title unit. Standard errors are in parentheses, clustered by state. One, two and three asterisks denote significance at the 5, 1 and 0.1 percent levels, respectively. We also add in a set of dummy variables for the length between two consecutive vacancy postings. The sample is vacancies in the 50 states, plus the District of Columbia and Puerto Rico. In some specifications, we reweight either to target the regional employment distribution from the 2010-2016 QCEW or the occupation employment distribution at the 6 digit SOC level from the 2014-2016 OES.

Table 11: Annual Posted Wage Cyclicality, Differenced by Job, Bartik Instrument

Dependent Variable:	Annual Posted Wage Growth, by Job			
	(1)	(2)	(3)	(4)
Independent Variable:				
Annual Unemployment Change	-1.463	0.651	-1.670	-2.391
Projected on Bartik	(1.804)	(0.569)	(2.112)	(4.160)
Time Effects	Y	Y	Y	Y
State Effects	N	Y	N	N
OES Weights	N	N	Y	N
QCEW Weights	N	N	N	Y
Number of Observations	656783	656780	630308	656783
State Clusters	52	52	52	52

Notes: the dependent variable is annual percentage posted wage growth, from the 2010-2016 Burning Glass data. Posted wages are averaged within each job-year. The independent variable is the change in state-year unemployment from the 2010-2016 LAUS. We project unemployment changes onto a Bartik instrument. The Bartik instrument is the national growth in 3 digit NAICS industries, scaled by 2010 3 digit industry shares by state, from the QCEW. When we calculate national growth, we leave out the own-state value. Posted wage growth is trimmed at the 1st and 99th percentiles. A job is an employer by location by pay frequency by salary type by job title unit. Standard errors are in parentheses, clustered by state. One, two and three asterisks denote significance at the 5, 1 and 0.1 percent levels, respectively. We also add in a set of dummy variables for the length between two consecutive vacancy postings. The sample is vacancies in the 50 states, plus the District of Columbia and Puerto Rico. In some specifications, we reweight either to target the regional employment distribution from the 2010-2016 QCEW or the occupation employment distribution at the 6 digit SOC level from the 2014-2016 OES.

Table 12: First Stage of Annual State Unemployment Change on Bartik Employment Growth

Dependent Variable:	Annual Unemployment Change	
	(1)	(2)
Independent Variable:		
Annual Bartik	-0.215***	-0.216***
Employment Growth	(0.0265)	(0.0262)
Time Effect	Y	Y
State Effect	N	Y
Number of Observations	312	312
R^2	0.248	0.457
F Statistic	33.4	15.3
State Clusters	52	52

Notes: the dependent variable is the quarterly change in state level unemployment, from the 2010-2016 LAUS. The independent variable is the quarterly growth in state level employment from the 2010-2016 QCEW. In columns (3) and (4), the regression is weighted least squares, reweighted to state level employment in the QCEW. Standard errors are in parentheses, clustered by state. One, two and three asterisks denote significance at the 5, 1 and 0.1 percent levels, respectively. The sample is vacancies in the 50 states, plus the District of Columbia and Puerto Rico.

Table 13: Quarterly Posted Wage Cyclicality, Differenced by Establishment

Dependent Variable:	Quarterly Posted Wage Growth by Establishment		
	(1)	(2)	(3)
Independent Variable:			
Quarterly Unemployment Change	-0.355**	-0.482***	-0.356*
	(0.121)	(0.136)	(0.138)
Time Effects	Y	Y	Y
State Effects	N	Y	N
QCEW Weights	N	N	Y
Number of Observations	1845695	1845695	1845695
State Clusters	52	52	52

Notes: the dependent variable is quarterly percentage posted wage growth, from the 2010-2016 Burning Glass data. Posted wages are averaged within each establishment-quarter. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS. We project unemployment changes onto state-quarter employment growth from the 2010-2016 QCEW. Posted wage growth is trimmed at the 1st and 99th percentile. An establishment is an employer by location by pay frequency by salary type unit. Standard errors are in parentheses, clustered by state. One, two and three asterisks denote significance at the 5, 1 and 0.1 percent levels, respectively. We also add in a set of dummy variables for the length between two consecutive vacancy postings. The sample is vacancies in the 50 states, plus the District of Columbia and Puerto Rico. In some specifications, we reweight to target the regional employment distribution from the 2010-2016 QCEW.

Table 14: Our Estimates of the Cyclicality of the Wage for New Hires Compared With the Literature

	Unemployment Semi-elasticity of New Hire Wage	Standard Error	Data Source	Standard Error Type	Frequency	Unemployment Rate
Gertler et al. (2016)	-0.33	0.51	SIPP 1990-2012	Robust	Monthly	National
Basu and House (2016)	-0.70	1.82	NLSY 1979-2012	Grouped	Annual	National
Hagedorn and Manovskii (2013)	-1.78	0.50	NLSY 1979-2004	Clustered	Quarterly	National
Haefke et al. (2013)	-2.44	1.50	CPS 1984-2006	Robust	Quarterly	National
Bils (1985)	-2.99	1.56	NLSY 1966-1981	Homoskedastic	Annual	National
Shin (1994)	-3.80	1.14	NLSY 1966-1982	Homoskedastic	Annual	National
Our Job-Level Estimate	-0.22	0.08	BG 2010-2016	Clustered	Quarterly	State Level

Notes: we adjust the estimates of Haefke et al. (2013) from the elasticity of wages with respect to real labour productivity, to the semi-elasticity of wages with respect to unemployment, using the estimate of the sensitivity of unemployment to real labour productivity estimated by Pissarides (2009). We take the median estimate from each paper, and use the more negative value where there is ambiguity. We use the wage for new hires, and only consider workers transitioning out of unemployment where these estimates are available. In Haefke et al. (2013), the CPS data is from the Outgoing Rotation Group. Grouped standard errors refer to data where the standard errors are computed after annually grouping the data. The BLS average hourly earnings measure is from the Current Employment Statistics, reported in Basu and House (2016).

Table 15: Regional Cyclicality of New Hire Wage from CPS

Dependent Variable:	Log Wage for New Hires	
	Quarterly	Annual
Independent Variable:		
Unemployment	-0.537	-1.013
	(1.033)	(1.030)
Time Effect	Y	Y
State Effect	Y	Y
Number of Observations	84984	84984
State Clusters	51	51

Notes: the dependent variable is usual hourly earnings, including overtime, for hourly and non-hourly workers, for new hires, which we construct following the "wage 4" series from CEPR. The wage is from the 2010-2016 CPS Merged Outgoing Rotation Group. We identify new hires by longitudinally linking workers to the previous three monthly survey waves, and isolating workers transitioning into new jobs. The independent variable is unemployment from the 2010-2016 LAUS. We project unemployment onto log employment from the QCEW. One, two and three asterisks denote significance at the 5, 1 and 0.1 percent levels, respectively. Wages are weighted by the CPS ORG earnings weights.

Table 16: Cyclicality of CPS Composition-Adjusted New Hire Wage for 1984-2006

Dependent Variable:	Quarterly New Hire Wage Growth, Composition Adjusted	
	Median	Mean
Independent Variable:		
ΔU_t	-4.513	-4.064
	(5.063)	(3.958)
$\Delta U_t \times I(\Delta U_t > 0)$	6.759	5.978
	(7.689)	(6.011)
Number of observations	83	83

Notes: the quarterly wage series is for 1984-2006 and is taken from Haefke, Sonntag & van Rens (2013), and uses their composition adjustment for demographics. Quarterly unemployment is taken from the BLS. Standard errors are robust.

Table 17: Quarterly Probability of Posted Wage Increase and Decrease

	Unweighted (1)	OES Weights (2)	QCEW Weights (3)	High Wage Jobs (4)
Median Quarterly Probability of Posted Wage Decrease for Job	0.036	0.037	0.036	0.036
Median Quarterly Probability of Posted Wage Increase for Job	0.107	0.109	0.106	0.111

Notes: a job is an establishment by region by job title by salary type by pay frequency observation. Posted wages are averaged within each job-quarter. The sample is the 2010-2016 Burning Glass data. We estimate the probability of posted wage increase and decrease for each job using a similar method to Klenow & Kryvtsvov (2008) and Nakamura & Steinsson (2008). We assume that the hazard rate of job increase/decrease is constant and identical for all jobs in the same 2 digit SOC code occupation. We then estimate the hazard rate by maximum likelihood. We then calculate the probability of increase/decrease for each occupation, and then take the median across occupations, weighted by the number of vacancies. In column (2), we reweight to target the distribution of jobs at the 6 digit SOC level from the 2014-2016 OES. In column (3) we reweight to target the distribution of employment across states from the 2010 QCEW. In column (4) we drop jobs in the bottom quartile of the wage distribution.

Table 18: Annual Probability of Posted Wage Increase and Decrease

	Unweighted	OES Weights	QCEW Weights	High Wage Jobs
Median Probability of Posted Wage Decrease for Job	0.088	0.095	0.09	0.087
Median Probability of Posted Wage Increase for Job	0.304	0.305	0.3	0.31

Notes: a job is an establishment by region by job title by salary type by pay frequency observation. Posted wages are averaged within each job-year. The sample is the 2010-2016 Burning Glass data. We estimate the probability of posted wage increase and decrease for each job using a similar method to Klenow & Kryvtsvov (2008) and Nakamura & Steinsson (2008). We assume that the hazard rate of job increase/decrease is constant and identical for all jobs in the same 2 digit SOC code occupation. We then estimate the hazard rate by maximum likelihood. We then calculate the probability of increase/decrease for each occupation, and then take the median across occupations, weighted by the number of vacancies. In column (2), we reweight to target the distribution of jobs at the 6 digit SOC level from the 2014-2016 OES. In column (3) we reweight to target the distribution of employment across states from the 2010 QCEW. In column (4) we drop jobs in the bottom quartile of the wage distribution.

Table 19: Cyclicality of the Probability of Quarterly Posted Wage Changes

Dependent Variables:	Quarterly Probability of Posted Wage Change		Quarterly Probability of Posted Wage Increase		Quarterly Probability of Posted Wage Decrease	
Independent Variable:						
Change in Quarterly	-0.0255*	-0.0326*	-0.0164 $^{+}$	-0.0267*	-0.00910*	-0.00596*
Unemployment	(0.00984)	(0.0142)	(0.00853)	(0.0132)	(0.00353)	(0.00257)
QCEW Weights	Y	N	Y	N	Y	N
Number of observations	1404	1404	1404	1404	1404	1404
State Clusters	52	52	52	52	52	52

Notes: the probability of a posted wage change is the share of vacancies for which the posted wage changes in each state-quarter, from the 2010-2016 Burning Glass data. The probability of increase and decrease is defined in the same way. Posted wages are averaged within each job-quarter. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS. We project unemployment changes onto state-quarter employment growth from the 2010-2016 QCEW. A job is an employer by location by pay frequency by salary type by job title unit. Standard errors are in parentheses, clustered by state. A plus sign, one, two and three asterisks denote significance at the 10, 5, 1 and 0.1 percent levels, respectively. The sample is vacancies in the 50 states, plus the District of Columbia and Puerto Rico. Regressions are weighted either by state employment share from the QCEW or the share of vacancies from Burning Glass.

Table 20: Cyclicality of the Probability of Annual Posted Wage Changes

Dependent Variables:	Annual Probability of Posted Wage Change		Annual Probability of Posted Wage Increase		Annual Probability of Posted Wage Decrease	
Independent Variable:						
Change in Annual	-0.0785	-0.119*	-0.0649	-0.111*	-0.0136	-0.00841
Unemployment	(0.0499)	(0.0478)	(0.0430)	(0.0457)	(0.0149)	(0.0135)
Time Effects	Y	Y	Y	Y	Y	Y
QCEW Weights	Y	N	Y	N	Y	N
Number of observations	312	312	312	312	312	312
State Clusters	52	52	52	52	52	52

Notes: the probability of a posted wage change is the share of vacancies for which the posted wage changes in each state-year, from the 2010-2016 Burning Glass data. The probability of increase and decrease is defined in the same way. Posted wages are averaged within each job-year. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS. We project unemployment changes onto state-year employment growth from the 2010-2016 QCEW. A job is an employer by location by pay frequency by salary type by job title unit. Standard errors are in parentheses, clustered by state. One, two and three asterisks denote significance at the 10, 5, 1 and 0.1 percent levels, respectively. The sample is vacancies in the 50 states, plus the District of Columbia and Puerto Rico. Regressions are weighted either by state employment share from the QCEW or the share of vacancies from Burning Glass.

Table 21: Quarterly Posted Wage Cyclicality, Differenced by Job, with Nonlinearity

Dependent Variable:	Quarterly Posted Wage Growth, by Job			
	(1)	(2)	(3)	(4)
Independent Variables:	Asymmetry Specification			
ΔU_{jt}	0.124	0.120	0.0238	0.135
	(0.120)	(0.160)	(0.236)	(0.127)
$\Delta U_{jt} \times I(\Delta U_{jt} < 0)$	**-0.532****	**-0.316***	**-0.500**$^{+}$	**-0.522****
	(0.154)	(0.136)	(0.250)	(0.164)
	Quadratic Specification			
ΔU_{jt}	-0.0571	0.00972	-0.0314	-0.105
	(0.0592)	(0.0433)	(0.0898)	(0.0701)
$\left(\Delta U_{jt}\right)^2$	**0.163*****	**0.130** $^{+}$	**0.198****	**0.152*****
	(0.0359)	(0.0670)	(0.0607)	(0.0406)
Time Effect	Y	Y	Y	Y
State Effect	N	Y	N	N
OES Weight	N	N	Y	N
QCEW Weight	N	N	N	Y
Number of observations	1566535	1566414	1511901	1566535
State Clusters	52	52	52	52

Notes: the dependent variable is quarterly percentage posted wage growth, from the 2010-2016 Burning Glass data. Posted wages are averaged within each job-quarter. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS. We project unemployment changes onto state-quarter employment growth from the 2010-2016 QCEW. In the asymmetric specification, we project positive and negative unemployment changes on positive and negative employment growth changes. In the quadratic specification, we project linear and quadratic terms in the unemployment change on linear and quadratic terms for employment growth. Posted wage growth is trimmed at the 1st and 99th percentiles. A job is an employer by location by pay frequency by salary type by job title unit. Standard errors are in parentheses, clustered by state. A plus sign, one, two and three asterisks denote significance at the 10, 5, 1 and 0.1 percent levels, respectively. The sample is vacancies in the 50 states, plus the District of Columbia and Puerto Rico. In some specifications, we reweight either to target the regional employment distribution from the 2010-2016 QCEW or the occupation employment distribution at the 6 digit SOC level from the 2014-2016 OES.

Table 22: Quarterly Posted Wage Cyclicality by Job, Time Varying Estimates

Dependent Variable:	Quarterly Posted Wage Growth, by Job			
	(1)	(2)	(3)	(4)
Independent Variables:				
ΔU_{jt}	-0.0173	0.00787	-0.0836	0.00479
	(0.107)	(0.102)	(0.158)	(0.122)
$\Delta U_{jt} \times I(\text{Year} = 2011)$	0.143	0.171	0.120	0.0728
	(0.131)	(0.124)	(0.268)	(0.182)
$\Delta U_{jt} \times I(\text{Year} = 2012)$	0.140	0.237	0.0795	0.128
	(0.149)	(0.159)	(0.259)	(0.162)
$\Delta U_{jt} \times I(\text{Year} = 2013)$	0.264*	0.367*	0.318	0.191
	(0.129)	(0.138)	(0.170)	(0.163)
$\Delta U_{jt} \times I(\text{Year} = 2014)$	0.0343	0.128	0.0445	-0.0207
	(0.122)	(0.118)	(0.169)	(0.148)
$\Delta U_{jt} \times I(\text{Year} = 2015)$	-0.247	-0.142	-0.270	-0.303
	(0.157)	(0.123)	(0.196)	(0.184)
$\Delta U_{jt} \times I(\text{Year} = 2016)$	-0.595**	-0.467***	-0.506*	-0.644**
	(0.180)	(0.119)	(0.229)	(0.193)
Time Effects	Y	Y	Y	Y
State Effects	N	Y	N	N
OES Weights	N	N	Y	N
QCEW Weights	N	N	N	Y
Number of Observations	1566535	1566414	1511901	1566535
State Clusters	52	52	52	52

Notes: the dependent variable is quarterly percentage posted wage growth, from the 2010-2016 Burning Glass data. Posted wages are averaged within each job-quarter. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS. We project unemployment changes onto state-quarter employment growth from the 2010-2016 QCEW, and both unemployment changes and employment are interacted with dummy variables for each year. Posted wage growth is trimmed at the 1st and 99th percentiles. A job is an employer by location by pay frequency by salary type by job title unit. Standard errors are in parentheses, clustered by state. A plus sign, one, two and three asterisks denote significance at the 10, 5, 1 and 0.1 percent levels, respectively. The sample is vacancies in the 50 states, plus the District of Columbia and Puerto Rico. In some specifications, we reweight either to target the regional employment distribution from the 2010-2016 QCEW or the occupation employment distribution at the 6 digit SOC level from the 2014-2016 OES.

Table 23: Regression of Log Labour Productivity on Unemployment

Dependent Variable:	Log Labour Productivity Change			
	Quarterly		Annual	
Independent Variable:				
Unemployment Change	-0.537	-0.858	-2.242	-6.450
	(1.012)	(1.790)	(1.141)	(3.286)
Time Effect	Y	Y	Y	Y
State Effect	N	Y	N	Y
Number of Observations	1377	1377	306	306
State Clusters	52	52	52	52

Notes: the dependent variable is the change log labour productivity for 2010-2016. Labour productivity is defined as gross state product from the BEA's regional economic accounts, divided by the number of employed from the QCEW. The independent variable is the change in state unemployment from the 2010-2016. We project changes in state unemployment on growth in state employment from the 2010-2016 QCEW. Standard errors are in parentheses, clustered by state. The sample is vacancies in the 50 states, plus the District of Columbia and Puerto Rico. The regressions are weighted by 2010 state level employment from the QCEW.

C Studying Wage Ranges

Roughly half of the wage data posts a range of wages, instead of a point wage. In the main paper, we take the mean wage for jobs that post a range of wages. In this section, we explore various other ways of dealing with ranges, and find that they do not alter our substantive conclusions.

The width of the wage bands is completely unresponsive to business cycles. It is therefore unlikely that the wage ranges reflect cyclical considerations. Table 24 regresses the width of the wage ranges on a cyclical indicator. We define the width as the ratio of the maximum of the range to the mean, and regress the growth in the log of the width, on the change in quarterly state unemployment, differenced by job and in the state-quarter panel. Across all specifications, the width is not correlated with regional business cycles.

Table 24: Cyclicality of Posted Wage Ranges, Differenced by Job

Dependent Variable:	Quarterly Posted Wage Range Growth, Differenced by Job			
	(1)	(2)	(3)	(4)
Independent Variable:				
Quarterly Unemployment Change	-0.00635	-0.0110	0.00402	-0.0108
	(0.0152)	(0.0143)	(0.0151)	(0.0184)
Time Effects	Y	Y	Y	Y
State Effects	N	Y	N	N
OES Weights	N	N	Y	N
QCEW Weights	N	N	N	Y
Number of Observations	745150	745012	715602	745150
State Clusters	52	52	52	52

Notes: the dependent variable is the quarterly percentage growth in the width of the posted wage range, from the 2010-2016 Burning Glass data. The width of the range is the ratio of the maximum salary to the mean salary (i.e. the midpoint between the maximum and minimum salary of the range). We restrict only to jobs that post a range, instead of a point wage. Posted wage ranges are averaged within each job-quarter. We restrict only to vacancies that post point wages, as opposed to ranges of wages. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS. We project unemployment changes onto state-quarter employment growth from the 2010-2016 QCEW. Posted wage range growth is trimmed at the 1st and 99th percentiles. A job is an employer by location by pay frequency by salary type by job title unit. Standard errors are in parentheses, clustered by state. One, two and three asterisks denote significance at the 5, 1 and 0.1 percent levels, respectively. We also add in a set of dummy variables for the length between two consecutive vacancy postings. The sample is vacancies in the 50 states, plus the District of Columbia and Puerto Rico. In some specifications, we reweight either to target the regional employment distribution from the 2010-2016 QCEW or the occupation employment distribution at the 6 digit SOC level from the 2014-2016 OES.

Next, we show that our finding that posted wages are weakly cyclical holds to a very similar extent if we consider only jobs that post a point wage, instead of a range of wages. Table 25 replicates the main result from section 4, in Table 9, but restricts only to jobs that post a point wage. The result is virtually unchanged.

Table 25: Quarterly Posted Wage Cyclicality, Differenced by Job, Point Wages Only

Dependent Variable:	Quarterly Posted Wage Growth, by Job, Point Wages Only			
	(1)	(2)	(3)	(4)
Independent Variable:				
Quarterly Unemployment Change	-0.141	-0.0642	-0.197	-0.139
	(0.0855)	(0.0325)	(0.131)	(0.0912)
Time Effects	Y	Y	Y	Y
State Effects	N	Y	N	N
OES Weights	N	N	Y	N
QCEW Weights	N	N	N	Y
Number of Observations	795370	795232	771704	795370
State Clusters	52	52	52	52

Notes: the dependent variable is quarterly percentage posted wage growth, from the 2010-2016 Burning Glass data. Posted wages are averaged within each job-quarter. We restrict only to vacancies that post point wages, as opposed to ranges of wages. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS. We project unemployment changes onto state-quarter employment growth from the 2010-2016 QCEW. Posted wage growth is trimmed at the 1st and 99th percentiles. A job is an employer by location by pay frequency by salary type by job title unit. Standard errors are in parentheses, clustered by state. One, two and three asterisks denote significance at the 5, 1 and 0.1 percent levels, respectively. We also add in a set of dummy variables for the length between two consecutive vacancy postings. The sample is vacancies in the 50 states, plus the District of Columbia and Puerto Rico. In some specifications, we reweight either to target the regional employment distribution from the 2010-2016 QCEW or the occupation employment distribution at the 6 digit SOC level from the 2014-2016 OES.

Finally, we show that occupations with a high share of jobs that post ranges, instead of point wages, do not have more cyclical wages. Therefore occupations that are likely to post ranges have similar wage rigidity to occupations that are likely to post point wages, again suggesting that the distinction between point wages and ranges is not important. To do this, we study regional wage cyclicality for new hires and incumbent workers, using the CPS. We classify 3 digit SOC occupations in the CPS, as either likely to post a range, or likely to post a point wage. We calculate which occupations are likely to post a range or point wage from the Burning Glass wage posting data. For either new hires or incumbent workers in the CPS, occupations that are

Table 26: Wage Cyclicality in Occupations with High vs. Low Share Posting Wage Ranges

Dependent Variable:	Log Wage, CPS	
	Newly Hired Workers	Incumbent Workers
Independent Variables:		
Quarterly Unemployment	-1.019	-3.153**
	(-1.11)	(-2.81)
Quarterly Unemployment ×	1.120	4.826**
High Share Posting Wage Ranges	(0.82)	(3.31)
Annual Unemployment	-1.131	-3.259**
	(-1.19)	(-2.83)
Annual Unemployment ×	1.174	4.816**
High Share Posting Wage Ranges	(0.83)	(3.30)
Time Effect	Y	Y
State Effect	Y	Y
Number of Observations	67327	843119

Notes: In Burning Glass, we classify three digit SOC occupations with an above-median and below-median share posting ranges instead of point wages. We link these occupations to the same three digit SOC occupations in the CPS. In the CPS, we denote three digit SOC occupations with above-median shares, as measured in the Burning Glass data, as having a high share posting wage ranges, and otherwise a low share. The dependent variable is usual hourly earnings, including overtime, for hourly and non-hourly workers, for new hires, which we construct following the "wage 4" series from CEPR. The wage is from the 2012-2017 CPS Merged Outgoing Rotation Group. We identify new hires by longitudinally linking workers to the previous three monthly survey waves, and isolating workers transitioning into new jobs. The independent variable is unemployment from the 2010-2016 LAUS. We project unemployment onto log employment from the QCEW. One, two and three asterisks denote significance at the 5, 1 and 0.1 percent levels, respectively.

likely to post a range instead of a point wage have slightly *less* cyclical wages. Therefore the distinction between posting a range or posting a point wage is unlikely to matter for understanding wage cyclicality.

D Additional Theory

D.1 Model Extensions

We generalise the model of section 6 in three respects. First, we allow for autoregressive labour demand shocks. Second, we let wages vary both at the beginning of the match, and also during the match. Thirdly, we allow for fixed costs of matching, as in the model of Pissarides (2009). None of these features alter our substantive conclusions.

Workers and firms engage in search and matching, in a standard frictional labour market. Firms create V_t vacancies, and U_t unemployed workers search for jobs in each period. Each vacancy costs γ to create, and there is free entry in vacancy creation. Unemployed workers match with vacancies, to initiate jobs. The number of matches is $m_t = AU_t^{\alpha} V_t^{1-\alpha}$. $\theta_t \equiv V_t/U_t$ is market tightness, the ratio of vacancies to unemployment. Unemployed workers each find jobs with probability $f(\theta_t) = \frac{m_t}{U_t} = A\theta_t^{1-\alpha}$. Each vacancy is filled with probability $q(\theta_t) = \frac{m_t}{V_t} = A\theta_t^{-\alpha}$.

Firms are risk neutral, and discount profits with discount factor β. In period $t+j$, a job that starts in period t produces output $y_{t,t+j}$ and pays wage $w_{t,t+j}$ to the worker. Each job ends with exogenous probability s in every period. Firms now pay a fixed cost H_t at the beginning of the match.

Then we have

$$\frac{d\log\theta_t}{d\log y_t} = \frac{1}{\alpha}\left(\frac{1-\beta(1-s)}{1-\rho\beta(1-s)} - \frac{dw_{t,t}}{dy_t} - \frac{d\tau_t}{dy_t}\right)\frac{y_t}{\frac{1-\beta(1-s)}{1-\rho\beta(1-s)}y_t - w_{t,t} - \tau_t - \left[1-\beta(1-s)\right]H_t},$$

where the *wage-tenure profile* is

$$\tau_t \equiv \left[1-\beta(1-s)\right]E_t\sum_{j=0}^{\infty}\left(\beta(1-s)\right)^j\left(E_t w_{t,t+j} - w_{t,t}\right).$$

Compare this formula with equation (2) from our baseline model. The two formulae are similar. When $\frac{d\tau_t}{dy_t} = 0$ and $\rho = 1$, the formulae are near-identical. For realistic calibrations, $\frac{d\tau_t}{dy_t}$ is near zero since incumbent wages are nearly acyclical in the data. For example, Gertler and Trigari (2009) find $\frac{d\tau_t}{dy_t} = 0.05$. In most calibrations of the DMP model, labour demand is persistent, so ρ is near 1. $\frac{y_t}{\frac{1-\beta(1-s)}{1-\rho\beta(1-s)}y_t - w_{t,t} - \tau_t - \left[1-\beta(1-s)\right]H_t}$ is equal to the labour share when $\rho = 1$, similarly to equation (2).

Since the extensions to the DMP model do not substantially alter the simple formula of equation (2), our substantive conclusions in Section 6 are unaffected.

D.2 Monetary Union Model

This section takes a standard model of a monetary union, and embeds a DMP labour market into the model. We show that our calibration in section 6 remains valid in this model.

There is a set of regions s, and firms in region s sell their output at price p_{st}. The overall price level is p_t. All firms price profits according to the same stochastic discount factor. Assume there is no labour mobility between regions. In each region, workers and firms engage in search and matching, in a frictional labour market. Firms create vacancies V_{st}, and there are U_{st} unemployed workers searching for jobs in each period. Each vacancy costs γ to create, and there is free entry in vacancy creation. Unemployed workers match with vacancies, to initiate jobs. The number of matches is $m_{st} = AU_{st}V_{st}$. $\theta_{st} \equiv V_{st}/U_{st}$ is market tightness in the region. Unemployed workers each find jobs with probability $f(\theta_{st}) = A\theta_{st}$. Each vacancy is filled with probability $q(\theta_{st}) = A\theta_{st}$.

Firms are risk neutral, and discount real profits with discount factor β. In period $t+j$, a job that starts in period t produces nominal output $y_{st,t+j}$ and pays wage w_{st} to the worker. Each job ends with exogenous probability s in every period. We can derive a formula analogous to equation (2). The elasticity of regional tightness to real regional labour productivity is.

$$\frac{d\log\theta_{st}}{d\log\left(\frac{p_{st}y_{st}}{p_t}\right)} = \frac{1}{\alpha}\left(1 - \frac{dw_{st}}{dp_{st}y_{st}}\right)\frac{p_{st}y_t}{p_{st}y_t - w_t} \tag{3}$$

In the data, we identify the sensitivity of regional nominal wages to regional nominal productivity, which is $\frac{dw_{st}}{dp_{st}y_{st}}$, the wage rigidity parameter in equation (3). Thus we identify the correct measure of wage rigidity in a monetary union, and so our calibration technique is correct in this setting.