Downward Rigidity in the Wage for New Hires

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If wages are more rigid downward than upward, then unemployment is volatile during recessions. In benchmark models, the wage for new hires is particularly important for unemployment fluctuations, but there is limited evidence of downward rigidity on this margin. We introduce a dataset that tracks the wage for new hires at the job level—that is, across successive vacancies posted by the same job title and establishment. We show that the wage for new hires is more rigid downward than upward, in two steps. First, the nominal wage rarely changes at the job level. When wages do change, they fall infrequently, suggesting a constraint from beneath. Second, when unemployment rises, wages do not fall for new hires—though wages rise strongly as unemployment falls. We show that prior work, which studies the average wage for new hires, cannot detect downward rigidity due to changing job composition. Finally, we match a standard labor search model to our estimates, and uncover state dependent asymmetry in unemployment dynamics. After contractions, unemployment responds symmetrically to labor demand shocks; after persistent expansions, unemployment is as much as twice as sensitive to negative than positive shocks.

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1 Introduction

Suppose that wages rise during business cycle expansions, but do not fall during contractions. This property, known as downward wage rigidity, rationalizes a well known fact: unemployment rises sharply during recessions, and changes more gently during booms (Keynes, 1936). If wages are downwardly rigid, then during contractions the cost of labor does not fall and unemployment rises sharply. But during expansions the cost of labor rises, muting the fall in unemployment. The wage for newly hired workers is key. In the United States, unemployment rises during recessions in large part because firms stop hiring workers (Shimer, 2012). The wage for new hires matters on this margin—wages for continuing workers may be less important (Pissarides, 2009). Wages do seem to be downwardly rigid for continuing workers (Kurmann and McEntarfer, 2017; Grigsby, Hurst, and Yildirmaz, 2018). But plausible mechanisms predict that continuing wages are rigid downward while new wages are flexible downward. There is limited direct evidence that the wage for new hires is more rigid downward than upward.

The wage for new hires faced by establishments deserves special attention. Hiring depends on whether establishments create jobs—which depends, in turn, on the establishment’s profit from creating new jobs. The wage for a new hire deducts from these profits. So, the wage for new hires faced by establishments governs job creation, and then hiring and unemployment. This logic is at the heart of canonical labor search models, once extended to having establishments (Gertler and Trigari, 2009). Previous work often studies the average wage for new hires, averaging across all newly hired workers, using worker-level survey data without establishment or job information (Haefke, Sonntag, and Van Rens, 2013). These studies do not find that the wage for new hires is more rigid downward than upward. But average wages may differ from the wage faced by establishments as the composition of hiring changes. Suppose that wages faced by a given establishment do not change. Average wages may still rise or fall, if overall hiring shifts towards higher or lower wage jobs. So, previous work may not detect downward wage rigidity for new hires, even when it matters for unemployment fluctuations.

Our paper makes two points. First, the wage for new hires faced by establishments is more rigid downward than upward. Second, given the form of downward rigidity in the data, the degree of asymmetry in unemployment dynamics is highly state dependent.

We study a proprietary dataset on the wage for new hires. Our data contains establishment level wages on new vacancies, with job titles and pay frequency, for 10% of US vacancies posted during 2010-2016. The dataset, from Burning Glass Technologies, collects vacancies from the

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1 For example, continuing workers may object to wage cuts due to morale (Campbell III and Kamlani, 1997; Bewley, 2002). Morale may matter less for new hires, who do not have a reference point of their own past wage. Firms might offer implicit contracts in the form of downwardly rigid wages to continuing workers, and not extend the same insurance to new hires (Beaudry and DiNardo, 1991).
near-universe of online job boards and company websites. Though not from a representative sample, our measure is a good proxy for the wage for new hires. Wages in Burning Glass closely track state-by-quarter measures of the wage for new hires from both survey and administrative data.

Our dataset has a particular advantage for studying downward wage rigidity. We track job level variation in the wage for new hires—that is, the wage across successive vacancies posted by the same job title and establishment.\(^2\) Consider a physical location of Starbucks, that regularly posts vacancies for baristas, and pays them an hourly wage. Our data tracks the hourly wage for baristas across multiple vacancies posted by the Starbucks. Moreover we can track the hourly wage for other jobs posted by the Starbucks, such as store managers. Therefore we measure the wage for new hires faced by the Starbucks establishment, across the various jobs into which it hires workers.

We have three findings indicating downward rigidity in the wage for new hires faced by establishments. First, the wage for new hires rarely changes between successive vacancies at the same job. When wages do change for a given job, they are three times more likely to rise than to fall. These findings imply a downward constraint on the wage in newly created jobs, even as workers are repeatedly hired into these jobs. As is well known, continuing wages change infrequently and rise more often than fall. Our finding suggests mechanisms that impose parity between the wage of new hires and continuing workers, such as internal equity.

Second, at the job level, the wage for new hires rises during expansions but does not fall during contractions. So, due to the constraint on wage setting, wages are rigid downward and flexible upward at the job level. Figure 1 shows the result. In the figure, the wage for new hires is averaged by job-quarter. On the y-axis is wage growth between two consecutive vacancies for the same job. On the x-axis is the growth in quarterly state level unemployment between the quarters in which the vacancies are posted.\(^3\) As state unemployment falls, the wage for new hires rises strongly. Wages do not fall when state unemployment rises. Figure 1 isolates job-level wage growth for new hires, thus removing variation from changing job composition, which might obscure downward wage rigidity. We confirm the finding with regressions. Similar results after reweighting to the occupation and region distribution of jobs; at annual frequency; with city, industry, or state-industry variation; for real wages; and after using an instrument for regional labor demand based on oil price shocks.\(^4\)

Third, across all jobs into which the establishment hires, wages are more rigid downward than upward. So, downward wage rigidity matters not only at the job level, but also at the estab-

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\(^2\)Here, a “job” is a job title at an establishment.
\(^3\)Since many jobs do not post in consecutive quarters, sometimes the fall in unemployment between postings is relatively large.
\(^4\)This instrument is similar to Acemoglu, Finkelstein, and Notowidigdo (2013) and Allcott and Keniston (2017).
Figure 1: Wage Growth for New Hires and Quarterly State Unemployment Changes

Notes: the graph plots binned wage growth for new hires, from Burning Glass, and binned state by quarter unemployment changes, from the Local Area Unemployment Statistics. To construct wage growth, we take the mean wage within each job and quarter, and then take log differences at the job level. We use 50 bins, partial out time fixed effects, and add a non-parametric regression line.

We show that establishment wages—pooling across jobs within the same establishment—rise when unemployment falls but do not fall when unemployment rises. The estimated comovement of wages with unemployment is of similar size at the job- and establishment-level. There is no evidence that establishments alter their mix of jobs to offset downward rigidity at the job level. So, the constraint at the job-level leads to downward rigidity in the wage faced by establishments, across all the jobs into which they hire.

However the *average* wage for new hires, the object of previous studies, is not more rigid downward than upward—in contrast to our job- and establishment-level results on downward rigidity. Average wages pool variation from across all new hires at a point in time, across all types of jobs and establishments. Average wages can then change for two reasons: wage changes at the job level, or changes in the composition of hiring between high and low wage jobs. We examine the average wage for new hires in Burning Glass. Average wages from Burning Glass do not respond differently to rises versus falls in unemployment. We also construct a measure of the average wage for new hires from worker-level survey data. This measure is similar to aver-
age wages in previous work, and does not fully adjust for job composition. Again, the average wage for new hires in survey data does not respond differently to rises versus falls in unemployment. We show that job composition leads to more noise in average wages for new hires, than in establishment or job level wages. So, regressions using average wages lack the power to detect downward rigidity.

In the second part of the paper, we argue that the form of downward rigidity in the data leads to state dependent asymmetry in unemployment dynamics. We proceed in four steps.

First, we document a new finding from our microdata: the wage for new hires displays state dependent flexibility upward. We show that in the aftermath of business cycle contractions, the wage for new hires does not rise as unemployment falls. Following business cycle expansions, the wage for new hires does rise as unemployment falls. Consistent with this pattern, we also show that wages are inflexible upward in 2010, and become more flexible upward over the recovery. This state dependence is consistent with downward rigidity. If wages are rigid downward, then wages are “trapped too high” after large contractions. A marginal increase in labor demand from the trough of the business cycle should not raise wages. After a long expansion, wages are at their frictionless level, and are free to adjust upward.

Second, we incorporate this form of downward wage rigidity into a standard labor search model, and match the model to our new evidence. We run the same regressions on simulated wages in the model as in our real-world data, and then minimize the distance between these regression coefficients. Though parsimonious, the model matches several untargeted moments, including the volatility, persistence and skewness of unemployment over current and previous US business cycles; and the dynamics of both continuing and new wages over 2010-2016. Importantly, downward rigidity lets us fit the time series pattern of slow wage growth until 2014, and faster growth thereafter—helping to explain puzzle of “missing wage growth” during the early part of the recovery from the Great Recession.\footnote{See, for example, Federal Reserve Bank of Atlanta (2014). In 2014, the rapid decline in unemployment and slow growth of real wages was deemed puzzling by many observers.}

Third, we show state dependent asymmetry in the impulse response of unemployment to labor demand.\footnote{Amongst several others, Daly and Hobijn (2014) discuss related forms of state dependence in unemployment dynamics.} We consider two scenarios in the model. In both scenarios, we study the impulse response of unemployment to positive and negative labor demand shocks at $t = 0$. In the first scenario, we assume the economy is at steady state. Then the peak impulse response of unemployment is as much as twice as large with respect to negative labor demand shocks as to positive shocks. Wages are rigid downward and flexible upward starting from the steady state, which leads to the asymmetry. In the second scenario, we suppose labor demand is at its steady state value at $t = 0$. But before $t = 0$, the economy experiences a contraction from some higher
level of labor demand. In this scenario, unemployment is *equally* sensitive to positive and negative labor demand shocks at $t = 0$. Since there is a contraction before $t = 0$, downward rigidity means wages are “trapped too high”, and respond little to either positive or negative labor demand shocks. Unemployment responds symmetrically to shocks as a result. The relevant state is not current labor demand, which is fixed across the two scenarios. Instead, prior contractions or expansions in labor demand govern the current degree of asymmetry.

Using the model, we estimate the sequence of labor demand shocks hitting the US economy, and study the asymmetry of unemployment dynamics over time. During and directly after recessions, unemployment is equally sensitive to expansions and contractions. At the peak of booms, unemployment is around twice as sensitive to negative shocks. Finally, we provide new time series evidence of state dependent asymmetry, from the response of unemployment to monetary shocks identified as in *Romer and Romer (2004)*. Overall, our model and empirics show that while downward wage rigidity leads to asymmetries in the response of unemployment shocks, the asymmetry varies depending on recent business cycle history.

### 1.1 Literature

Pissarides (2009) emphasizes that in benchmark labor search models, the wage for newly hired workers is key for employment fluctuations. Since employment is a long term relationship, the present value of wages is key. Wage changes for continuing workers may then matter less for unemployment fluctuations (Barro, 1977). These models are motivated by the empirical finding that hiring explains the majority of unemployment fluctuations, in the US (Hall, 2005; Elsby, Michaels, and Solon, 2009; Fujita and Ramey, 2009; Shimer, 2012).

Gertler and Trigari (2009) show that the wage for new hires faced by establishments is especially important for unemployment. Hagedorn and Manovskii (2013) and Gertler, Huckfeldt, and Trigari (2016) emphasize that when job composition can vary, the wage faced by establishments may differ from average wages. In other labor search models extended to have a notion of an establishment, the wage for new hires plays a similar role (e.g. Michaillat, 2012; Acemoglu and Hawkins, 2014). We study the wage for new hires faced by establishments, in line with these theories.

Yet there is limited evidence that the wage for new hires is more rigid downwards than upwards. Many papers study wage cyclicality in the average wage for new hires, from survey data on workers, with limited information on jobs or establishments. These papers include Bils (1985), Shin (1994), Haefke et al. (2013), Hagedorn and Manovskii (2013), Kudlyak (2014), Basu

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7Continuing 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 continuing wage rigidity to generate unemployment fluctuations.
and House (2016) and Gertler et al. (2016) with US data. Martins, Solon, and Thomas (2012) study Portuguese data on the wage for new hires with establishment and job identifiers, as with our US data. These papers document varying degrees of wage rigidity, but none of them present evidence that the wage for new hires is more rigid downwards than upwards, as in our paper.

An enormous literature asks whether downwards wage rigidity can rationalize business cycle asymmetries in unemployment. A seminal contribution is Akerlof et al. (1996). Recent contributions include Kim and Ruge-Murcia (2009), Kim and Ruge-Murcia (2011), Benigno and Ricci (2011), Daly and Hobijn (2014), Schmitt-Grohé and Uribe (2016), Dupraz, Nakamura, and Steinsson (2016), Chodorow-Reich and Wieland (2017) and Petrosky-Nadeau, Zhang, and Kuehn (2018). On the empirical side, we provide evidence on downward rigidity for new hires, which validates the assumptions in these models. On the modelling side, we show that the form of downward rigidity in the data leads to a quantitatively large degree of state dependence, in the asymmetry of unemployment fluctuations.

A prominent conjecture by, amongst others, Gertler and Trigari (2009), Menzio and Moen (2010) and Rudanko (2019), holds that wages for new hires inherit the rigidity of continuing workers’ wages, due to internal equity concerns or firm wide pay scales (Bewley, 2002). Continuing workers’ wages seem to be more rigid downwards than upwards (Card and Hyslop, 1997; Le Bihan et al., 2012; Barattieri et al., 2014; Daly and Hobijn, 2014; Sigurdsson and Sigurardottir, 2016; Elsby et al., 2016; Kurmann and McEntarfer, 2017; Mian, Sufi, and Verner, 2017; Grigsby et al., 2018; Elsby and Solon, 2018; Jardim et al., 2019; Kaur, 2019; ). We show that the wage for new hires inherits this property, in line with the conjecture.

2 Data

We study a proprietary establishment level dataset of wages for new vacancies, with job titles, covering 2010-2016. The dataset was developed by Burning Glass Technologies, and draws from company websites and online job boards. The vacancy data contains wages and occupation information at the 2- 4- or 6-digit SOC code level.\footnote{These occupation codings are granular—a 6 digit SOC code is at the detail of, for example, a high school Spanish teacher.}

The dataset covers approximately 10% of vacancies posted in the US, either online or offline (Carnevale et al., 2014). Burning Glass draws from the near-universe of job vacancy postings, from 40,000 distinct online sources. No more than 5% come from any one source. The company employs a sophisticated deduplication algorithm, to avoid double counting vacancies that post on multiple job boards.

The dataset contains detailed information on the wage in new vacancies. The data reports
the pay frequency of the contract, for example, whether pay is annual or hourly; and the type of salary, e.g. base pay or bonus pay. Given pay frequency, we can measure hourly earnings for workers, i.e. the wage attached to the vacancy. The hours measure is an important advantage. In the United States, administrative data typically does not contain hours worked, though it is available for some smaller states such as Washington and Minnesota. Survey data tend to have measurement error.

The data report establishment and job title. Each physical location at which a firm employs workers is an establishment, measured by company name and zip code. Job titles are extracted from the text of the vacancies and cleaned using Burning Glass’ algorithms. Throughout the paper, we 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).

The dataset overweights certain occupations that disproportionately post online. Appendix Figure 14 plots the relative share of Burning Glass occupations versus the 2014-2016 Occupational Employment Statistics. In our empirical results we explore robustness by reweighting to the occupational or regional distribution of jobs.

Importantly, Hershbein and Kahn (2016) show that the representativeness of Burning Glass is stable over time at the occupation level. Though Burning Glass under-represents some occupations relative to the CPS, the degree to which these occupations are under-represented does not change. Hershbein & Kahn construct the share of new jobs in each 3 digit SOC occupation, in both Burning Glass and the CPS. The occupations that are underweight in Burning Glass at the start of the sample period, are typically underweight by the same amount at the end of the sample period. Hershbein and Kahn’s Online Appendix Figure A3 reports this result. By contrast, the accuracy of other popular online vacancy data, such as the Help Wanted Online series, is declining (Cajner and Ratner, 2016).

Table 1 reports summary statistics. There are many vacancies within each state-quarter. The dataset covers almost all 6-digit SOC occupations. A large fraction of jobs contain establishment and job title identifiers. Roughly half of the vacancies with wage information post a range of salaries. The rest post a point salary. For jobs that post a range, we use the mean of the range. Appendix Section D explores in detail alternative ways of treating jobs that post a range.

The dataset of wages is a subset of the online vacancies provided by Burning Glass. Only 17% of vacancies include wages. It is not clear why a minority of firms include wages on their vacancies. However these considerations are likely not relevant for business cycles: in Appendix Section B, we show that firms’ decisions to attach wages to vacancies are not cyclical.

In many specifications, we study regional business cycle variation. We use quarterly unemployment from the Local Area Unemployment Statistics (LAUS) and state employment from the QCEW.
2.1 Burning Glass Measures the Wage for New Hires

We show that Burning Glass wages accurately measure the wage for new hires at business cycle frequency, by comparing to the best available survey and administrative data on the wage for new hires. This step is important because Burning Glass is neither a representative sample, nor a census, of the wage for new hires. This finding sets the stage for our main empirical results: we can use the special features of our dataset to investigate wage rigidity for new hires.

First, we construct an alternative measure of the wage for new hires from the Current Population Survey, at the state-by-quarter level for 2010-2016. The wage for new hires is from workers switching jobs over the previous quarter, or entering jobs from unemployment. We use the rotating panel component of the CPS's basic monthly files, and wage data from the CPS Outgoing Rotation Group, following Haefke et al. (2013). Wages are usual hourly earnings for hourly and non-hourly workers.

We regress log CPS wages on log wages from Burning Glass, also at the state-quarter level. To overcome measurement error in Burning Glass wages, we use the same method as Beraja, Hurst, and Ospina (2016). We halve the data in each state-quarter and calculate average state-quarter wages in each sub-sample. We then instrument for wages in one sub-sample with the other.

Table 2, Panel A, reports the regressions, and Appendix Figure 13 presents a binned scatterplot of the regression. The elasticity of CPS new hire wages with respect to Burning Glass wages is near one. The results are similar if we add state or time fixed effects. Our estimates are fairly precise, and we cannot reject that the regression coefficient is 1. Thus the Burning Glass and CPS measures of the wage for new hires comove one-for-one—Burning Glass closely tracks other measures of the new hire wage. When restricted to the sample containing job identifiers, which form much of the analysis that follows, our estimates are virtually unchanged. Despite small sample sizes and measurement error in CPS data, the large Burning Glass dataset lets us obtain meaningfully precise estimates.

We then study average earnings for newly hired workers, from administrative data at the state-quarter level for 2010 to 2016. This measure is administrative, from the Quarterly Workforce Indicators, and does not suffer from the small samples or measurement error in reported wages. However, the data reports earnings for new hires—inclusive of both hours worked and hourly wages—and cannot isolate a measure of hourly wages. We regress log state-quarter earnings for new hires, in the Quarterly Workforce indicators, on log wages from Burning Glass, also at the state-quarter level. As before, we split the Burning Glass sample, and instrument for one half of the sample with the other.

Table 2, Panel B, reports the regressions. The elasticity of new hire earnings with respect to Burning Glass wages is near, but above one. After one percent of growth in Burning Glass wages,
earnings for new hires grow by 1.25 percent. The larger movement in earnings than in Burning Glass wages likely reflects a positive comovement between hours and wages, so that earnings increase by more than wages. The results are similar after adding state or time fixed effects, and the estimates are again fairly precise. Again, when restricted to the sample containing job identifiers, which form much of the analysis that follows, our estimates are virtually unchanged. So, reassuringly, two different measures of the wage for new hires with different shortcomings and advantages, match the Burning Glass measure of wages. Appendix Table 16 compares Burning Glass wages to occupational and regional wages, and again finds a close match.

There are likely three reasons why vacancies on job boards accurately reflect the wage for new hires. First, Hall and Krueger (2012) report that 70-80% of workers do not bargain over the wage of the new vacancies to which they apply, and instead receive a wage dictated to them by their employer. Therefore for many newly hired workers, the wage attached to the vacancy is the relevant wage at the start of the match. Second, online vacancy posting is costly, which discourages firms from posting out-of-date wage information. The median cost of posting a vacancy on the largest four online job boards, by sales, was $419 in 2017.9 Companies posting on their own websites typically pay monthly fees to subcontractors. Gavazza, Mongey, and Violante (2018) show that company websites and online job boards are a large share of total recruiting costs for the typical US firm. Third, the duration of vacancies is short, which prevents “stale” vacancies. Online job boards typically remove vacancies after one month, or request a further fee for the vacancy to remain open. On company websites, the median duration of vacancies is 21 days, and 92% of vacancies are removed within the quarter.10

Data from survey and administrative data therefore confirm that Burning Glass wages are a valid measure of the wage for new hires. We now explain what differentiates us from prior datasets.

3 Job and Establishment Data on the Wage for New Hires

Our dataset has a particular advantage—it tracks the wage for new hires at both the job and the establishment level. We can track wages across multiple vacancies posted by the same job, within the same establishment. In coming sections, we use this feature to document downward rigidity in new hires.

Figure 2 displays job-level variation. We present a job that posts multiple vacancies. The firm is Progressive Car Insurance. The establishment is the branch of the firm in Pasadena, Cal-

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10 The duration of vacancies is similar to the mean vacancy duration reported in Davis et al. (2013) from the BLS's JOLTS survey, of 20 days.
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.

iforni. The job title is claims adjuster. The salary is an annual wage, base pay, averaged by quarter. Then according to our definition, a job is a claims adjuster at the Pasadena establishment of Progressive Car Insurance. The job posts 11 vacancies over three years. We can track the wage across these vacancies—that is, we can track job-level changes in the wage for new hires. We can also track establishment level wage changes. We can study how wages change for the establishment of Progressive Car Insurance, pooling across all the jobs into which they hire workers in a quarter.

Job- and establishment-level changes in the wage for new hires are key for unemployment fluctuations. In US data, unemployment fluctuations are primarily determined by hiring (Shimer, 2012). Hiring, in turn, depends on establishments’ profits from job creation. The wage for a new hire deducts from these profits. So, the wage for new hires faced by establishments governs job creation, and then hiring and unemployment. If the wage for new hires faced by an establishment does not fall during recessions, then the establishment’s profits from job creation fall, and the establishment creates fewer jobs. In aggregate, hiring falls and unemployment rises.

\[\text{See also }\text{Hall (2005), Fujita and Ramey (2009) and Elsby et al. (2009).}\]
This logic—that the wage faced by establishments matters for unemployment fluctuations—is at the heart of many labor search models, once extended to have a concept of an establishment. A seminal paper making the argument is Gertler and Trigari (2009). But the wage for new hires faced by establishments plays a similar role in other labor search models with firms, such as Michaillat (2012), Acemoglu and Hawkins (2014), and Gertler et al. (2016).

These models differ on the precise definition of the wage faced by establishments. In some models, such as Gertler et al. (2016), the wage that matters is for a given type of job within an establishment—which we refer to as the job-level wage. In this model, there are multiple types of jobs within the establishment, with no opportunity for the firm to substitute between job types. In other models, such as Gertler and Trigari (2009) or Acemoglu and Hawkins (2014), the wage that matters is the average establishment wage, pooling across all jobs within an establishment—which we refer to as the establishment-level wage. In these models, there is a single type of job within each firm. In practice, the relative importance of job- versus establishment-level wages may depend on establishments’ ability to substitute between different types of jobs. However we will study both job- and establishment-level wages, and consistently find downward wage rigidity. So, the possibility of studying both job and establishment wages is a key strength of our data.

Previous work often studies the average wage for new hires, averaging across all newly hired workers, using worker-level survey data that lacks establishment or job information. Average wages may differ from the wage faced by establishments, if the composition of hiring changes. Suppose that wages faced by a given establishment do not change. Average wages may still rise or fall, if overall hiring shifts towards higher or lower wage jobs.

Appendix Section E outlines a model which formalizes the points made in this section. The model extends the standard Diamond-Mortensen-Pissarides model, to allow for high and low wage types of jobs. In a sense we make concrete, job-level changes in the wage for new hires govern unemployment fluctuations. In the model, changes in wages due to job composition, which do not reflect job-level wage changes, do not matter for unemployment fluctuations.

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12 See also Pissarides (2009), which emphasizes the importance of the wage for new hires in a model without establishments.
13 The emphasis on the wage faced by establishments may have limitations if, for example, there is directed reallocation between high and low wage establishments. We present evidence arguing against this possibility in subsection 6.3.
14 See, amongst others, Haefke et al. (2013) and Kudlyak (2014). See Martins et al. (2012) for a paper with Portuguese worker level data on new hires, that does include job level information.
4 Downward Constraints on Wage Setting in New Jobs

The example of a job in Figure 2 hints at a new finding. In the job, the wage changes infrequently across vacancies, with three changes and no decreases over eleven vacancies and three years.

We ask whether this pattern of infrequent changes and rare falls holds more broadly. We present a range of findings. The wage for new hires rarely changes between successive vacancies at the same job. When wages do change for a given job, they rarely fall and rise more often. Meanwhile, the probability that the wage for new hires increases is sensitive to the business cycle; the probability of decrease is insensitive.

Each finding implies a downward constraint on the wage in newly created jobs—even as workers are repeatedly hired into these jobs. Wages are free to rise at the job level, but may not be able to fall.

4.1 Our Approach to Measuring the Probability of Wage Changes

We start by studying how often wages change, rise and fall at the job level.

First, we explain our treatment of the data. We aim to study wages across successive vacancies for the same job, and so restrict to jobs with that post multiple vacancies. We take the mean wage for new hires within each job-quarter. After these steps, there are roughly 1.6 million observations. Table 3 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.

We next confront a measurement challenge. We only observe wages for the quarters in which jobs post vacancies—wages are “missing” in other quarters. Therefore we cannot directly observe the probability that the wage for new hires changes, nor the duration of time for which wages are unchanged. We adapt a standard approach from the price letting literature to overcome this problem, first developed in Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008).

We treated the wage as a latent variable, which evolves stochastically when it is unobserved, and treat the observed sequence of wages as draws from the latent process. We estimate the latent process with a constant hazard model. We can then calculate the probability that the wage changes, even if jobs do not post in all quarters. The constant hazard model has several desirable properties. If the observed wage does not change between successive vacancies, the latent wage also does not change. If the observed wage does change, the latent 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. One can easily adapt this process to separately estimate the probability of wage increase and decrease. One can assume a constant hazard of wage increase or decrease, and estimate this process using the observed sequence of wage increases or decreases.

We use implied durations to measure for how long wages are unchanged, as in the price setting literature. Other simple procedures for calculating duration are biased downwards in the presence of left-censored spells (Heckman and Singer, 1984).

4.2 The Wage For New Hires Changes Infrequently at the Job Level

We find that the nominal wage for new hires changes infrequently, implying a constraint on wage setting at the job level.

Table 4 reports the results. Across all columns, the probability of wage change is similar, and low—the corresponding implied durations are 5-6 quarters. Column (1) estimates the quarterly probability of wage change according to our method. Column (2) reweights vacancies at a granular level, to target the distribution of jobs from the 2014-6 Occupational Employment Statistics, 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, since minimum wages might cause infrequent changes. Results are similar in all cases, confirming that the wage for new hires changes infrequently at the job level. In Appendix Section B, we document the same statistics at annual frequency. The results are similar, again showing infrequent changes.

Infrequent changes in the wage for new hires already suggest a constraint on wage setting at the job level. We now show asymmetry—this constraint matters more for preventing wage falls than for wage rises.

4.3 Job-Level Wages Rise More Often Than Fall

At the job level, wages in new hires are more likely to rise than to fall. There is a downwards constraint on wage setting—while wages are more able to increase.

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15The hazard rate of the latent wage change is constant across time and common across all jobs within each 2 digit SOC occupation. Let \( \{w_{it}\} \) be the sequence of log wages for job \( i \) and quarter \( t \). Let \( \gamma_{it} \) be the gap in quarters between the wage at \( t \) and wage in the previous vacancy that was posted. Let \( I_{it} \) be an indicator for whether the wage changed, where \( I_{it} = 1 \) if \( w_{it} \neq w_{i,t-\gamma_{it}} \). The quarterly hazard rate of wage change, assumed to be time-invariant, is given by \( \lambda \), 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 wage change for each occupation is \( f = 1 - e^{-\lambda} \). The implied duration of time for which a wage is unchanged is \( d = 1/\lambda \). The overall probability of wage change is the median probability across occupations, weighted by the number of vacancies in each occupation. Similarly, the overall implied duration is the weighted median of the implied duration for each occupation. We discard left-censored wage spells.
Figure 3: Distribution of Non-Zero Wage Growth for New Hires

Notes: this graph is the distribution in the growth of wages for new hires, excluding zeros. A job is an establishment by job-title by salary type by pay frequency unit. Wages are averaged by job-quarter. Wage growth is the growth in wages between two consecutive vacancies posted 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 3 plots the distribution of nonzero wage growth. There are two clear points. First, wages in new hires rise more often than they fall. Secondly, wages “pile up” against the constraint—there are many small positive wage increases, but far fewer small wage decreases. Both points suggest a downward constraint on wage setting for new vacancies of a given job. We take the distribution of wage growth for new hires 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 ±10% wage growth. Unsurprisingly, a McCrary test detects a discontinuity at the point of zero wage changes.

We then estimate the probability of wage increases and decreases for new hires. The results are in Table 4. As expected, wages are more likely to rise than to fall. Table 4 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. In Appendix Section B, we repeat the analysis at annual frequency, with similar results.
Figure 4: Probability of Job-Level Change in Wage for New Hires

Notes: this graph estimates the job-level probability of wage change, increase and decrease, using the same method as in table 4, separately for each year.

4.4 Wage Increases Are Cyclically Sensitive, Wage Decreases Are Not

The probability of wage increase is sensitive to business cycles, 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.

We estimate time varying probabilities of the change, increase, and decrease in the wage for new hires at the job level. We estimate these probabilities separately for each year of our sample, over 2010-2016, using the hazard model of subsection 4.2.

Figure 4 shows the results. As the labor market tightens over 2010-2016, the probability of wage change rises—as expected, given that wages rise over this period. However, the probability of wage change rises entirely because wage increases are more likely. Wage decreases are not more likely as the business cycle evolves. Thus wage increases for new hires are cyclically sensitive, and wage decreases are not—consistent with downwards wage rigidity.\footnote{Granted, Figure 4 uses variation from only one business cycle expansion. In further support, Appendix Table 18 shows that the probability of increase is more cyclical than the probability of decrease, after state business cycles. We calculate the probability of wage increase and decrease within each state-quarter. We regress these}
4.5 Wages For New Hires vs. Continuously Employed Workers

Our finding, that the wage for new hires changes infrequently and falls rarely, is novel. We provide context with a fact that has previously been documented: wages in continuing jobs also change infrequently. Workers in continuing employment—as opposed to workers newly hired into jobs—rarely experience wage changes.

The duration for which wages do not change is similar, for new and continuing jobs. Figure 5 presents estimates of the duration that base wages are unchanged in continuing jobs. Two estimates are close to ours: the estimate of Grigsby et al. (2018), which studies high quality payroll data; and the estimate of Barattieri et al. (2014), which corrects for measurement error in survey wages.\(^\text{17}\)

Our findings suggest that new and continuing wage changes are governed by the same underlying forces. Previous work conjectures that new and continuing wages behave similarly due to internal equity between new hires and continuing workers, or firm wide pay scales (Bewley, probabilities on the change in unemployment for each state-quarter. The probability of wage increase comoves strongly with unemployment changes, the probability of decrease does not.\(^\text{17}\)

\(^{17}\)Other estimates are from survey data without correcting for measurement error, which biases downwards the estimated duration for which wages are unchanged.
Then wages change infrequently across successive new hires. Our finding lends support to this argument. However, the wage for new hires is especially relevant for unemployment fluctuations, while continuing wages may matter less.

Our finding that wage setting is similar for new and continuing jobs is not obvious. Some plausible mechanisms predict the opposite pattern. For example, implicit contracting models imply that continuing wages should be rigid downwards, while wages in new hires should be flexible downwards (Harris and Holmstrom, 1982; Beaudry and DiNardo, 1991).

5 Downward Rigidity in Job Level Wages

This section asks whether the wage for new hires responds differently to business cycle contractions and expansions at the job level. We find strong asymmetries. Across successive vacancies posted by the same job, the wage for new hires does not fall during contractions, but does rise during expansions. Thus the downward constraint at the job level, which we previously documented, leads to downward wage rigidity.

5.1 Regional Unemployment Variation

In our regressions, we study the response of wages to regional business cycles. By studying regional data, we surmount the relatively short time series in our data. State level unemployment is measured with noise. We instrument for state-level unemployment with an administrative measure of employment, from the QCEW, to avoid attenuation bias.

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. 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). Appendix Section A documents further statistics about regional business cycles over this period.

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18Within 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 continuing workers have more rigid wages than new hires, though their interpretation of the data is disputed (Hagedorn and Manovskii, 2013).
5.2 Job-Level Specification

Our benchmark regression for measuring downwards wage rigidity in new hires, at the job level, is

\[
\Delta \log w_{jst} = \alpha + \gamma_t + \beta \Delta U_{st} + \delta I[\Delta U_{st} < 0] \Delta U_{st} + \epsilon_{jst}.
\] (1)

\(w_{jst}\) is the nominal wage for a new match in job \(j\) and quarter \(t\). We difference wages between the successive quarters in which the job posts a vacancy. This step isolates job-level wage changes. \(\Delta U_{st}\) is the change in quarterly state level unemployment. \(\gamma_t\) is a time fixed effect. \(\beta\) and \(\delta\) measure the sensitivity of the wage for new hires to regional unemployment. A more negative number indicates greater sensitivity. If \(\delta < 0\), then wages comove more with unemployment during expansions, that is, when \(\Delta U_{st} < 0\). If \(\beta = 0\), then wages do not comove with unemployment during contractions. We project \(\Delta U_{st}\) onto state-quarter employment growth from the QCEW.19

We study the same sample as in section 4, that is, jobs that post multiple vacancies, averaging wages at the job-quarter level. Time fixed effects sweep away aggregate variation, to focus on regional variation. Time effects also control for variation in the national price level. Therefore our results measure real wage rigidity, deflated by national prices. For a valid structural interpretation, regression (1) must assume that unemployment is driven by labor demand shocks. We explore robustness to this assumption in our regressions.

5.3 Job-Level Wages Rise, But Do Not Fall, with Unemployment

Figure 1, from the introduction, showed non-parametrically the main empirical result of the paper. When unemployment rises, the wage for new hires does not fall—meanwhile wages do rise as unemployment falls.

Table 5 confirms these results by estimating regression equation (1). In Column (1) of Table 5, \(\beta\) is not significantly different from zero, and indeed is slightly positive—thus the wage for new hires does not fall during contractions. Meanwhile \(\delta\) is negative and statistically significant. Wages are more sensitive to expansions than contractions in unemployment, and rise during expansions. The results—both that \(\beta\) is near zero and \(\delta\) is significantly negative—are robust across several specifications. In column (2) we add in state-specific trends, and in column (3) we reweight to the occupational distribution of jobs in the US economy, to ensure representativeness. We reweight at the 6 digit SOC code level, using the 2014-2016 Occupational Employment Statistics.

19Appendix Section B reports the first stage regression projecting quarterly state unemployment changes onto employment growth. As expected, the two series are closely correlated.
Column (4) drops the \( I[\Delta U_{st} < 0] \Delta U_{st} \) term from our benchmark regression (1), and instead measures the average sensitivity of wage growth to unemployment changes. On average wages do comove negatively and significantly with unemployment—but this average comovement is entirely driven by expansions and not contractions.

We doubt labor supply fluctuations could rationalize the sharp asymmetries that we document. Nevertheless, column (5) presents evidence of downward wage rigidity from an identified labor demand shock. We instrument for state unemployment using a Bartik-style instrument based on states’ regional exposure to the global oil price.\(^{20}\) Again \( \delta \) is negative and significant and \( \beta \) is insignificantly different from zero. Thus wages do not fall during contractions, and are more rigid downward than upward, in response to labor demand shocks. The identifying assumption is that states who are exposed to contractions in the global oil price do not receive labor supply shocks at the same time. This assumption is similar to Acemoglu et al. (2013) and Allcott and Keniston (2017). The assumption seems plausible in our setting. The variation in this instrument comes from the large contraction in the oil price in 2015—Appendix Figure 17 displays the oil price. Appendix Figures 16 and 15 show that the regional contractions during this period come mostly from oil producing states, such as Texas, Wyoming and Alaska.

Table 6 reports further robustness tests. We estimate versions of our benchmark regression, and report the coefficient on \( I[\Delta U_{st} < 0] \Delta U_{st} \). If this coefficient is negative, then wages are more rigid downward than upwards. We reweight vacancies to target the regional distribution of employment in the Quarterly Census of Employment and Wages, ameliorating representativeness concerns. We seasonally adjust, either by applying the BLS’s X-11 algorithm to unemployment or by adding state by quarter of year fixed effects to the regression. We study only wages that post a point wage, instead of a wage range. We run the same regression at annual frequency. We remove wages with bonuses from the data. We study a broader definition of a job. We consider a new definition of a job, as a job title within an establishment, while pooling across pay frequencies.\(^{21}\) In all cases, the coefficient negative and significant, implying that the wage for new hires is more rigid downward than upward. In the final row of Table 6, we estimate nonlinearity with a quadratic. Our regression replaces the term \( I[\Delta U_{st} < 0] \Delta U_{st} \) in equation (1) with squared unemployment changes \( (\Delta U_{st})^2 \). The squared term is positive and

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\(^{20}\)The first stage regression is \( \Delta U_{st} = \sum_s [\alpha_s + \beta_s \Delta \log(\text{oil price}_{t-1}) + \gamma_s I(\Delta \log(\text{oil price}_{t-1}) < 0) \Delta \log(\text{oil price}_{t-1})] + \text{error}_{st} \), where \( \alpha_s, \beta_s \) and \( \gamma_s \) are estimated, similarly to Nakamura and Steinsson (2014). There are many instruments, which biases the estimates towards OLS, and therefore strengthens the interpretation of our finding, because our IV estimate of the downward wage rigidity coefficient \( \delta \) is greater in magnitude than our OLS estimate. Nakamura and Steinsson report for their instrument that the standard error is unbiased, because of the high \( R^2 \) of the instruments as a whole. Though we cluster standard errors by state in other regressions, we two way cluster standard errors by state and year in this regression, following the recommendation for inference in Bartik instruments by Adao, Kolesár, and Morales (2018).

\(^{21}\)In the baseline, a job is a job title within an establishment at a given pay frequency (e.g. hourly or annual).
significant, again suggesting substantial nonlinearity.

Our Appendix contains numerous additional robustness checks. Appendix Table 19 shows that wages are more rigid downward than upward at the 3-digit industry level. When industry employment or industry output per worker rises, job-level wages for new hires rise; whereas after a contraction in industry employment or industry output per worker, job-level wages do not fall. Appendix Table 20 shows the same result, using 2- and 3-digit by state variation. These regressions include state-by-time fixed effects, sweeping away common state level labor supply shocks over this period, such as unemployment benefit extensions (Hagedorn, Karahan, Manovskii, and Mitman, 2013). Appendix Table 21 studies real wages for new hires at the city level, deflated by BLS measures of city prices. These regressions show that real wages are more rigid downward than upward, and that the magnitude of nominal and real wage rigidity is similar. Appendix Table 22 estimates our baseline regression for five broad occupations, and finds that downward wage rigidity is pervasive across all broad occupations.

A large share of vacancies post while state unemployment is increasing, letting us estimate asymmetries despite the national labor market recovery over 2010-2016. Where does this variation come from? Appendix Figure 15 plots the share of vacancies in each state that experience rising state unemployment. Appendix Figure 16 plots the share of vacancies in each year that experience rising state unemployment.

5.4 Discussion of Job-Level Results

We briefly discuss two potential complications to our finding of downward rigidity at the job level. While both are important, we suspect that neither fully undermines our result.

First, the pool of unemployed workers tends to have a higher past wage during recessions (Mueller, 2017). Therefore the productivity of the typical unemployed worker seems to be higher during recessions. Thus quality adjusted wages, accounting for workers’ productivity, may be flexible—even if unadjusted wages are rigid. On the other hand, though worker composition is no doubt important, we are unaware of evidence that worker composition responds asymmetrically to business cycle contractions versus expansions. Without such asymmetries, it is not clear how worker quality can offset the sharp asymmetries that we document in job-level wages.

Second, suppose that workers bargain, so that there is a gap between wages posted in Burning Glass, and wages for newly hired workers. If this gap varies over the business cycle, it could affect the interpretation of the job-level wage rigidity that we estimate. However, if this force operates, we expect it to amplify our conclusion that the wage for new hires is more rigid downward than upward. Survey evidence suggests that workers are less likely to bargain after con-
tractions and more likely to bargain during expansions, even conditional on a wide range of worker observables (Brenzel, Gartner, and Schnabel, 2014). So, new hires’ wages might be even more flexible upward than posted wages, after expansions. Meanwhile, posted and new hire wages should be similar after contractions—which is precisely when the downward constraint on job level wages matters. In any case, we previously showed that wages posted in Burning Glass closely track other measures of the wage for new hires from survey and administrative data—which points against a gap between wages posted in Burning Glass, and the wage for new hires. Meanwhile, survey evidence suggests that the large majority of workers accept posted wages, which again points minimizes the issue due to bargaining (Hall and Krueger, 2012).

So, job level wages seem to be downwardly rigid. Job-level wages affect the wage faced by establishments—which we argued is key for unemployment fluctuations. But establishments hire multiple types of jobs. The overall wage for new hires at the establishment, averaging over the establishments’ jobs, may also matter for establishments’ job creation. We therefore ask whether establishment wages inherit the downward rigidity present in job level wages.

6 Downward Rigidity in Establishment Level Wages

We find downward rigidity in establishment wages, similar to the job-level results. Establishment wages do not fall when unemployment rises, but rise strongly when unemployment falls. So, the constraint at the job level leads to downward rigidity in the wage faced by establishments, across all the jobs into which they hire.

6.1 Establishment-Level Specification and Result

We start with an establishment level version of our regression that tests for downward rigidity. We study the regression

$$\Delta \log w_{et} = \alpha + \gamma t + \beta \Delta U_{st} + \delta I[\Delta U_{st} < 0] \Delta U_{st} + \varepsilon_{et},$$

where $w_{et}$ is the mean nominal establishment wage, pooling across all jobs posted by an establishment in a given quarter. We difference wages between the successive quarters in which the establishment posts a vacancy. This step isolates establishment-level wage changes.

The establishment-level regression has a different outcome variable from our job-level regression that tests for downward wage rigidity, equation (1)—but otherwise, the two regressions are identical. The variation in the outcome variable of the establishment-level regression (2), is akin to wage changes across all hires at a location of Starbucks, between successive quarters.
The variation in the job-level regression, from the previous section 5, is akin to wage changes for a Starbucks barista, at the location of Starbucks, across successive quarters.

Table 7 reports the results. In Column (1) of Table 7, $\beta$ is not significantly different from zero—thus the wage for new hires does not fall during contractions at the establishment level. Meanwhile $\delta$ is negative and statistically significant. At the establishment level, wages are more sensitive to expansions than contractions in unemployment, and rise during expansions. The results—both that $\beta$ is near zero and $\delta$ is significantly negative—are robust across several specifications. In column (2) we add in state-specific trends, and in column (3) we reweight to the regional distribution of jobs in the US economy, to ensure representativeness. Column (4) drops the $I [\Delta U_{st} < 0] \Delta U_{st}$ term from our benchmark regression (1), and instead measures the average sensitivity of wage growth to unemployment changes. On average wages do comove negatively and significantly with unemployment—but this average comovement is entirely driven by expansions and not contractions.

Importantly, the magnitude of downward wage rigidity is similar at the job and establishment level. Across all columns in Table 7, the establishment-level regression, the coefficients are of similar magnitude to their counterparts in Table 5, the job level regression. Therefore establishment wages are affected by the downward constraint on wage setting at the job level.

### 6.2 Can Establishment Level Hiring Offset Downward Wage Rigidity?

One potential concern is that establishments alter the jobs into which they hire workers, in a way that offsets downward rigidity at the job level. Granted, since establishment- and job-level wages display a similar degree of downward rigidity, this concern does not seem to matter in practice. Nevertheless, we explain the concern and how we deal with it.

Consider a simple example. Suppose that in the Starbucks establishment, wages are downwardly rigid for “senior baristas” and “junior baristas”. During expansions, Starbucks hires higher wage senior baristas. During contractions, Starbucks hires lower wage junior baristas. Either way, newly hired workers brew coffee. The wage for new hires falls despite downward rigidity at job level, without any effect on the output of the Starbucks. More generally, establishments could avoid wage rigidity at the job title level. During booms, establishments could hire in high wage jobs; and during busts, hire in low wage jobs. Then the the wage faced by the establishment might fall during contractions. Of course, this concern supposes that establishments can easily substitute between high and low wage workers, which may not be possible in reality.

We test whether establishments circumvent job level wage rigidity in this manner, by asking whether establishments increase their hiring in low wage jobs during contractions. For each
establishment, and in each quarter, we calculate the share of high wage vacancies, with three methods. First, we calculate the share of establishment-quarter vacancies that are above the weighted median wage in Burning Glass. Second, we calculate the share of vacancies that are above the median 6 digit SOC occupation wage, that is the share of vacancies in high wage occupations. Third, we calculate the share of vacancies in high wage occupations, within each establishment and broad occupation group. A broad occupation group is at the 1 digit SOC level. This third method contemplates that establishments might substitute jobs differently, depending on the broad occupation group to which the job belongs.

We regress the quarterly change in the high wage establishment share, from these three measures, on the change in quarter-by-state unemployment. The regression is identical to regression equation (2)—but for the outcome variable, which is the quarterly change in the high wage establishment share.

Table (8) presents the results. Row (1) of column (1) shows that when unemployment rises by one percentage point, the share of high wage occupations in the establishment rises by 0.1 percentage points. This coefficient is small in magnitude, not statistically significant. The sign of the coefficient suggests that, if anything, establishments raise the high wage share of jobs during recessions. Row (2) of column (1) shows that the share of establishment high wage vacancies does not respond significantly differently to contractions versus expansions in unemployment. Thus the establishment share of vacancies cannot be moving in a way that offsets the asymmetric response of wages to contractions versus expansions. The results are similar with the other two methods for calculating establishments’ high wage shares. So, the mix of jobs into which establishments are hiring cannot be moving to offset the downward constraint on wage setting at the job level.

6.3 Reallocation Between Establishments and Downward Wage Rigidity

Our discussion of establishment level hiring suggests a more nuanced concern: reallocation between establishments might also undo wage rigidity. Let us explain the concern with another example. Suppose that, on average, wages are downwardly rigid at the Starbucks establishment, but there is a neighboring establishment of Dunkin’. On average, wages are higher at Starbucks than Dunkin’. After a contraction in labor demand, Starbucks stops hiring. However Dunkin’, with its lower wages, is able to hire the workers who cannot find jobs at Starbucks. Either way, the same workers still make coffee.

More generally, reallocation between establishments might undo downward wage rigidity at the establishment level. During a contraction, high wage establishments stop hiring. But low wage establishments could increase their hiring in response, and absorb the excess workers
with minimal effects on the overall labor market. But this concern supposes a high degree of substitution between establishments that hire high and low wage workers, which again may not be true in practice.

We test for the concern by asking whether the share of low wage jobs in the overall labor market increases during contractions. For each state and quarter, we calculate the share of high wage vacancies, that is, vacancies with above median wages in Burning Glass. We regress the quarterly change in the high wage state share of vacancies, on the change in quarterly state unemployment. The regression is identical to the regressions of subsections 6.1 and 6.2, but for the outcome variable—which is the quarterly change in the state share of high wage vacancies.

Table 9 presents the results. Row (1) of column (1) shows that when state unemployment rises by one percentage point, the share of high wage jobs falls by a statistically insignificant 0.6 percentage points. Moreover, row (2) of column (1) shows that the share of high wage vacancies at the state level does not respond significantly differently to rises versus falls in unemployment. Thus the state share of vacancies are not moving in a way that offsets the asymmetric response of wages to contractions versus expansions. Columns (2) and (3) study the same regression after adding in state trends and reweighting to target regional employment. The regression coefficients are noisy and unstable, but none of them suggest that the state share of high wage vacancies responds differently to rises versus falls in unemployment.

Equally, our evidence does suggest that the high wage share of vacancies falls slightly during recessions. Column (4) of Panel A reports the coefficient from regressing the quarterly change in high wage vacancies on the quarterly change in state unemployment. This regression studies the average effect, and does not separate out the effect of expansions versus contractions in unemployment. On average, as unemployment rises, the high wage share of vacancies falls very slightly. However, the estimated coefficient is small. This finding is somewhat consistent with previous work, such as Barlevy (2002), which finds that workers often switch to lower wage jobs during recessions. The small effect size that we estimate may reflect other factors such as upskilling (Hershbein and Kahn, 2016), which raises the share of high wage vacancies during recessions.

7 Job Composition and the Average Wage for New Hires

To summarize the results so far: we provided new evidence that the wage for new hires is more rigid downward than upward, at the job and establishment level. Why is there such limited prior evidence of downward rigidity? Previous work studies the *average* change in the wage for new hires, from survey data that averages across all newly hired workers in a given quarter. This section shows that due to job composition, average wages must be noisier than job or
establishment wages. Thus regressions with average wages will have limited power to detect downward wage rigidity for new hires. Indeed, in the data, estimates of downward rigidity using average wages are far too noisy to detect downward wage rigidity.

First, we precisely define the job level measure of the wage for new hires, to contrast with the average wage for new hires used in prior work. Consider an economy with $I$ job types, $S$ states, and $T$ time periods. The wage for a newly hired worker in job type $i$, state $s$, and quarter $t$ is $w_{ist}$. The share of new hires in job type $i$ during the state-quarter is $\nu_{ist}$.

Our dataset measures growth in the job-level wage for new hires, $\Delta \log w_{ist}$. That is, we observe growth in the wage for new hires, for the same job, in the same state, between successive quarters.\(^{22}\) Previous work studies growth in the average wage for new hires—see, for example, Haefke et al. (2013), Kudlyak (2014) or Basu and House (2016). Researchers measure the wage for newly hired workers from survey data without information on jobs or establishments, such as the Current Population Survey or the National Longitudinal Survey of Youth. Researchers then calculate the average log wage of newly hired workers, and approximate the growth in the average wage for new hires by

$$\Delta \log w_{ist} = \sum_i \nu_{ist} \log w_{ist}, \quad (3)$$

which is the change in average log wages.\(^{23}\)

Average and job-level wage growth can differ if job composition changes. A first order expansion of equation (3) yields

$$\Delta \log w_{st} = \sum_i \nu_{ist} \Delta \log w_{ist} + \sum_i \log w_{ist} \Delta \nu_{ist}, \quad (4)$$

Average wage growth depends on two components: job-level wage growth, and wage growth due to composition. Average wages can change, even if job-level wages do not change. Suppose that wages are unchanged at the job-level during a given quarter—that is, the first term on the left hand side of equation (4) is fixed. If the share of high wage hires increases, wages change due to composition. The second term on the left hand side of equation (4) increases, and average wages rise. If the share of low wage hires increases, average wages fall. More generally, as high and low wage types of job churn in and out of the data, average wages for new hires will vary—even if job-level wages are unchanged.

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\(^{22}\)Recall that in our empirics, we define a “job” as a job title by establishment unit.

\(^{23}\)For practical reasons, researchers typically study the change in the average of log wages, instead of the change in the log of average wages.
From inspecting equation (4), we can see how job composition might add noise to average wages. If job-level wage growth and wage growth due to job composition are independent, then the variance of average wages must be higher than the variance of job-level wages. Due to the noise, average wages may not manifest downward rigidity, even when it is present at the job level.

Our benchmark regression estimates downward rigidity using job level wage variation. That is, we study the population regression function

$$\Delta \log w_{ist} = \alpha + \gamma_t + \beta \Delta U_{st} + \delta_{\text{Benchmark}} I[\Delta U_{st} < 0] \Delta U_{st} + \varepsilon_{ist},$$

(5)

where $\varepsilon_{ist}$ has bounded variance $\sigma^2_{ist}$. We are interested in $V[\hat{\delta}_{\text{Benchmark}}]$, the variance of the OLS estimator of $\delta_{\text{Benchmark}}$. If $\delta_{\text{Benchmark}}$ is negative, then the wage for new hires is more rigid downward than upward at the job level.

Suppose a researcher only has access to average wages for new hires, as in prior work. A natural regression to study downward wage rigidity in average wages is

$$\Delta \log w_{st} = \bar{\alpha} + \bar{\gamma}_t + \bar{\beta} \Delta U_{st} + \delta_{\text{Average}} I[\Delta U_{st} < 0] \Delta U_{st} + \bar{\varepsilon}_{st}.$$

(6)

This regression is the analogue of our job-level regression, with average wages as the outcome variable. If estimates of $\delta_{\text{Average}}$ are negative, then one concludes that average wages are downwardly rigid. If average wages are noisy, then the variance of the OLS estimator of $\delta_{\text{Average}}$, which we term $V[\hat{\delta}_{\text{Average}}]$, will be large.

In the following proposition, we show that job composition inflates the variance of $\hat{\delta}_{\text{Average}}$ relative to $\hat{\delta}_{\text{Benchmark}}$. Thus regressions using average wages may lack the power to detect downward rigidity, even if it is present at the job level.

**Proposition 1.** For $S, T < \infty$, and if $\sum_i \log w_{ist} \Delta v_{ist}$ and $\sum_i \log w_{ist} \Delta v_{ist}$ are independent conditional on $\Delta U_{st}$, then

$$V[\hat{\delta}_{\text{Average}}|\Delta U_{st}] > V[\hat{\delta}_{\text{Job Level}}|\Delta U_{st}]$$

**Proof:** Appendix Section C.

The proposition makes a simple point. The variance of the estimator for downward rigidity that uses job level wages is lower than the estimator that uses average wages. The difference between the two variances comes from changing job composition. From equation (3), the only difference between job-level and average wage changes comes from changing job composition. Intuitively, in any given quarter, high and low wage jobs churn in and out of the data. Average wages for new hires will vary regardless of whether wages are changing for the same type of job over time. In a regression with average wages, the residual variance is higher, creating noisier
estimates. By contrast, regressions with job level data purge noise due to job composition, and become precise.

Proposition 1 supposes that job composition \( \sum_i \log w_{ist} \Delta v_{ist} \) and job level wage growth \( \sum_i \log w_{ist} \Delta v_{ist} \) are independent. Alternatively, if job composition correlates with job level wage growth, then estimates of \( \delta \) from state level data could suffer from omitted variable bias, as in the “composition bias” of Solon, Barsky, and Parker (1994). Subsection 6.3 showed that unemployment changes do not seem strongly correlated with job composition over our sample period, and job composition does not display the sharp asymmetries apparent in job-level wages.

In real-world data, noise due to job composition dramatically raises the variance of estimators that use average wages. We estimate \( \hat{\delta}_{\text{Average}} \) in equation (6). For the outcome variable, we construct average wage growth for new hires at the state-quarter level, from Burning Glass, and from the Current Population Survey.\(^{24}\) We study quarter-by-state data for 2010-2016, as in our benchmark regression. We report the estimated variance of \( \hat{\delta}_{\text{Average}} \). We contrast with the estimated variance of \( \hat{\delta}_{\text{Benchmark}} \). In both cases, we cluster standard errors at the state level. This procedure consistently estimates the variance of the estimators \( \hat{\delta}_{\text{Average}} \) and \( \hat{\delta}_{\text{Benchmark}} \), given that the regressor \( \Delta U_{st} \) varies at the state level.

Figure 6 reports the estimated variance of downward wage rigidity, from job level and average wages. Table 10 reports the point estimates and standard errors. The difference in precision between the estimates on average and job level wages is enormous. Job composition does, indeed, inflate the variance of estimates of downward rigidity. The top row of Figure 6 reports the estimated variance of our job level estimator of downward wage rigidity, \( \hat{\delta}_{\text{Benchmark}} \). The second row reports the estimated variance of \( \hat{\delta}_{\text{Average}} \), the estimator of downward rigidity from average wages, with average wages for new hires from Burning Glass. The third row reports the estimated variance of \( \hat{\delta}_{\text{Average}} \), with average wages for new hires from the Current Population Survey. The fourth row estimates \( \hat{\delta}_{\text{Average}} \) using national wage growth for new hires and national unemployment changes, for 1985-2006. The sample period and measure of wages is the same as Haefke et al. (2013). In all the regressions that use average wages instead of job level wages, the estimated variance is far higher. Therefore the noise associated with job composition is large in practice, and precludes researchers from detecting downward rigidity in average wages. The third row of Figure 6 does suggest a significant result. But given the wide confidence intervals and insignificance of the other results using average wages, we suspect a type I error. Moreover, the estimated variance of of \( \hat{\delta}_{\text{Average}} \) is higher for average wages in the CPS, versus

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\(^{24}\)To construct the average wage for new hires in the CPS, we follow the procedure in Haefke et al. (2013). To construct the average wage for new hires in Burning Glass, we regress log wages for new hires on a set of state-by-quarter dummies, as well as dummy variables for the pay frequency and salary type of the wage. The state-by-quarter dummies are then mean log wages in the state quarter.
Figure 6: Estimates of Downward Rigidity in Job Level and Average Wage for New Hires

The top row reports the estimate of $\delta$, from regression (5), which estimates downward rigidity with job-level data on the wage for new hires. The next three rows report various estimates of $\delta$ from regression (6), which estimates downward rigidity with average wages for new hires. The second through fourth rows use, as the average wage measure, state-quarter average wages from Burning Glass, state-quarter average wages from the CPS, and national average wages from the CPS. See Table 10 for details.

average wages in Burning Glass, though both estimators are imprecise. This difference likely reflects measurement error from misreporting in CPS wages (Bound and Krueger, 1991).

The precision of the job-level estimates does not simply reflect a larger sample size in the regression that studies job level wages. Though the outcome variable, wage growth, is measured at the job level, the regressor varies at the state level. Hence the degrees of freedom in the regression that studies job level wages is the number of states, and not the number of jobs.\(^{25}\) Put differently, we cluster standard errors in the benchmark regression at the state level. Holding fixed the number of states, more observations within the state may not lower the standard error.

Appendix Figure 18 shows that many different measures of the average wage for new hires

\[ \sum_i \nu_{ist} \Delta \log w_{ist} = \alpha + \gamma_t + \beta \Delta U_{ist} + \delta_{\text{Benchmark}} I[\Delta U_{ist} < 0] \Delta U_{ist} + \sum_i \nu_{ist} \epsilon_{ist}. \]

The left hand side variable is the state average of job-level wage growth within each quarter. Thus all variables in this regression vary only at the state-by-quarter level.

\(^{25}\text{To see this point formally, note that we can estimate } \delta_{\text{Benchmark}} \text{ using only data aggregated at the state by quarter level. The benchmark regression equation (5) is numerically equivalent to the regression}\]
suffer from noise due to job composition. Appendix Figure 18 collects OLS estimates, from regressions of average wage growth for new hires on unemployment changes, from multiple studies. Appendix Figure 18 reports the variance of these estimates. These studies do not fully adjust for job composition, since they lack job-level wage measures. If average wages are noisy due to job composition, then these estimates will be imprecise. Indeed, in all of the studies, OLS estimates are imprecise. Many of these studies use worker level measures of the wage for new hires, constructed from worker-level microdata on workers switching jobs—instead of average wages for new hires. These worker-level measures do not adjust for the composition of jobs that workers switch into. As a result, the estimates that use worker-level microdata are still noisy, again reflecting the role of job composition.

Let us summarize. This section shows that job composition inflates the variance of estimators of downward wage rigidity that use average wages for new hires. Thus regressions using average wages have no power to detect downward wage rigidity. By contrast, our job level estimates purge the noise associated with changing job composition. Since job composition changes little within establishments, given the results of subsection 6.2, establishment level estimates are also minimally affected by noise due to job composition. We reiterate that wage changes at the job and establishment level are important for unemployment fluctuations. Therefore average wages cannot detect downward rigidity even when it matters for business cycles.

Changes in average wages due to job composition may be less important for business cycles. Granted, if changes in job composition were correlated with business cycles, one might suspect reallocation of workers between high and low wage jobs. Reallocation of this sort could have substantive implications for business cycles (Barlevy, 2002). However the results of subsection 6.3 do not suggest much reallocation of workers across establishments, at least over this sample period.

8 State Dependent Asymmetry in Unemployment Dynamics

In the second part of the paper, we argue that the form of downward wage rigidity in the data leads to new implications for unemployment dynamics.\textsuperscript{26} Our argument proceeds in four steps. First, we show a new result: the wage for new hires displays state dependent flexibility upward. Second, we introduce downward wage rigidity into a standard labor search model, and estimate the model with our new evidence. Third, in the model, the degree of asymmetry in unemployment dynamics is state dependent. After contractions, the response of unemployment to labor

\textsuperscript{26}See, amongst others, Daly and Hobijn (2014), Chodorow-Reich and Wieland (2017) and Petrosky-Nadeau and Zhang (2013) for related arguments about the state dependence of unemployment dynamics.
demand is symmetric; whereas after persistent expansions, unemployment is much more sensitive to negative than to positive shocks.

8.1 State Dependent Asymmetry: Outline of The Argument

Let us explain the basic mechanics of our argument. Suppose that wages are downwardly rigid. A simple model for downward wage rigidity is

\[ w_t = \max \left[ w_{t-1}, w_t^* \right] \]

\[ w_t^* = b + \phi y_t \quad b, \phi > 0. \]

Wages today, \( w_t \), are the maximum of previous wages \( w_{t-1} \), and a frictionless wage \( w_t^* \). If the frictionless wage is low, wages today may be constrained by previous wages. The frictionless wage depends positively on labor demand \( y_t \).

In this simple model, wage flexibility upward is state dependent, due to downward wage rigidity. After a large contraction in labor demand at \( t-1 \), \( w_t \) is much greater than \( w_t^* \). Then if a slight rise in labor demand follows at time \( t+1 \), we have \( w_{t+1} = w_t > w_{t+1}^* \), that is, wages do not rise as labor demand marginally increases from the trough of the contraction. Wages are “trapped too high” by the downward constraint. Suppose instead that the economy has been expanding, so downward constraints do not bind and \( w_t = w_t^* \). Then after a rise in labor demand, \( w_{t+1} = w_{t+1}^* > w_t \), and wages rise after the increase in labor demand.

As a result, the degree of asymmetry in unemployment dynamics should be state dependent. After deep contractions, wages are rigid both upward and downward. The cost of labor is similarly insensitive to positive and negative labor demand shocks. So, unemployment should respond similarly to positive and negative shocks. After long expansions, wages are flexible upward and rigid downward. Then unemployment should respond much more to negative than to positive shocks. The cost of labor rises after positive shocks, muting the subsequent fall in unemployment. However the cost of labor remains high after negative shocks, amplifying the fall in unemployment.

We will see that this force is quantitatively powerful when disciplined in a model by our new data, leading to a large degree of state dependence in the asymmetry of unemployment dynamics.

\[^{27}\text{This simple model is similar to, amongst others, Schmitt-Grohé and Uribe (2016), Chodorow-Reich and Wieland (2017) and Dupraz et al. (2016).}\]
8.2 Evidence: Wage for New Hires and State Dependent Flexibility Upward

We provide new evidence for the first step of our argument, that the wage for new hires should display state dependent flexibility upward due to downward wage rigidity.

We estimate the regression

$$\Delta \log w_{jst} = \alpha + \gamma_t + \kappa \Delta U_{st} + \nu \Delta U_{st} \times I(U_{s,t-1} - U_{s,t-13} < 0) + \epsilon_{jst}$$

The dependent variable is quarterly job-level wage growth for new hires, from Burning Glass. The independent variable is the change in state-quarter unemployment. We interact state-quarter unemployment changes with an indicator for whether state unemployment fell over the previous three years. As before, we project unemployment changes on employment growth from the QCEW to deal with measurement error.

We restrict the sample only to observations for which $\Delta U_{st} < 0$. Therefore $\kappa$ measures the sensitivity of the job-level wage for new hires to falls in state unemployment, when unemployment has contracted over the previous three years. If $\kappa$ is near to zero, then wages grow little as unemployment falls, in the aftermath of a previous contraction. If $\nu$ is significantly negative, then wages are more sensitive to falls in unemployment, in the aftermath of an expansion over the previous three years. So if $\nu$ is negative, there is state dependent wage flexibility upwards: wages are more sensitive to increases in labor demand when the economy has previously been expanding.

Table 11 presents the results. Across all specifications, $\nu$ is large in magnitude and significantly negative. Therefore in the aftermath of expansions, the wage for new hires is more responsive to increases in labor demand. Wage flexibility upward is state dependent.

A corollary of our state dependence argument is that wages should be inflexible upward in 2010, in the aftermath of a severe contraction. Wages should become progressively more flexible upward over the course of the expansion. We find evidence for precisely this phenomenon.

We estimate the regression

$$\Delta \log w_{jst} = \alpha_y + \gamma_y + \beta_y \Delta U_{st} + \epsilon_{jst},$$

for $y \in \{2010, ..., 2016\}$, and again restrict the sample to observations where $\Delta U_{st} < 0$. That is, we estimate the regression for every year $y$. $\beta_y$ measures the sensitivity of wage growth to falls in unemployment, estimated separately for every year $y$. A more negative number indicates that wage growth is more sensitive to falls in unemployment. Hence $\beta_y$ is estimated using state-by-quarter panel variation, within each year $y$. As before, we project unemployment changes on employment growth from the QCEW to deal with measurement error.
Table 12 reports the results. During the early part of the sample period, the wage for new hires does not rise after falls in unemployment. At the end of the period, when labor markets are tighter, the wage for new hires rises strongly as unemployment falls. The rich variation also 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.

8.3 Model Setup

We now embed downward wage rigidity into a standard Diamond-Mortensen-Pissarides labor search model, discipline the model with our new evidence, and show that it matches non-targeted wage and unemployment dynamics.

8.3.1 Frictional Labor Market

The model of the frictional labor market follows the standard Diamond-Mortensen-Pissarides framework. There is a unit measure of homogeneous workers, who are either employed and producing output $y_t$ in each period, or unemployed and searching for work. Workers are risk neutral, and derive utility from consumption only. Workers have discount factor $\beta \in (0, 1)$ over future utility flows. Workers consume their wage in the periods that they are employed, and derive no flow utility from unemployment.

At the end of period $t-1$, $l_{t-1}$ workers are employed in jobs. An exogenous fraction $s$ of these workers separate from their jobs. At the start of period $t$, there are $u_t$ unemployed workers searching for jobs in frictional labor market. Thus at the beginning of period $t$, the number of unemployed workers searching for jobs of type $i$ satisfies

$$u_t = 1 - (1 - s)l_{t-1},$$

since there is a unit measure of workers either employed or searching for work in each job type at the start of period $t$, and $(1 - s)l_{t-1}$ workers remain employed from the previous period.

There is a large measure of risk neutral establishments, with discount factor $\beta \in (0, 1)$. Establishments post $v_t$ vacancies in total, to match with the unemployed workers. In period $t$, total matches $m_t$ are given by the matching function

$$m_t = \frac{v_t u_t}{(v_t' + u_t')^\gamma} \quad t > 0.$$
The key state variable governing labor market dynamics is market tightness is

\[ \theta_t \equiv v_t / u_t. \]  

The per-period cost of posting vacancies is \( c > 0 \). Vacancy posting costs capture firms’ recruiting expenses, as they search for workers in the frictional labor market. The vacancy filling rate is \( q_t = m_t / v_t = (1 + \theta_t)^{-\frac{1}{2}} \). The vacancy filling rate is decreasing in \( \theta_t \)—in a tight labor market, firms cannot find workers easily.\(^{28}\)

Workers start working in the same period that they are hired. If a worker finds a job in period \( t \), they start producing output in the same period. The job finding rate of a worker is \( f(\theta_t) = \left( 1 + \theta_t^{-1} \right)^{\frac{1}{2}} \). The job finding rate is increasing in \( \theta_t \)—in a tight labor market, workers find jobs easily.

Tightness and employment comove positively. When the labor market is tight, firms hire many workers and employment rises. In particular, employment during period \( t \) satisfies

\[ l_t = 1 - (1 - f(\theta_t))(1 - (1 - s) l_{t-1}). \]  

8.3.2 Labor Demand

Again following the standard framework, unemployment fluctuations are driven by output per worker \( y_t \), which follows an exogenous AR(1) process with mean value 1, that is

\[ y_t = (1 - \rho) + \rho y_{t-1} + \epsilon_t \quad \epsilon_t \sim N(0, \sigma^2). \]  

\( y_t \) is a measure of labor demand. In the model \( \epsilon_t \) is a generic labor demand shock. Though it is literally a shock to output per worker, it can be interpreted more broadly as a shock to labor demand, that could reflect monetary or fiscal shocks.\(^{29}\)

8.3.3 Downward Wage Rigidity for New Hires

We now introduce our modification to the standard model: downward wage rigidity. When a worker and firm match at time \( t \), wages are set. \( w_t \) is the real wage for a worker newly matched

\(^{28}\)Our model does not have directed search or wage posting. Firms cannot alter their vacancy fill rates by changing the wages on their vacancies. However it is well known that the dynamics of the benchmark “competitive search” model of wage posting are similar to the Diamond-Mortensen-Pissarides model that we present here (Moen, 1997). In this latter model, the wage on vacancies does affect vacancy fill rates.

\(^{29}\)In appendix section F, we make this argument concrete by extending the model to include nominal rigidities and demand shocks. The model dynamics are similar.
with a job, and wages are fixed for the duration of the match. The wage for new hires satisfies

\[
w_t = \begin{cases} 
\text{frictionless} \\
\text{real wage} \\
\hat{b} + \phi y_t, (1 - \xi) w_{t-1} \\
\text{prior real} \\
wage 
\end{cases} .
\] (12)

This specification of wage settings means that the wage for new matches is more rigid downwards than upwards. Wages can fall by a maximum of \((1 - \xi)\) between successive hires made by establishments. Yet wages can rise if labor demand \(y_t\) increases sufficiently, with a pass through from \(y_t\) into \(w_t\) governed by the parameter \(\phi\). When wages rise, their dynamics are similar to wages with Nash bargaining, as in the canonical model of Shimer (2005) and others.\(^{30}\) We will estimate the parameter \(\phi\) using our new data.

Since workers and firms are both risk neutral, and the job is a long term contract, what matters to both parties is the present value of wages. The timing of wage payments that we choose, with wages are fixed throughout the match, is a convenient normalization that emphasizes the role of the wage for new matches.\(^{31}\)

We model downward rigidity in real and not nominal wages, for two reasons. Firstly, the evidence of Appendix Table 21 shows that the degree of downward wage rigidity is similar in nominal and real wages, suggesting little gain from modelling the distinction between nominal and real wages. Second, without nominal rigidities, our model is parsimonious. Nevertheless Appendix Section F extends our model to include downward rigidity in nominal wages, alongside nominal rigidity in price setting, and finds little difference to our quantitative results.

### 8.3.4 Firm Profits

If a match is filled at time \(t\), it immediately starts to produce output. For periods \(t + j\) in which a match is not destroyed, the match in job type \(i\) produces output \(y_{t+j}\), common across job types, and pays wage \(w_t\) to the worker. The firm receives flow profit \(y_{t+j} - w_t\).

The value of an unfilled vacancy depends on the chance that a vacancy is filled, and the cost of posting vacancies, as well as its continuation value. Then if \(K_t\) is the value of an unfilled vacancy and \(J_{t,t}\) is the value in period \(t\) of a vacancy that is filled in period \(t\), \(K_t\) is given by

\[
K_t = -c + q(\theta_t) J_{t,t} + \beta(1 - q(\theta_t)) \mathbb{E}_t K_{t+1} .
\] (13)

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\(^{30}\)See Michaillat (2012), Dupraz et al. (2016) and Chodorow-Reich and Wieland (2017) for similar approaches to modelling downwards wage rigidity.

\(^{31}\)We also explored a model extension in which wages could vary after the start of a match. This extension made little difference to our quantitative results, because after the start of the match, wages for continuing workers are insensitive to business cycles (Kudlyak, 2014).
The value of a filled vacancy to a firm is the flow profit, and the continuation value, after deducting the risk of job destruction. $J_{t,t+j}$ is given by

$$J_{t,t+j} = y_{t+j} - w_t + \beta \left[ (1 - s) \mathbb{E}_{t+j} J_{t,t+j+1} + [1 - (1 - s)] \mathbb{E}_{t+j} K_{t+j+1} \right]$$

(14)

where $\mathbb{E}_{t+j}$ denotes the expectation conditional on time $t+j$ information.

### 8.3.5 Free Entry and Equilibrium

There is free entry in vacancy posting. Vacancy posting continues until the labor market becomes tight. Then vacancies are hard to fill, driving the ex ante value of vacancies to zero. Free entry implies

$$K_t \geq 0 \quad u_t \geq 0$$

for all $t$ with complementary slackness. When labor productivity rises, job creation becomes more profitable. Firms create many vacancies and the labor market tightens. If the downward wage constraint binds and labor demand falls sufficiently far, then job creation may not be profitable because wages are too high. Then firms do not create vacancies by the complementary slackness condition.

An equilibrium is a collection of stochastic processes $\{ l_t, u_t, \theta_t, u_t, w_t \}_{t=0}^{\infty}$ that satisfy the law of motion for unemployment (8), the definition of labor market tightness (9), downward wage rigidity (12), the Bellman equations for the value of an unfilled vacancy (13) and the value of a filled vacancy (14), and the free entry condition (15). The equilibrium is conditional on initial employment $l_{-1}$ and the AR(1) process (11) for labor demand $y_t$.

We solve the model with a global algorithm similar to Petrosky-Nadeau and Zhang (2013), which accounts both for the nonlinearity associated with downward wage rigidity, and the occasionally binding constraint associated with the free entry condition (15).

### 8.3.6 Calibrating the Model

So far, we have added downward wage rigidity to a standard labor search model. Part of our contribution is to pin down the key parameters of the model with our new evidence on downward wage rigidity for new hires.

We estimate $\phi$, the pass through of labor demand into frictionless wages, by indirect inference. We simulate the model at weekly frequency. We aggregate the data from the model to quarterly frequency, and run the benchmark regression equation (1) on the data. We minimize the distance between the estimate of $\delta$ from regression equation (1) on simulated data, with the counterpart of $\delta$ estimated on real world data. $\delta$ measures the extent to which wages are more
rigid downward than upward in the data. Thus we run the same regressions on simulated and real world data, at the same time frequency.

Our discussion of the identification of $\phi$ is heuristic, because we jointly estimate $\phi$ alongside three other model parameters. Heuristically, we choose $b$, the intercept in the equation for frictionless wages, to target mean postwar US unemployment. We choose the autocorrelation of the labor demand shock $\epsilon_t$, to match the first autocorrelation of filtered log value added, where the filter follows Hamilton (2018). We choose the standard deviation of the labor demand shock to match the standard deviation of Hamilton-filtered log value added. Table 13 reports the moments in the model and in the data, and our estimated parameters.

We choose standard parameter values to calibrate the rest of the model, at weekly frequency. Table 14 reports these moments. $\beta$ is the discount factor, chosen to target an annual interest rate of 4 percent. $s$ is the weekly separation rate. $\iota$ governs the scale of the matching function. $c$ is the cost of vacancy posting, relative to labor productivity. These previous three parameters are the same as Hagedorn and Manovskii (2008). $\xi$ governs the extent to which real wages can fall. We choose $\xi$ to match composition-adjusted trend real wage growth for 1988-2008 from Acemoglu and Autor (2011).

We make two further comments about our calibration. First, our model does not feature regional labor markets. We had experimented with extending our model to a setting with multiple regions. We found that the equations linking unemployment changes to wage changes was the same at the regional level as at the aggregate level, if the persistence of regional and aggregate shocks were the same. This argument is similar to Beraja, Hurst, and Ospina (2016). Thus our calibration strategy is valid provided that regional and aggregate unemployment are similarly persistent.\footnote{We find that regional and aggregate unemployment are both strongly and similarly persistent, with a first order autocorrelation of differenced unemployment of around 0.7 in both cases.}

Second, our model features a single job type. But in the empirical exercise, we use job-level wage growth. Appendix Section E studies an extension of the model presented in the main text, to include both high and low wage types of jobs. In that model extension, the sensitivity of unemployment to labor demand shocks depends on a weighted average of job level wage changes. The coefficients mapping from job-level wage changes to unemployment changes, in the multiple job model extension; are the same as the coefficients mapping from wage changes to unemployment changes, in the benchmark one job model that we have introduced in the main text. Therefore we lose little by focussing on a one-job model in the main text, instead of a model with multiple jobs.
8.4 Validating the Model with Un-targeted Moments

We now validate the model against various untargeted moments. The model successfully key features of both unemployment and wage dynamics. Equipped with a model that can match the data, we can then study impulse responses in the model.

As a preliminary step, we use the model to estimate the sequence of labor demand shocks in the US time series. We choose the sequence of labor demand shocks $\epsilon_t$, such Hamilton-filtered log output in the model matches the time series of Hamilton-filtered log output in US data, over 1948-2019. By construction, there must be some sequence of shocks $\epsilon_t$ such that the model-generated and real-world data match exactly. Appendix Figure 19 reports model-generated and real-world filtered output, which by the nature of the exercise match exactly.

We then validate the model against three sets of untargeted moments. First, we show that the model, though disciplined with new microdata on the wage for new hires, matches the dynamics of time series US unemployment. We feed the estimated sequence of labor demand shocks into the model, simulate the sequence of unemployment produced by the model, aggregate to quarterly frequency, and apply the Hamilton filter. We compare to Hamilton filtered unemployment from the US time series. Figure 7 reports this result. The match is close. Visually, the model is able to replicate the persistence, volatility, and skewness of unemployment dynamics. Appendix Table 15 confirms this message by calculating the these moments in the model and data, showing that they are similar.

Importantly, in US data, output is relatively symmetric. Thus the sequence of labor demand shocks must be relatively symmetric, implying that skewness in the unemployment rate comes from propagation mechanisms in the labor market (McKay and Reis, 2008). As a simple way of showing how downward rigidity affects the fit of the model, Figure 7 also simulates unemployment in a counterfactual in which the wage is always equal to its frictionless value, and the downward constraint on wage setting is “switched off”. The fit deteriorates, and the skewness of model-generated unemployment falls. Thus downward wage rigidity helps to rationalize the dynamics of unemployment. Therefore the standard labor search model, when matched against our new evidence on downward wage rigidity, can replicated US unemployment dynamics.

Second, we show that the model replicates a salient feature of the wage for new hires that we documented in subsection 8.2. Wages are rigid in response to positive labor demand shocks in 2010, and become increasingly flexible upward. Figure 8 reports the peak impulse response of wages to labor demand shocks, at the start of each year between 2010 and 2016. As in the data, wages become more flexible over time. Intuitively, in 2010, wages are “trapped too high” due to

\[33\] There are limits to this exercise, because we do not re-estimate the sequence of labor demand shocks hitting the economy when the downward constraint on wage setting is “switched off”.

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the previous contraction over the Great Recession. Thus they are rigid in response to positive labor demand shocks. As labor demand increases after 2010, wages are less likely to face the binding constraint, and so become more flexible upward.

Third, we show that the model does a reasonable job of matching *continuing* real wage growth over this time period. Figure 9 reports this result. We plot wage growth for continuing workers in the US time series, and compare with the equivalent quantity in the data. The match is fairly close, despite the noisiness of high frequency wage measures.\(^{34}\) The wage measure in the data is for continuing workers, the wage measure in the model is for new hires. Recall that, in section 4, we found that wage setting seems to be similar for new hires and continuing workers. The results of Figure 9 point in the same direction. Our model therefore helps to explain the puzzle of “missing wage growth” before 2015 (see, e.g. Atlanta Fed, 2014). In the model\(^{34}\)

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\(^{34}\)We add an important caveat: the fit deteriorates before 2012. There is a large supply shock, likely due to oil prices, just before 2012. Thus real wages are highly volatile during that time period. Our model does not model such supply shocks. Inflation is more stable afterwards, hence the closer fit of our model.
as in the data, wage growth picks up at the end of 2014. In the model, this pattern reflects the increasing flexibility of wages with respect to positive labor demand shocks after 2010.

8.5 Model Result: State Dependent Asymmetry

We now show our main quantitative result: state dependent asymmetry. After contractions, unemployment responds similarly to positive and negative labor demand shocks. After persistent expansions, unemployment is as much as twice as sensitive to contractions as to expansions in labor demand.

We consider two scenarios in the model. We study the impulse response of unemployment to positive and negative labor demand shocks at $t = 0$. We consider different paths for labor demand prior to $t = 0$. Figure 10 plots these scenarios. In the first scenario, we assume the economy is at steady state. In the second scenario, we suppose labor demand is at its steady state value at $t = 0$. But before $t = 0$, the economy experiences a contraction from a level of labor demand that is higher than the steady state by one unconditional standard deviation. Thus the state that differs is not current labor demand, which is fixed across the two scenarios. Instead,
Figure 9: Wage Growth in the Model and Data

Notes: continuing real wage grow in the data is semianual, from the BLS’s Employment Cost Index deflated by the Consumer Price Index excluding energy and food. We compare to semi-annual real wage growth simulated and then time-aggregated in the model.

these scenarios isolate the impact of prior contractions or expansions in labor demand, on the current degree of asymmetry in the impulse response of unemployment.

Figure 11 plots the impulse response of unemployment to positive and negative labor demand shocks, at $t = 0$, from each scenario. In the first scenario, the response of unemployment is asymmetric; in the second scenario, the response of unemployment is asymmetric. On the left hand axis, the figure plots the impulse response of unemployment after a positive shock. The dashed line is minus one times the impulse response of unemployment after a negative shock. Clearly, the impulse response after a negative shock is bigger, roughly twice as large at peak. On the right hand axis, the figure plots the impulse response of unemployment to positive and negative shocks in scenario 2, after a contraction in labor demand. Again, the solid line is the impulse response of unemployment to a positive shock, the dashed line is the impulse response of unemployment to a negative labor demand shock. The impulse response is similar for positive and negative shocks.
In the first scenario, wages are rigid downward and flexible upward. Hence the cost of labor rises after positive labor demand shocks, which mutes the fall in unemployment. The cost of labor does not fall after negative demand shocks, and the rise in unemployment is large. In the second scenario, wages are rigid both downward and upward—since there has been a previous contraction, wages are “trapped too high” by the downward constraint. Thus wages are equally rigid both downward and upward, and the impulse response of unemployment inherits this symmetry. We reiterate that the relevant state is not current labor demand, which is fixed across the two scenarios. Rather, prior contractions or expansions in labor demand govern the current degree of asymmetry by determining whether the downward constraint is binding.

We now show that the degree of state dependence varies substantially over time. Figure 12 plots the ratio of the peak impulse response with respect to a negative shock, versus the peak impulse response with respect to a positive shock. During contractions and the early part of recoveries, the impulse response is similar, so unemployment dynamics are symmetric. During the late part of recoveries, the degree of asymmetry grows, so that unemployment is much more sensitive to negative shocks. The quantitative difference is large. For example, between 2000 and 2003, unemployment was similarly sensitive to positive and negative shocks. At the peak of the labor market in 2005-2006, unemployment was twice as sensitive to negative shocks.
Figure 11: State Dependent Asymmetry in Impulse Response of Unemployment

Notes: this graph plots the impulse response of unemployment with respect to positive and negative labor demand shocks, in two scenarios. In the first scenario, which is on the left hand side axis, the impulse response occurs when the economy is at the steady state. In the second scenario, which is on the left hand side axis, the impulse response occurs when the economy’s current labor demand is at its steady state value, but there was a contraction prior to the impulse response. The contraction is equal to one unconditional standard deviation of labor demand. For both scenarios, the solid line is the impulse response after a positive labor demand shock, and the dashed line is minus one times the impulse response after a negative shock. In each case, the impulse is a conditional standard deviation of labor demand.

As a further over-identifying test of our argument, we present novel time series evidence of state dependent asymmetry. We relegate the details to Appendix Section G. In brief, we study the impulse response of unemployment to monetary shocks identified as in Romer and Romer (2004). When the labor market is below its prior peak, as measured by the level of employment, the impulse response of unemployment to monetary shocks is symmetric. When the labor market is at its peak, the impulse response of unemployment to monetary shocks is asymmetric.\textsuperscript{35}

\textsuperscript{35}In the model of the main text, we do not have nominal rigidities, and hence no role for monetary shocks. How-
Notes: we calculate the peak impulse response of unemployment to positive and negative labor demand shocks, at the start of each year since 1990. We calculate minus one times the ratio of these impulse responses. The impulse is equal to one conditional standard deviation of labor demand.

This evidence is in line with our model’s prediction of state dependent asymmetry.

9 Conclusion

There is limited evidence that the wage for new hires is more rigid downward than upward. We have three findings indicating downward rigidity in the wage for new hires faced by establishments. First, the wage for new hires rarely changes between successive vacancies at the same job. When wages do change for a given job, they are three times more likely to rise than to fall. These findings imply a downward constraint on the wage in newly created jobs. Second, at the job level, the wage for new hires rises during expansions but does not fall during contractions. So, due to the constraint on wage setting, wages are rigid downward and flexible upward at the job level. Third, across all jobs into which the typical establishment hires, wages are more

ever, in Appendix Section F we consider a model extension with nominal rigidity and a role for nominal demand shocks such as monetary policy. The dynamics of unemployment are similar in this latter model.
rigid downward than upward. However the average wage for new hires, the object of previous studies, is not more rigid downward than upward, due to job composition.

In the second part of the paper, we argue that the form of downward rigidity in the data leads to state dependent asymmetry in unemployment dynamics. We document a new finding from our microdata, consistent with downward wage rigidity. The wage for new hires displays state dependent flexibility upward. Next, we incorporate this form of downward wage rigidity into a standard labor search model, and match the model to our new evidence. Then we show state dependent asymmetry in the impulse response of unemployment to labor demand. After contractions, unemployment responds similarly to positive and negative shocks. After expansions, unemployment is as much as twice as sensitive to positive shocks.

One important question that our paper does not answer is why the wage for new hires is more rigid downward than upward at the job level. Several plausible mechanisms for downward wage rigidity largely apply to continuing workers and not for new hires. For example, firms might offer implicit contracts in the form of downwardly rigid wages to continuing workers, and not extend the same insurance to new hires (Beaudry and DiNardo, 1991). In ongoing work, we seek to understand the mechanisms behind downward rigidity for new hires.
References


## 10 Tables

### Table 1: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>Max</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Posts Per State</td>
<td>4799</td>
<td>3012689</td>
<td>421412</td>
</tr>
<tr>
<td>Posts Per Quarter</td>
<td>279252</td>
<td>1278327</td>
<td>782622</td>
</tr>
<tr>
<td>Posts Per State-Quarter</td>
<td>49</td>
<td>190582</td>
<td>15050</td>
</tr>
<tr>
<td>Posts Per 6 Digit SOC Code</td>
<td>1</td>
<td>1925439</td>
<td>25500</td>
</tr>
<tr>
<td>Total Posts</td>
<td></td>
<td>21913422</td>
<td></td>
</tr>
<tr>
<td>Share Missing Job Title</td>
<td>.57</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Share Missing Establishment Code</td>
<td>.57</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Share of 6 digit SOC occupations</td>
<td>.99</td>
<td></td>
<td></td>
</tr>
<tr>
<td>covered in the OES</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Share posting wage range</td>
<td>.44</td>
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<td></td>
</tr>
<tr>
<td>Average width of range</td>
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### Pay Categories:

<table>
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<tr>
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<th>Bonus</th>
<th>Total Pay</th>
<th>Total</th>
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<tr>
<td>Annual</td>
<td>3962172</td>
<td>530169</td>
<td>3648138</td>
<td>8234372</td>
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<tr>
<td>Daily</td>
<td>330899</td>
<td>306405</td>
<td>857674</td>
<td>1520389</td>
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<tr>
<td>Hourly</td>
<td>6067618</td>
<td>376666</td>
<td>918815</td>
<td>10397359</td>
</tr>
<tr>
<td>Monthly</td>
<td>380414</td>
<td>438023</td>
<td>743509</td>
<td>1577650</td>
</tr>
<tr>
<td>Weekly</td>
<td>80038</td>
<td>22368</td>
<td>68401</td>
<td>183652</td>
</tr>
<tr>
<td>Total</td>
<td>10821141</td>
<td>1673631</td>
<td>9236537</td>
<td>21913422</td>
</tr>
</tbody>
</table>

Notes: the width of the wage range is defined as (Max − Min) / Max, where Max and Min are the maximum and minimum of the wage range.
Table 2: Comparison of Wage for New Hires in CPS and BG, by State-Quarter

Panel A: Log CPS New Hire Wage, by State-Quarter

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Burning Glass Wage, All Vacancies</td>
<td>0.970***</td>
<td>1.034***</td>
<td>0.715***</td>
<td>(0.174)</td>
<td>(0.252)</td>
<td>(0.108)</td>
</tr>
<tr>
<td>Log Burning Glass Wage, Vacancies with Job Code only</td>
<td>0.957***</td>
<td>1.017***</td>
<td>0.706***</td>
<td>(0.171)</td>
<td>(0.246)</td>
<td>(0.106)</td>
</tr>
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</table>

Panel B: Log QWI New Hire Earnings, by State-Quarter

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Burning Glass Wage, All Vacancies</td>
<td>1.246***</td>
<td>1.184***</td>
<td>1.007***</td>
<td>(0.203)</td>
<td>(0.347)</td>
<td>(0.140)</td>
</tr>
<tr>
<td>Log Burning Glass Wage, Vacancies with Job Code only</td>
<td>1.234***</td>
<td>1.168***</td>
<td>0.997***</td>
<td>(0.201)</td>
<td>(0.341)</td>
<td>(0.139)</td>
</tr>
<tr>
<td>State Effects</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Time Effects</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>1428</td>
<td>1428</td>
<td>1428</td>
<td>1428</td>
<td>1428</td>
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<td>State Clusters</td>
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<td>52</td>
<td>52</td>
<td>52</td>
<td>52</td>
<td>52</td>
</tr>
</tbody>
</table>

Notes: in Panel A, the dependent variable is the log of the hours-weighted mean wage for newly hired workers from the 2010-2016 CPS, by quarter and state. Newly hired workers are identified using the rotating panel structure of the Basic Monthly File, and wages are from the Outgoing Rotation Group. Wages are trimmed at the first and 99th percentile. The wage is usual hourly earnings for hourly and non-hourly workers, constructed following CEPR's "wage 3" series, for non-farm workers. The regression in panel A is weighted by the number of CPS observations in each state-quarter.

In Panel B, the dependent variable is the log of the mean hourly earnings for newly hired workers from the 2010-2016 Quarterly Workforce Indicators (QWI), by quarter and state. The regression in panel B is weighted by the number of hires in the quarter, also from the QWI.

In the 2010-2016 Burning Glass, the wage is the log of workers’ salaries. Salaries are reported by pay frequency (e.g. hourly or annual) and salary type (e.g. base pay or total pay). Salaries are trimmed at the 5th and 95th percentiles in each year, within each pay frequency and salary type. To uncover state-quarter salaries, we regress

$$\log(\text{salary}_{ist}) = \alpha + \sum_{p,s} \beta_{ps}D_{ps} + \sum_{s,t} \gamma_{st}W_{st} + \text{error}_{ist}$$

where $D_{ps}$ denotes a set of salary type by pay frequency dummies and $W_{st}$ is a set of state by quarter dummies. Observations are weighted by the 2014-2016 OES. Then $W_{st}$ is the log mean salary in the state-quarter, after adjusting for pay frequency and salary type. We split the sample in half in each state-quarter, and instrument for salaries in one sub-sample with salaries in the other, to overcome measurement error. A vacancy has a job code if it has a non-missing establishment and job title identifier.

Standard errors are two way clustered by quarter and state. One, two and three asterisks denote significance at the 5, 1 and 0.1 percent levels, respectively.
### Table 3: Summary Statistics, for Data Differenced by Job

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>Max</th>
<th>Average</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Vacancy Posts</td>
<td></td>
<td></td>
<td></td>
<td>1598505</td>
</tr>
<tr>
<td>Share of 6 digit SOC occupations covered in the OES</td>
<td></td>
<td></td>
<td></td>
<td>.99</td>
</tr>
<tr>
<td>Posts Per Job</td>
<td>2</td>
<td>23</td>
<td>2.5</td>
<td></td>
</tr>
<tr>
<td>Jobs per 6 digit SOC</td>
<td>1</td>
<td>176081</td>
<td>1247.2</td>
<td></td>
</tr>
<tr>
<td>occupation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jobs per State</td>
<td>264</td>
<td>118076</td>
<td>19909</td>
<td></td>
</tr>
<tr>
<td>Jobs per Quarter</td>
<td>7519</td>
<td>117566</td>
<td>38343</td>
<td></td>
</tr>
</tbody>
</table>

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 4: Quarterly Job-Level Statistics On Wage for New Hires

<table>
<thead>
<tr>
<th></th>
<th>Unweighted</th>
<th>OES Weights</th>
<th>QCEW Weights</th>
<th>High Wage Jobs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Probability of Job-Level Wage Change</td>
<td>0.17</td>
<td>0.16</td>
<td>0.16</td>
<td>0.16</td>
</tr>
<tr>
<td>Probability of Job-Level Wage Increase</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>Probability of Job-Level Wage Decrease</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>Implied Duration for which Job-Level Wages Are Unchanged (Quarters)</td>
<td>5.45</td>
<td>5.77</td>
<td>5.53</td>
<td>5.46</td>
</tr>
<tr>
<td>N</td>
<td>1598505</td>
<td>1598505</td>
<td>1598505</td>
<td>1198879</td>
</tr>
</tbody>
</table>

Notes: a job is an establishment by region by job title by salary type by pay frequency observation. The wage for new hires is averaged within each job-quarter. The sample is the 2010-2016 Burning Glass data. We estimate the probability of job-level wage change using a similar method to Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008). We assume that the hazard rate of job change/increase/decrease is constant and identical for all jobs in the same 2 digit SOC code occupation. We then estimate the hazard rate of job change/increase/decrease by maximum likelihood. We then calculate the implied duration and probability of change/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 5: Regression of Job-Level Wage Growth for New Hires on Unemployment Changes

<table>
<thead>
<tr>
<th>Independent Variable:</th>
<th>Quarterly Job-Level Growth in Wage for New Hires</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ΔU_{st}</strong></td>
<td>(1) 0.0517 (2) 0.152 (3) 0.0454 (4) -0.946*** (5) 0.367</td>
</tr>
<tr>
<td><strong>ΔU_{st} × I(ΔU_{st} &lt; 0)</strong></td>
<td>(1) -1.255*** (2) -1.413*** (3) -1.309*** (4) -2.397*</td>
</tr>
<tr>
<td>Time Effect</td>
<td>Y Y Y Y Y</td>
</tr>
<tr>
<td>State Effect</td>
<td>N Y N N N</td>
</tr>
<tr>
<td>OES Weight</td>
<td>N N Y N N</td>
</tr>
<tr>
<td>Oil Shock IV</td>
<td>N N N N Y</td>
</tr>
<tr>
<td>N</td>
<td>52 52 52 52 52</td>
</tr>
<tr>
<td>State Clusters</td>
<td>52 52 52 52 52</td>
</tr>
</tbody>
</table>

Notes: The dependent variable is quarterly percentage wage growth for new hires, from the 2010-2016 Burning Glass data. Wages are averaged within each job-quarter. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS, in percentage points. We project unemployment changes onto state-quarter employment growth from the 2010-2016 QCEW, in all but the final column. In columns (1)-(3), we project positive and negative unemployment changes on positive and negative employment growth changes. In the final column, we instrument for unemployment with a Bartik-style instrument based on the oil price. The first stage regression is \( ΔU_{st} = \sum_s [α_s + β_s Δ\log\text{oil price}_{t-1} + γ_s I(Δ\log\text{oil price}_{t-1} < 0) Δ\log\text{oil price}_{t-1}] + error_{st} \), where \( α_s, β_s \) and \( γ_s \) are estimated, similarly to Nakamura and Steinsson (2014). Oil price \( t \) is the price of Brent crude oil averaged over quarter \( t \).

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; except for the last column, which clusters by state and quarter. 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 to target the occupation employment distribution at the 6 digit SOC level from the 2014-2016 OES.
Table 6: Estimates of Downward Wage Rigidity—Robustness

<table>
<thead>
<tr>
<th></th>
<th>Coefficient $\Delta U_{st} \times I(\Delta U_{st} &lt; 0)$</th>
<th>S.E.</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>-1.255***</td>
<td>(0.265)</td>
<td>1566182</td>
</tr>
<tr>
<td>QCEW Weighted</td>
<td>-1.161***</td>
<td>(0.257)</td>
<td>1566182</td>
</tr>
<tr>
<td>State $\times$ Quarter-of-year FEs</td>
<td>-0.931*</td>
<td>(0.435)</td>
<td>1566182</td>
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<tr>
<td>X11 adjustment</td>
<td>-4.366***</td>
<td>(1.536)</td>
<td>1566182</td>
</tr>
<tr>
<td>No wage ranges</td>
<td>-1.174***</td>
<td>(0.303)</td>
<td>795316</td>
</tr>
<tr>
<td>Annual</td>
<td>-2.703**</td>
<td>(0.959)</td>
<td>656596</td>
</tr>
<tr>
<td>No bonuses</td>
<td>-1.290***</td>
<td>(0.287)</td>
<td>1410347</td>
</tr>
<tr>
<td>Alternative job definition</td>
<td>-1.744***</td>
<td>(0.233)</td>
<td>1229020</td>
</tr>
<tr>
<td>Quadratic coefficient</td>
<td>0.265***</td>
<td>(0.0531)</td>
<td>1566182</td>
</tr>
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</table>

Notes: The first row reports the coefficient on $\Delta U_{st} \times I(\Delta U_{st} < 0)$ from the benchmark regression, that is, column (1) of Table 5. The second row reports the coefficient from the benchmark regression, after reweighting to target mean employment in each state over 2010-2016, from the Quarterly Census of Employment and Wages. The third row reports the coefficient from the benchmark regression, after also controlling for the interaction of quarter-of-year and state fixed effects. The fourth row reports the coefficient from the benchmark regression, after seasonally adjusting using the Census Bureau's X-11 algorithm. We seasonally adjust at the state-quarter level for 1980-2017 data, for both unemployment and employment. The fifth row drops from the sample all vacancies that post a range of wages, instead of a point wage. The sixth row runs the baseline regression at annual frequency. The seventh row excludes vacancies with bonus pay. The eighth row uses an alternative definition of a job, by taking the mean wage across job titles by establishments, averaging over workers paid at different frequencies (e.g. averaging over hourly and annual paid workers). In the final row, we report the coefficient from the quadratic term, after regressing wage growth on unemployment changes, and its square. A plus sign, one, two and three asterisks denote significance at the 10, 5, 1 and 0.1 percent levels, respectively. Standard errors are clustered by state.
Table 7: Regression of Establishment Wages for New Hires on Unemployment

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Quarterly Establishment-Level Growth in Wage for New Hires</th>
</tr>
</thead>
<tbody>
<tr>
<td>Independent Variable:</td>
<td>(1)</td>
</tr>
<tr>
<td>$\Delta U_{st}$</td>
<td>0.00392</td>
</tr>
<tr>
<td></td>
<td>(0.313)</td>
</tr>
<tr>
<td>$\Delta U_{st} \times I(\Delta U_{st} &lt; 0)$</td>
<td>-1.082**</td>
</tr>
<tr>
<td></td>
<td>(0.382)</td>
</tr>
<tr>
<td>$(\Delta U_{st})^2$</td>
<td></td>
</tr>
</tbody>
</table>

| Time Effect | Y | Y | Y | Y |
| State Effect | N | Y | N | N |
| QCEW Weight | N | N | Y | N |
| $N$ | 1845695 | 1845695 | 1845695 | 1845695 |
| State Clusters | 52 | 52 | 52 | 52 |

Notes: the dependent variable is quarterly percentage wage growth for new hires, from the 2010-2016 Burning Glass data. Wages are averaged within each establishment-quarter, separately for each pay frequency (e.g. hourly, monthly or annual) and salary type (e.g. base pay or total pay). The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS, in percentage points. We project unemployment changes onto state-quarter employment growth from the 2010-2016 QCEW. In the asymmetric specifications, 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. Wage growth is trimmed at the 1st and 99th percentiles. An establishment is an employer by location by pay frequency by salary type 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 to target the average regional employment distribution at the state level from the 2010-2016 QCEW.
### Table 8: Regression of Establishment Share in High Wage Occupations on Unemployment

<table>
<thead>
<tr>
<th></th>
<th>Quarterly Change in Share of Establishment Vacancies</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>in High Wage Occupations</td>
</tr>
<tr>
<td>( \Delta U_{st} )</td>
<td>0.158</td>
</tr>
<tr>
<td></td>
<td>(0.370)</td>
</tr>
<tr>
<td>( \Delta U_{st} \times I(\Delta U_{st} &lt; 0) )</td>
<td>0.167</td>
</tr>
<tr>
<td></td>
<td>(0.441)</td>
</tr>
<tr>
<td>Time Effect</td>
<td>Y</td>
</tr>
<tr>
<td>Size Weighted</td>
<td>N</td>
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<tr>
<td>( N )</td>
<td>1770257</td>
</tr>
<tr>
<td>State Clusters</td>
<td>52</td>
</tr>
</tbody>
</table>

Notes: In the first two columns, the dependent variable is the change in the quarterly share of establishment vacancies in high wage occupations. High wage occupations are occupations with wages above the weighted median wage, by occupation, in 2010-2016 Burning Glass. The occupations are defined at the 6 digit SOC code level, occupation wages are the median hourly wage according to the 2014-2016 Occupational Employment Statistics.

In the middle two columns, the dependent variable is the change in the quarterly share of high wage establishment vacancies. High wage vacancies are vacancies with wages above the weighted median wage within each pay frequency (e.g. hourly or annual) and salary type (e.g. total or base pay). The occupations are again at the 6 digit SOC level.

In the final two columns, the dependent variable is the change in the quarterly share of establishment vacancies in high wage occupations, within broad occupation groups. A high wage occupation within a broad occupation group, is a 6 digit SOC occupation, that is above the vacancy-weighted median hourly wage within the set of 6 digit SOC occupations belonging to the same broad occupation group. For example, CEOs (6 digit SOC code 11-1011) have above the median wage of the occupations belonging to the 1 digit SOC occupation group of Management, Business, Science, and Arts Occupations. The broad occupation groups are the set of 6 occupation groupings defined by the BLS in 2018. Size weighted denotes weighted by establishment-quarter size.

In all columns, the independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS, in percentage points. We project unemployment changes onto state-quarter employment growth from the 2010-2016 QCEW. In the asymmetric specifications, we project positive and negative unemployment changes on positive and negative employment growth changes. 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.
Table 9: Regression of State Share in High Wage Vacancies on Unemployment

<table>
<thead>
<tr>
<th>Panel A:</th>
<th>Quarterly Change in State Share of High Wage Vacancies</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta U_{st}$</td>
<td>-0.654</td>
<td>-1.040</td>
<td>4.815</td>
<td>-0.0414</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.831)</td>
<td>(1.286)</td>
<td>(2.677)</td>
<td>(0.393)</td>
<td></td>
</tr>
<tr>
<td>$\Delta U_{st} \times I(\Delta U_{st} &lt; 0)$</td>
<td>0.982</td>
<td>1.549</td>
<td>-3.537</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.270)</td>
<td>(1.927)</td>
<td>(5.138)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time Effect</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>State Effect</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>QCEW Weight</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>1404</td>
<td>1404</td>
<td>1404</td>
<td>1404</td>
<td></td>
</tr>
<tr>
<td>State Clusters</td>
<td>51</td>
<td>51</td>
<td>51</td>
<td>51</td>
<td></td>
</tr>
</tbody>
</table>

Notes: the dependent variable is the change in the quarterly share of high wage vacancies within each state. High wage vacancies have a wage above the national median wage, by salary type and pay frequency, in 2010-2016 Burning Glass. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS, in percentage points. We project unemployment changes onto state-quarter employment growth from the 2010-2016 QCEW. In the asymmetric specifications, we project positive and negative unemployment changes on positive and negative employment growth changes. 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. In some specifications, we reweight to target the average regional employment distribution at the state level from the 2010-2016 QCEW, otherwise we weight by state number of vacancies in Burning Glass.
Table 10: Estimates of Downward Wage Rigidity from Pooled and Worker-Level Wages

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Independent Variable:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔUnemployment</td>
<td>0.788</td>
<td>-5.748</td>
<td>3.770</td>
</tr>
<tr>
<td></td>
<td>(1.048)</td>
<td>(4.359)</td>
<td>(3.468)</td>
</tr>
<tr>
<td>ΔUnemployment × I (ΔUnemployment &lt; 0)</td>
<td>1.182</td>
<td>10.59*</td>
<td>-5.108</td>
</tr>
<tr>
<td></td>
<td>(1.338)</td>
<td>(4.560)</td>
<td>(5.151)</td>
</tr>
<tr>
<td>Time Effect</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>State Effect</td>
<td>N</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>N</td>
<td>1377</td>
<td>1377</td>
<td>83</td>
</tr>
<tr>
<td>State Clusters</td>
<td>51</td>
<td>51</td>
<td>-</td>
</tr>
</tbody>
</table>

Notes: each column regresses a measure of wage growth for new hires on unemployment changes. In the first and second columns, the dependent variable is the percentage growth in pooled state wages, from Burning Glass. The independent variables are state unemployment changes, an indicator if state unemployment is falling, and the interaction of the indicator with state unemployment. We project the dependent variables onto state-quarter employment growth from the 2010-2016 QCEW, and interact employment growth with an indicator for whether employment growth is positive. The sample period is 2010-2016, the sample is vacancies in the 50 states plus the District of Columbia. Pooled state wages in Burning Glass are measured in the same way as in Table 2.

In the third and fourth columns, the dependent variable is the percentage growth in state wages for newly hired workers, from the CPS. The independent variables and sample details are the same as in columns (1) and (2). State wages in the CPS are measured in the same way as in Table 2.

In the fifth column, the dependent variable is the quarterly percentage growth in the national median wage for newly hired workers. This wage series is for 1984-2006, and is measured using the Outgoing Rotation Group of the CPS. Newly hired workers are identified in the same way as Table 2. The wage series is taken from Haefke et al. (2013). We regress wage growth on the change in national unemployment, an indicator for whether national unemployment is falling, and the interaction of the change in national unemployment with the indicator. Standard errors are clustered by state in the first five columns, and are heteroskedasticity robust in the final column. A plus sign, one, two and three asterisks denote significance at the 10, 5, 1 and 0.1 percent levels, respectively.
Table 11: Wage Rigidity After Contractions and Expansions

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Quarterly Job-Level Growth in Wage for New Hires</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Independent Variables:</td>
<td></td>
</tr>
<tr>
<td>$\Delta U_{st}$</td>
<td>-0.557**</td>
</tr>
<tr>
<td></td>
<td>(0.184)</td>
</tr>
<tr>
<td>$\Delta U_{st} \times$</td>
<td>-0.727***</td>
</tr>
<tr>
<td>$I\left(U_{s,t-1} - U_{s,t-13} &lt; 0\right)$</td>
<td>(0.138)</td>
</tr>
<tr>
<td></td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>-0.486**</td>
</tr>
<tr>
<td></td>
<td>(0.168)</td>
</tr>
<tr>
<td></td>
<td>-0.744***</td>
</tr>
<tr>
<td></td>
<td>(0.130)</td>
</tr>
<tr>
<td></td>
<td>-0.646***</td>
</tr>
<tr>
<td></td>
<td>(0.0561)</td>
</tr>
<tr>
<td>Time Effects</td>
<td>Y</td>
</tr>
<tr>
<td>State Effects</td>
<td>N</td>
</tr>
<tr>
<td>State ×Quarter-of-Year Effects</td>
<td>N</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>1089785</td>
</tr>
<tr>
<td>State Clusters</td>
<td>52</td>
</tr>
</tbody>
</table>

Notes: We estimate the regression

$$\Delta \log w_{jst} = \alpha + \gamma t + \kappa \Delta U_{st} + \nu \Delta U_{st} \times I\left(U_{s,t-1} - U_{s,t-13} < 0\right) + \epsilon_{jst}$$

The dependent variable is quarterly job-level wage growth, in percentage points, for new hires, from the 2010-2016 Burning Glass data. Wages are averaged within each job-quarter. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS, also in percentage points. We interact state-quarter unemployment changes with an indicator for whether state unemployment fell over the previous three years. We restrict the sample only to observations for which $\Delta U_{st} < 0$. We project unemployment changes onto state-quarter employment growth from the 2010-2016 QCEW, employment is interacted with the same indicator. 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.
Table 12: Regression of Wage Growth on State Unemployment Declines

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Job-Level Growth in Wage for New Hires</th>
<th>Establishment-Level Growth in Wage for New Hires</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
<td></td>
</tr>
<tr>
<td><strong>Independent Variables:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta U_{st}$</td>
<td>-0.208</td>
<td>0.0261</td>
</tr>
<tr>
<td></td>
<td>(0.167)</td>
<td>(0.493)</td>
</tr>
<tr>
<td>$\Delta U_{st} \times I (\text{Year} = 2011)$</td>
<td>-0.0330</td>
<td>-0.691</td>
</tr>
<tr>
<td></td>
<td>(0.240)</td>
<td>(0.786)</td>
</tr>
<tr>
<td>$\Delta U_{st} \times I (\text{Year} = 2012)$</td>
<td>-0.462*</td>
<td>-0.850</td>
</tr>
<tr>
<td></td>
<td>(0.221)</td>
<td>(0.720)</td>
</tr>
<tr>
<td>$\Delta U_{st} \times I (\text{Year} = 2013)$</td>
<td>-0.415</td>
<td>-0.964</td>
</tr>
<tr>
<td></td>
<td>(0.244)</td>
<td>(0.506)</td>
</tr>
<tr>
<td>$\Delta U_{st} \times I (\text{Year} = 2014)$</td>
<td>-0.451*</td>
<td>-1.045</td>
</tr>
<tr>
<td></td>
<td>(0.193)</td>
<td>(0.540)</td>
</tr>
<tr>
<td>$\Delta U_{st} \times I (\text{Year} = 2015)$</td>
<td>-1.014***</td>
<td>-1.216*</td>
</tr>
<tr>
<td></td>
<td>(0.184)</td>
<td>(0.516)</td>
</tr>
<tr>
<td>$\Delta U_{st} \times I (\text{Year} = 2016)$</td>
<td>-1.746***</td>
<td>-1.253*</td>
</tr>
<tr>
<td></td>
<td>(0.176)</td>
<td>(0.474)</td>
</tr>
<tr>
<td><strong>Time Effects</strong></td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td><strong>State Effects</strong></td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td><strong>State \times Quarter-of-Year Effects</strong></td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td><strong>Number of Observations</strong></td>
<td>1090035</td>
<td>1090035</td>
</tr>
<tr>
<td><strong>State Clusters</strong></td>
<td>52</td>
<td>52</td>
</tr>
</tbody>
</table>

Notes: We estimate the regression

$$\Delta \log w_{jst} = \sum_{y \in \{2010,...,2016\}} \alpha_y + \gamma_t + \sum_{y \in \{2010,...,2016\}} \beta_y I(\text{year} = y) \Delta U_{st} + \epsilon_{jst}.$$  

The dependent variable in the first three columns is quarterly job-level wage growth, in percentage points, for new hires, from the 2010-2016 Burning Glass data. Wages are averaged within each job-quarter. The dependent variable in the last column is quarterly establishment-level wage growth, in percentage points, for new hires. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS, also in percentage points. We restrict the sample only to observations for which $\Delta U_{st} < 0$. 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. 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. An establishment is an employer by location by pay frequency by salary type 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.
Table 13: Estimated Parameters and Moments in Model and Data

<table>
<thead>
<tr>
<th></th>
<th>Autocorr [logVA]</th>
<th>SD [logVA]</th>
<th>Mean u</th>
<th>δ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data</td>
<td>0.908</td>
<td>0.0329</td>
<td>0.0575</td>
<td>-1.26</td>
</tr>
<tr>
<td>Model</td>
<td>0.915</td>
<td>0.0331</td>
<td>0.0573</td>
<td>-1.28</td>
</tr>
</tbody>
</table>

Table 14: Model Calibration

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>β</td>
<td>0.9912</td>
<td>Galí (2015)</td>
</tr>
<tr>
<td>s</td>
<td>0.0081</td>
<td>Hagedorn and Manovskii (2008)</td>
</tr>
<tr>
<td>ι</td>
<td>0.407</td>
<td>Hagedorn and Manovskii (2008)</td>
</tr>
<tr>
<td>c</td>
<td>0.58</td>
<td>Hagedorn and Manovskii (2008)</td>
</tr>
<tr>
<td>1/(1 − ξ)</td>
<td>1.0012</td>
<td>Acemoglu and Autor (2011)</td>
</tr>
</tbody>
</table>

Notes: log VA is log value added for 1948-2019. We apply the filter of Hamilton (2018) to both the model and the data, before comparing the autocorrelation and standard deviation of the model and data moments. Mean u is mean unemployment from the BLS for 1948-2019. δ is the coefficient from regression equation (1). We simulate the same moments in the model and the data, and minimize the distance between them, to estimate the parameters, Autocorr [ε_t], SD [ε_t], b and φ.

Table 14: Model Calibration

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>β</td>
<td>0.9912</td>
<td>Galí (2015)</td>
</tr>
<tr>
<td>s</td>
<td>0.0081</td>
<td>Hagedorn and Manovskii (2008)</td>
</tr>
<tr>
<td>ι</td>
<td>0.407</td>
<td>Hagedorn and Manovskii (2008)</td>
</tr>
<tr>
<td>c</td>
<td>0.58</td>
<td>Hagedorn and Manovskii (2008)</td>
</tr>
<tr>
<td>1/(1 − ξ)</td>
<td>1.0012</td>
<td>Acemoglu and Autor (2011)</td>
</tr>
</tbody>
</table>

Notes: β is the discount factor, chosen to target an annual interest rate of 4 percent. s is the weekly separation rate. ι governs the scale of the matching function. c is the cost of vacancy posting, relative to labor productivity. ξ governs the extent to which real wages can fall.
Table 15: Moments of Unemployment Dynamics in Model and Data

<table>
<thead>
<tr>
<th></th>
<th>Model</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Deviation</td>
<td>0.917</td>
<td>0.919</td>
</tr>
<tr>
<td>Autocorrelation</td>
<td>0.0232</td>
<td>0.0142</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.794</td>
<td>0.904</td>
</tr>
</tbody>
</table>

Notes: we study the standard deviation, first autocorrelation, and skewness of Hamilton-filtered unemployment for 1948-2019. We simulate the quarterly-aggregated and Hamilton-filtered unemployment in the model, and compare the moments.
Appendix

A Additional Figures

Figure 13: Binned Scatter of State-Quarter Wages for New Hires, in the CPS and Burning Glass

Notes: the y axis variable is the log of hours-weighted mean state-quarter wage for newly hired workers, from the 2010-2016 CPS. The x axis variable is the log of mean state-quarter wages for new hires, from the 2010-2016 Burning Glass data. The graph plots the weighted mean value of the y variable, for 50 equally sized weighted bins of the x variable. Bins and means are weighted by the size of each state-quarter in the CPS. The line is from a least squares regression, weighted the same way, the standard error is clustered by state. Mean state-quarter wages for new hires in the CPS, and for new hires in Burning Glass, are calculated in the same way as in table 2.
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 15: Share of Wage Growth Observations in Each State with Falling Unemployment

Notes: this graph plots the share of wage growth observations in each state, for which annual state unemployment is falling during the year of the wage posting, for the state in which the vacancy is posted. Log wages are differenced by job. The time period is 2010-2016. Unemployment is from the LAUS. Wages are averaged by job-year, where a job is a job title by establishment by salary type by pay frequency unit.
Notes: this graph plots the share of wage growth observations in each year, for which annual state unemployment is falling during the year of the wage posting, for the state in which the vacancy is posted. Log wages are differenced by job. The time period is 2010-2016. Unemployment is from the LAUS. Wages are averaged by job-year, where a job is a job title by establishment by salary type by pay frequency unit.
Figure 17: Quarterly Global Oil Prices

Notes: this figure plots the quarterly average oil price for 2010 to 2016, using the Brent Crude measure.
Figure 18: Cyclicality of New Hire Wages in Other Studies

![Graph showing cyclicality of new hire wages from various studies.]

Notes: this graph collects the point estimate and standard error from a quarterly regression of log new hire wages on national unemployment, from various papers. Other papers typically estimate a regression of a similar form to

\[ \Delta \log(w_{it}) = \alpha + \beta \Delta U_t + \gamma x_{it} + \text{error}_{it}, \]

where \( \Delta \log(w_{it}) \) is wage growth for newly hired workers, \( \Delta U_t \) is the change in aggregate unemployment, and \( x_{it} \) is a vector of controls. Where papers report multiple specifications, we choose the median estimate. Each paper studies a survey measure of the wage for new hires, from worker level data—either the Current Population Survey, Survey of Income and Program Participation, or the National Longitudinal Survey of Youth. We adjust the estimates of Haefke et al. (2013) from the elasticity of wages with respect to real labour productivity, to the semielasticity of wages with respect to unemployment, using the estimate of the sensitivity of unemployment to real labour productivity estimated by Pissarides (2009). We use the wage for new hires, and only consider workers transitioning out of unemployment where these estimates are available.
Notes: we feed a sequence of labor demand shocks $\varepsilon_t$ into the model, simulate output from the model, aggregate to quarterly frequency, and then apply the filter of Hamilton (2018). We solve for the sequence of $\varepsilon_t$ such that filtered output in the model matches the data exactly.
### B Additional Tables

#### Table 16: Comparison of Burning Glass Wages with Occupation Wages and City Earnings

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Log Median Hourly Wage by Occupation (OES)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Independent Variable:</td>
<td></td>
</tr>
<tr>
<td>Log Median Salary by Occupation (BG)</td>
<td>1.139***</td>
</tr>
<tr>
<td>(0.0945)</td>
<td>(0.0678)</td>
</tr>
<tr>
<td>BG Contract Type</td>
<td>Base Pay, Annual</td>
</tr>
<tr>
<td>Observations</td>
<td>742</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Log Average Weekly Earnings by CBSA (QCEW)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Independent Variable:</td>
<td></td>
</tr>
<tr>
<td>Log Median Salary by CBSA (BG)</td>
<td>1.295***</td>
</tr>
<tr>
<td>(0.0754)</td>
<td>(0.127)</td>
</tr>
<tr>
<td>BG Contract Type</td>
<td>Base Pay, Annual</td>
</tr>
<tr>
<td>Observations</td>
<td>928</td>
</tr>
</tbody>
</table>

Notes: in the top panel, 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.

In the bottom panel, 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>
<thead>
<tr>
<th></th>
<th>Unweighted</th>
<th>OES Weights</th>
<th>QCEW Weights</th>
<th>High Wage Jobs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median Annual Probability of</td>
<td>0.405</td>
<td>0.418</td>
<td>0.402</td>
<td>0.418</td>
</tr>
<tr>
<td>Job-Level Wage Change</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median Probability of Job-Level</td>
<td>0.088</td>
<td>0.095</td>
<td>0.09</td>
<td>0.087</td>
</tr>
<tr>
<td>Wage Decrease</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median Probability of Job-Level</td>
<td>0.304</td>
<td>0.305</td>
<td>0.3</td>
<td>0.31</td>
</tr>
<tr>
<td>Wage Increase</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Implied Duration that Job-Level</td>
<td>1.841</td>
<td>1.836</td>
<td>1.875</td>
<td>1.841</td>
</tr>
<tr>
<td>Wages Are Unchanged (Quarters)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: A job is an establishment by region by job title by salary type by pay frequency observation. The wage for new hires is averaged within each job-year. The sample is the 2010-2016 Burning Glass data. We estimate the probability of job-level wage change using a similar method to Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008). We assume that the hazard rate of job change/increase/decrease is constant and identical for all jobs in the same 2 digit SOC code occupation. We then estimate the hazard rate of job change/increase/decrease by maximum likelihood. We then calculate the implied duration and probability of change/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: Cyclicity of the Probability of Quarterly Wage Change for New Hires

<table>
<thead>
<tr>
<th>Dependent Variables:</th>
<th>Quarterly Probability of Wage Change</th>
<th>Quarterly Probability of Wage Increase</th>
<th>Quarterly Probability of Wage Decrease</th>
</tr>
</thead>
<tbody>
<tr>
<td>Independent Variable:</td>
<td>Change in Quarterly Unemployment</td>
<td>-0.0255* (0.00984)</td>
<td>-0.0326* (0.0142)</td>
</tr>
<tr>
<td>QCEW Weights</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Number of observations</td>
<td>1404</td>
<td>1404</td>
<td>1404</td>
</tr>
<tr>
<td>State Clusters</td>
<td>52</td>
<td>52</td>
<td>52</td>
</tr>
</tbody>
</table>

Notes: the probability of a wage change for a new match is the share of vacancies for which the wage changes at the job level, in each state-quarter, from the 2010-2016 Burning Glass data. The probability of increase and decrease is defined in the same way. Wages for new hires are averaged within each job-quarter. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS, in percentage points. 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 19: Job-Level Growth in Wage for New Hires and Industry Labor Demand Growth

#### Panel A:

<table>
<thead>
<tr>
<th>Quarterly Job-Level Growth in Wage for New Hires</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \log(\text{employment}_{it})$</td>
<td>-0.00416</td>
<td>-0.00188</td>
<td>-0.00632</td>
<td>0.00571**</td>
</tr>
<tr>
<td></td>
<td>(0.00301)</td>
<td>(0.00321)</td>
<td>(0.00348)</td>
<td>(0.00206)</td>
</tr>
<tr>
<td>$\Delta \log(\text{employment}<em>{it}) \times I(\Delta \log(\text{employment}</em>{it}) &gt; 0)$</td>
<td>0.0180***</td>
<td>0.0157***</td>
<td>0.0249***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00425)</td>
<td>(0.00440)</td>
<td>(0.00525)</td>
<td></td>
</tr>
<tr>
<td>Time Effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Industry Effects</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Seasonally Adjusted</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Number of observations</td>
<td>791270</td>
<td>791269</td>
<td>791270</td>
<td>791270</td>
</tr>
<tr>
<td>Industry clusters</td>
<td>75</td>
<td>75</td>
<td>75</td>
<td>75</td>
</tr>
</tbody>
</table>

#### Panel B:

<table>
<thead>
<tr>
<th>Annual Job-Level Growth in Wage for New Hires</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \log(\text{labor productivity}_{it})$</td>
<td>-0.126</td>
<td>-0.122</td>
<td>-0.0125</td>
</tr>
<tr>
<td></td>
<td>(0.0693)</td>
<td>(0.0921)</td>
<td>(0.0465)</td>
</tr>
<tr>
<td>$\Delta \log(\text{labor productivity}<em>{it}) \times I(\Delta \log(\text{labor productivity}</em>{it}) &gt; 0)$</td>
<td>0.210 +</td>
<td>0.244 +</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.108)</td>
<td>(0.137)</td>
<td></td>
</tr>
<tr>
<td>Time Effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Industry Effects</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Number of observations</td>
<td>135977</td>
<td>135976</td>
<td>135977</td>
</tr>
<tr>
<td>Industry clusters</td>
<td>49</td>
<td>49</td>
<td>49</td>
</tr>
</tbody>
</table>

Notes: In Panel A, the dependent variable is quarterly percentage wage growth for new hires, from the 2010-2016 Burning Glass data. Wages are averaged within each job-quarter. The independent variable is the growth in industry-quarter employment from the 2010-2016 Current Employment Statistics, in percentage points, at the 3 digit NAICS level. We regress quarterly job-level wage growth on quarterly industry employment growth, and interact employment growth with an indicator variable for whether employment growth is positive, in all columns but the last. Wage growth is trimmed at the 1st and 99th percentiles.

In Panel B, the dependent variable is annual percentage wage growth for new hires, from the 2010-2016 Burning Glass data. Wages are averaged within each year. The independent variable is the growth in industry-year labor productivity from the 2010-2016 BLS multifactor productivity industry accounts, in percentage points, at the 3 digit NAICS level. Labor productivity is defined as real value added per hour worked. We regress annual job-level wage growth on annual industry labor productivity growth, and interact labor productivity growth with an indicator variable for whether labor productivity growth is positive, in all columns but the last. 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 industry. A plus sign, one, two and three asterisks denote significance at the 10, 5, 1 and 0.1 percent levels, respectively.
Table 20: Job-Level Growth in Wage for New Hires and State-Industry Labor Demand Growth

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Quarterly Job-Level Growth in Wage for New Hires</th>
<th>State by 2 digit Industry</th>
<th>State by 3 digit Industry</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \log(\text{employment}_{ist})$</td>
<td>-0.00313** (0.00118)</td>
<td>-0.00248* (0.00122)</td>
<td>-0.00276* (0.00131)</td>
</tr>
<tr>
<td>$\Delta \log(\text{employment}<em>{ist}) \times I(\Delta \log(\text{employment}</em>{ist}) &gt; 0)$</td>
<td>0.0147*** (0.00193)</td>
<td>0.0125*** (0.00199)</td>
<td>0.0115*** (0.00193)</td>
</tr>
</tbody>
</table>

Time Effects | Y | Y | Y | Y |
State-Time Effects | Y | Y | Y | Y |
Industry-State Effects | N | Y | N | Y |
Number of observations | 1172426 | 1172418 | 1030536 | 1030354 |

Notes: the dependent variable is quarterly percentage wage growth for new hires, from the 2010-2016 Burning Glass data. Wages are averaged within each job-quarter. The independent variable is the growth in industry-state quarterly employment from the 2010-2016 Quarterly Census of Employment and Wages, in percentage points. The first two columns are at the 2 digit NAICS level, the last two columns at the 3 digit NAICS level. We regress quarterly job-level wage growth on quarterly state-industry employment growth, and interact employment growth with an indicator variable for whether employment growth is positive. Wage growth is trimmed at the 1st and 99th percentiles.
### Table 21: Job-Level Growth in Wage for New Hires and City Labor Demand Growth

<table>
<thead>
<tr>
<th></th>
<th>Quarterly Job-Level Growth in Wage for New Hires</th>
<th>Real</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Nominal</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Δlog(employment&lt;sub&gt;mt&lt;/sub&gt;)</td>
<td>0.118</td>
<td>0.120</td>
</tr>
<tr>
<td></td>
<td>(0.0601)</td>
<td>(0.0684)</td>
</tr>
<tr>
<td>Δlog(employment&lt;sub&gt;mt&lt;/sub&gt;) × I(Δlog(employment&lt;sub&gt;mt&lt;/sub&gt;) &gt; 0)</td>
<td>0.225**</td>
<td>0.227*</td>
</tr>
<tr>
<td></td>
<td>(0.0708)</td>
<td>(0.0832)</td>
</tr>
<tr>
<td>Time Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>City Effects</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Seasonally Adjusted</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Number of observations</td>
<td>581862</td>
<td>581862</td>
</tr>
</tbody>
</table>

Notes: in Panel A, the dependent variable is quarterly percentage wage growth for new hires, from the 2010-2016 Burning Glass data. Wages are averaged within each job-quarter. The independent variable is the growth in city-quarter employment from the 2010-2016 State and Area Employment, in percentage points, at the MSA level. We regress quarterly job-level wage growth on quarterly city employment growth, and interact employment growth with an indicator variable for whether employment growth is positive. Wage growth is trimmed at the 1st and 99th percentiles. Real wages are deflated by semiannual city prices, excluding shelter, from the Consumer Price Index.

A job is an employer by location by pay frequency by salary type by job title unit. Standard errors are in parentheses, clustered by industry. A plus sign, one, two and three asterisks denote significance at the 10, 5, 1 and 0.1 percent levels, respectively.
Table 22: Downward Wage Rigidity by Occupation group

<table>
<thead>
<tr>
<th>Occupation Group:</th>
<th>Management</th>
<th>Services</th>
<th>Sales</th>
<th>Construction</th>
<th>Production</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta U_{st} \times I(\Delta U_{st} &lt; 0) )</td>
<td>-1.177**</td>
<td>-1.410***</td>
<td>-0.983*</td>
<td>-1.043*</td>
<td>-1.552***</td>
</tr>
<tr>
<td></td>
<td>(0.348)</td>
<td>(0.310)</td>
<td>(0.447)</td>
<td>(0.433)</td>
<td>(0.321)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>568307</td>
<td>195274</td>
<td>342738</td>
<td>75637</td>
<td>329647</td>
</tr>
</tbody>
</table>

Notes: the dependent variable is quarterly percentage wage growth for new hires, from the 2010-2016 Burning Glass data. Wages are averaged within each job-quarter. We estimate the regression separately for every broad occupation group, at the 1 digit SOC code level. The independent variable is the change in state-quarter unemployment from the 2010-2016 LAUS, in percentage points. We project unemployment changes onto state-quarter employment growth from the 2010-2016 QCEW. We project positive and negative unemployment changes on positive and negative employment growth changes, and report the coefficient on the interaction term. 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.
Table 23: First Stage of Quarterly State Unemployment Change on Employment Growth

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

Notes: the dependent variable is the quarterly change in state level unemployment, from the 2010-2016 LAUS, in percentage points. The independent variable is the quarterly growth in state level employment from the 2010-2016 QCEW, in percentage points. 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 24: Cyclicality of Whether Firms Include Wages In Vacancies

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Change in Share of State Vacancies with Wage</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quarterly State Unemployment Change</td>
<td>0.0102</td>
<td>0.00746</td>
<td>(0.0136)</td>
<td>(0.0214)</td>
<td></td>
</tr>
<tr>
<td>Annual State Unemployment Change</td>
<td>0.00304</td>
<td>-0.0111</td>
<td>(0.00542)</td>
<td>(0.0139)</td>
<td></td>
</tr>
<tr>
<td>Time Effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>State Effects</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>1377</td>
<td>1377</td>
<td>306</td>
<td>306</td>
<td></td>
</tr>
<tr>
<td>State Clusters</td>
<td>52</td>
<td>52</td>
<td>52</td>
<td>52</td>
<td></td>
</tr>
</tbody>
</table>

Notes: the dependent variable is the change in the share of vacancies in the state that post a wage in the time period, from a 5% sample of the 2010-2016 Burning Glass dataset, inclusive of all vacancies that do or do not post wages. The independent variable is the change in state-quarter or state-year unemployment from the 2010-2016 LAUS, projected onto employment growth from the 2010-2016 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. Observations are weighed by 2010 state employment from the QCEW.
C Proof of Proposition 1

Summing regression equation (5) over $i$ yields

$$\sum_i v_{ist} \Delta \log w_{ist} = \alpha + \gamma_t + \beta \Delta U_{st} + \delta_{\text{Benchmark}} I[\Delta U_{st} < 0] \Delta U_{st} + \epsilon_{st}$$ (16)

where $\epsilon_{st} = \sum_i v_{ist} \epsilon_{ist}$. We can substitute equation (4) into equation (6) to rewrite the regression that uses average wages as

$$\sum_i v_{ist} \Delta \log w_{ist} + \sum_i \log w_{ist} \Delta v_{ist} = \bar{\alpha} + \bar{\gamma}_t + \bar{\beta} \Delta U_{st} + \delta_{\text{Average}} I[\Delta U_{st} < 0] \Delta U_{st} + \bar{\epsilon}_{st}.$$ (17)

For notational simplicity, we can rewrite equation (16) as

$$y_{st} = x_{st}^\prime b + \epsilon_{st}$$

and equation (17) as

$$y_{st} + u_{st} = x_{st}^\prime \bar{b} + \bar{\epsilon}_{st}$$

where

$$y_{st} = \sum_i v_{ist} \Delta \log w_{ist}$$

$$u_{st} = \sum_i \log w_{ist} \Delta v_{ist}.$$  

$x_{st}^\prime b$ and $x_{st}^\prime \bar{b}$ collect the covariates and coefficients in regressions (16) and (17) respectively. The OLS estimator of $b$, which we term $\hat{b}$, is

$$\hat{b} = \left( \frac{1}{ST} \sum_{s,t} x_{st} x_{st}' \right)^{-1} \left( \frac{1}{ST} \sum_{s,t} x_{st} y_{st} \right).$$

The variance of $\hat{b}$ conditional on $x_{st}$ is

$$V[\hat{b}|x_{st}] = V \left[ \left( \frac{1}{ST} \sum_{s,t} x_{st} x_{st}' \right)^{-1} \left( \frac{1}{ST} \sum_{s,t} x_{st} y_{st} \right) \right]|x_{st}$$

$$= \left( \frac{1}{ST} \sum_{s,t} x_{st} x_{st}' \right)^{-1} \frac{1}{(ST)^2} V \left[ \sum_{s,t} x_{st} y_{st} \right]|x_{st} \left( \frac{1}{ST} \sum_{s,t} x_{st} x_{st}' \right)^{-1}.$$
The OLS estimator of $\bar{b}$, which we term $\hat{b}$, is
\[
\hat{b} = \left( \frac{1}{ST} \sum_{s,t} x_{st} x_{st}' \right)^{-1} \left( \frac{1}{ST} \sum_{s,t} x_{st} (y_{st} + u_{st}) \right).
\]

Then the variance of $\hat{b}$ conditional on $x_{st}$ is
\[
V[\hat{b}|x_{st}] = V[\hat{b}|x_{st}] + \left( \frac{1}{ST} \sum_{s,t} x_{st} x_{st}' \right)^{-1} \frac{1}{(ST)^2} V \left[ \sum_{s,t} x_{st} u_{st}|x_{st} \right] \left( \frac{1}{ST} \sum_{s,t} x_{st} x_{st}' \right)^{-1}.
\] (18)

The second term in equation (18) is a matrix with strictly positive entries on its leading diagonal for $S, T < \infty$. Hence every entry on the leading diagonal of $V[\hat{b}|x_{st}]$ is greater than the corresponding entry on the leading diagonal of $V[\hat{b}|x_{st}]$.

**D Wage Ranges**

Roughly half of the wage data posts a range of wages, instead of a point wage. In most specifications in the main text, we take the mean wage for jobs that post a range of wages.

Here, we show that workers in occupations with a high share of jobs that post ranges, instead of point wages, do not have more cyclical wages. Instead, dynamics in the wage for new hires are similar for jobs that post either point wages or ranges. Wage ranges do not create an additional source of wage flexibility.

To do this, we study the wage for newly hired workers in the CPS. For each worker, we classify their 3 digit SOC occupations in the CPS, as either likely to post a range, or likely to post a point wage. We classify an occupation as likely to post a wage, if the occupation has an above median share of vacancies posting a point wage in Burning Glass data.

We regress log wages for newly hired workers on quarterly state unemployment. We also interact state unemployment with an indicator for whether the worker’s occupation is likely to post a wage range. If this indicator is significant, then occupations that tend to post wage ranges have different wage dynamics from occupations that tend to post point wages.

Table 25 reports the results. Occupations that are likely to post a range instead of a point have wages that are less responsive to regional unemployment fluctuations. The coefficient is not significant. Therefore the distinction between posting a range or posting a point wage is unlikely to matter for understanding wage cyclical.

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Table 25: Wage Cyclicality in Occupations with High vs. Low Share Posting Wage Ranges

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Log Wage, CPS, Newly Hired Workers</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Independent Variables:</strong></td>
<td></td>
</tr>
<tr>
<td>Quarterly Unemployment</td>
<td>-1.019 (1.11)</td>
</tr>
<tr>
<td>Quarterly Unemployment × High Share Posting Wage Ranges</td>
<td>1.120 (0.82)</td>
</tr>
<tr>
<td>Annual Unemployment</td>
<td>-1.131 (1.19)</td>
</tr>
<tr>
<td>Annual Unemployment × High Share Posting Wage Ranges</td>
<td>1.174 (0.83)</td>
</tr>
<tr>
<td>Time Effect</td>
<td>Y</td>
</tr>
<tr>
<td>State Effect</td>
<td>Y</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>67327</td>
</tr>
</tbody>
</table>

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. Standard errors are clustered by state.
E  Model with Job-Level Wage Rigidity

This section extends the standard Diamond-Mortensen-Pissarides model, to allow for high and low wage types of jobs. We use the model to make two points. First, job-level changes in the wage for new hires govern unemployment fluctuations. Second, changes in wages due to job composition, which do not reflect job-level wage changes, do not matter for unemployment fluctuations. For consistency with the rest of the paper, we make this argument with a model that has downward wage rigidity.

E.1  Environment and Equilibrium

Time is discrete and infinite. Unemployment fluctuations are driven by output per worker \( y_t \), which follows an exogenous AR(1) process with mean value 1, that is

\[
y_t = (1 - \rho) + \rho y_{t-1} + \epsilon_t \quad \epsilon_t \sim N(0, \sigma^2). \tag{19}
\]

\( y_t \) is a measure of labor demand.\[^{36}\] There is a unit measure of homogeneous workers, who are either employed and producing output \( y_t \), or unemployed and searching for work.\[^{37}\] Workers are risk neutral, and derive utility from consumption only. Workers have discount factor \( \beta \in (0, 1) \) over future utility flows. Workers consume their wage in the periods that they are employed, and derive no flow utility from unemployment.

E.1.1  Wage Setting: Downward Rigidity and Job Types

We now introduce our two modifications to the standard DMP model: high and low wage job types, and downwards wage rigidity at the job level.

Workers search for employment in either high or low wage job types during period \( t \). In each job type, risk neutral firms post vacancies to match with workers. When a worker and firm match at time \( t \), wages are set. \( w_{it} \) is the real wage for a worker newly matched with a job of type \( i \), and wages are fixed for the duration of the match. The wage for new matches in each job type satisfies

\[
w_{it} = \max \left[ w_{it-1}, \phi_i y_t^\gamma \right] \tag{20}
\]

[^36]: In practice, many shocks other than labor productivity may affect labor demand, such as monetary or fiscal policy. Labor productivity stands in for this more general set of shocks.

[^37]: We focus on job heterogeneity by assuming homogeneous workers. In practice, worker heterogeneity also matters for wage dynamics and unemployment fluctuations—see Solon et al. (1994), Basu and House (2016) and Mueller (2017), amongst others.
\[ w_{Lt} = \max \left[ w_{Lt-1}, \phi_L y_i^T \right] \]  

(21)

where

\[ 0 < \phi_L < \phi_H < 1. \]

his specification of wage setting has two implications. First, there are high and low wage job types. Since \( \phi_H > \phi_L \), the wage for new matches is higher for job type \( H \). Second, the wage for new matches is more rigid downwards than upwards at the job level. Wages cannot fall between successive matches made by the same job type. Yet wages can rise if labor demand \( y_t \) increases sufficiently, with a pass through from \( y_t \) into \( w_{it} \) governed by the parameters \( \phi_i \) and \( \gamma \).

### E.1.2 Frictional Labor Market

There is a separate frictional labor market for each job type.

We model worker transitions between labor markets in a simple way. At the end of period \( t-1 \), an exogenous share \( \omega \) of workers in each job type switch to being unemployed and searching for work in the other job type. The probability that a worker switches job types does not depend on whether she is employed or unemployed at the end of period \( t-1 \).\(^{38}\) Also at the end of period \( t-1 \), an additional share \( s \) of the \( l_{i,t-1} \) workers employed in job type \( i = H, F \) separate from their jobs, in order to search for jobs of the same type.

Thus at the beginning of period \( t \), the number of unemployed workers searching for jobs of type \( i \) satisfies

\[ u_{it} = \frac{1}{2} - (1 - \omega)(1 - s) l_{i,t-1}, \]  

(22)

since there is a measure 1/2 of workers either employed or searching for work in each job type at the start of period \( t \), and \( (1 - \omega)(1 - s) l_{i,t-1} \) workers remain employed from the previous period. Aggregate unemployment is \( u_t = u_{Ht} + u_{Lt} \).

There is a large measure of risk neutral firms of each job type, with discount factor \( \beta \in (0, 1) \). Firms in each job type post \( v_{it} \) vacancies in total, to match with the unemployed workers. In period \( t \), total matches \( n_{it} \) are given by a matching function \( n_{it} = M(u_{it}, v_{it}) = \Psi u_{it}^a v_{it}^{1-a}, \alpha \in (0, 1) \). The key state variable governing each labor market is labor market tightness

\[ \theta_{it} \equiv v_{it}/u_{it}. \]  

(23)

The per-period cost of posting vacancies is \( c > 0 \). Vacancy posting costs capture firms’ recruiting expenses, as they search for workers in the frictional labor market. The vacancy filling rate is \( q(\theta_{it}) = \Psi \theta_{it}^{-a} \). The vacancy filling rate is decreasing in \( \theta_{it} \)—in a tight labor market, firms cannot

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\(^{38}\)Thus there is no on-the-job search—when workers switch job types, they first leave their current job, and then search for a new type of job. For simplicity, we abstract from directed search across job types.
find workers easily. Workers start working in the same period that they are hired.

If a worker finds a job in period $t$, they start producing output in the same period. The job finding rate of a worker searching for either job type is $f(\theta_{it}) = \Psi \theta_{it}^{1-\alpha}$. The job finding rate is increasing in $\theta_{it}$—in a tight labor market, workers find jobs easily.

Tightness and employment comove positively. When the labor market is tight, firms hire many workers and employment rises. In particular, employment during period $t$ satisfies

$$l_{it} = \frac{1}{2} - \left(1 - f(\theta_{it})\right) \left[\frac{1}{2} - (1 - \omega)(1 - s) l_{i,t-1}\right].$$

(24)

E.1.3 Firm Profits

If a match is filled at time $t$, it immediately starts to produce output. For periods $t+j$ in which a match is not destroyed, the match in job type $i$ produces output $y_{t+j}$, common across job types, and pays job-type-specific wage $w_{it}$ to the worker. The firm receives flow profit $y_{t+j} - w_{it}$.

The value of an unfilled vacancy depends on the chance that a vacancy is filled, and the cost of posting vacancies, as well as its continuation value. Then if $K_{it}$ is the value of an unfilled vacancy and $J_{i,t,t}$ is the value in period $t$ of a vacancy that is filled in period $t$, $K_{it}$ is given by

$$K_{it} = -c + q(\theta_{it}) J_{i,t,t} + \beta \left(1 - q(\theta_{it})\right) \mathbb{E}_t K_{i,t+1}. \quad (25)$$

The value of a filled vacancy to a firm is the flow profit, and the continuation value, after deducting the risk of job destruction. $J_{i,t,t+j}$ is given by

$$J_{i,t,t+j} = y_{t+j} - w_{it} + \beta \left[ (1 - s)(1 - \omega) \mathbb{E}_{t+j} J_{i,t,t+j+1} + [1 - (1 - s)(1 - \omega)] \mathbb{E}_{t+j} K_{i,t+j+1}\right] \quad (26)$$

where $\mathbb{E}_{t+j}$ denotes the expectation conditional on time $t+j$ information.

E.1.4 Free Entry and Equilibrium

There is free entry in vacancy posting. Vacancy posting continues until the labor market becomes tight. Then vacancies are hard to fill, driving the ex ante value of vacancies to zero. Free entry implies

$$K_{it} \geq 0 \quad v_{it} \geq 0 \quad (27)$$

for all $t$ with complementary slackness. When labor productivity rises, job creation becomes more profitable. Firms create many vacancies and the labor market tightens.

An equilibrium is a collection of stochastic processes $(l_{it}, v_{it}, \theta_{it}, u_{it}, w_{it})_{t=0}^\infty$ for $i = H, L$, that satisfy the law of motion for unemployment (22), the definition of labor market tightness
E.2 Job-level Wages Are Allocative for Unemployment Fluctuations

We now show that job-level wage changes are allocative for unemployment fluctuations. We derive a formula linking unemployment changes to wage changes, and show that job-level wage changes are what matter.

**Proposition.** In a neighborhood of the steady state and to a first order

\[
\frac{\Delta \log u_t}{\Delta \log y_t} = -A + B \left[ \mu \Delta \log w_{Ht} + (1-\mu) \Delta \log w_{Lt} \right]
\]

(28)

where \( A, B > 0, \mu \in (0, 1) \) and \( \Delta x_t \equiv x_t - x_{t-1} \) is the difference operator, for constants \( A, B \) and \( \mu \).

The proof of this proposition is available on request from the authors.

The left hand side of equation (28) is the response of aggregate unemployment in the economy to labor demand shocks \( y_t \). The term in the square brackets of the RHS is the response of a weighted average of job-level wage growth to labor demand. \( \Delta \log w_{it} \) is wage growth across successive matches in job type \( i \), which depends on the wage setting equations (20) and (21). \( A \) and \( B \) capture other time-invariant factors affecting the sensitivity of unemployment to shocks.

Equation (28) reveals two key insights. First, job level wage changes are allocative for unemployment fluctuations. The response of unemployment to labor demand shocks depends entirely on how job-level wages respond to labor demand shocks. When job-level wages are more flexible, so \( \Delta \log w_{it} / \log \Delta y_t \) is higher, then unemployment is less sensitive to labor demand, and \( \Delta \log u_t / \log \Delta y_t \) is smaller in magnitude.

Second, it is job-level and not average wage changes which matter for unemployment fluctuations. Let the share of high wage jobs in the economy be \( \nu_{Ht} = n_{Ht} / (n_{Ht} + n_{Lt}) \). In this economy, the change in the average wage for new hires is

\[
\Delta \left[ \nu_{Ht} w_{Ht} + (1-\nu_{Ht}) w_{Lt} \right] \approx \nu_{Ht} \Delta w_{Ht} + (1-\nu_{Ht}) \Delta w_{Lt} + (w_{Ht} - w_{Lt}) \Delta \nu_{Ht}.
\]

(29)

The term in the square brackets on the right hand side of equation (29) represents job level wage changes, and affects unemployment fluctuations by equation (28). The second term represents changes in average wages due to shifting composition between high and low wage jobs,
as represented by the $\Delta v_{Hi}$ term. $\Delta v_{Hi}$ does not enter the right hand side of equation (28). Thus changes in wages due to composition do not affect the sensitivity of unemployment to labor demand shocks. Regardless of how composition affects wages, a weighted average job-level wage growth $\mu \Delta \log w_{Hi} + (1 - \mu) \Delta \log w_{Li}$ pins down unemployment fluctuations.

### E.3 Comparison with Model in Main Text

We derive an equivalent result to equation (28), for the model presented in the main in the main text.

**Proposition.** For the model in the main text, in a neighborhood of the steady state and to a first order

$$\frac{\Delta \log u_t}{\Delta \log y_t} = -\hat{A} + \hat{B} \frac{\Delta \log w_t}{\Delta \log y_t}$$

(30)

where $\hat{A}, \hat{B} > 0$.

The proof of this proposition is also available on request. One can show that when $\bar{u}_H = \bar{u}_L$ in the model with multiple jobs, we have $\hat{A} = A$ and $\hat{B} = B$. Therefore equation (30), which links wage changes to unemployment changes in the single job model presented in the main text; is equivalent to equation (28), which links wage changes to unemployment changes in the model extension with multiple jobs, presented in this appendix.

### F Model with Nominal Rigidity

In this section, we augment the model in the main text, and show that it does not alter our quantitative conclusions.

#### F.1 Model Setup

We augment the model with sticky prices, similarly to Gertler, Sala, and Trigari (2008), Blanchard and Gali (2010) and Christiano et al. (2016). There is a frictional labor market, in which hiring firms match with workers and produce output. There is a goods market, in which price setting firms buy from hiring firms, and then set prices with Calvo frictions.

In the labor market block of the model, hiring firms match with workers. This block is virtually identical to the model in the main text, so we present only the equations that differ. In periods when a match is active, instead of producing output per worker $y_t$ as in the main text, the match produces output $P_h^h / P_t$. $P_t$ is the price level of final goods. $P_h^h$ is the price of goods produced by hiring firms. These goods are sold to price setting firms.
There is downward nominal wage rigidity for new hires. That is, the wage for new hires follows
\[
P_t w_t = \max\left\{ P_t w_t^*, (1 - \xi) P_{t-1} w_{t-1} \right\}
\]
where \( w_t \) is the current real wage, and \( P_t \) is the current price level. The frictionless real wage is
\[
w_t^* = b + \phi \left( \frac{A P_t^h}{P_t} \right).
\]
Thus \( \phi \) parameterizes the pass through of real value added per worker into the wage for new hires.

Next, we turn to the goods market. We make assumptions so that there is a linear Phillips Curve in the price setting market. Price setting firms buy output from hiring firms in a perfectly competitive market, at real price \( P_t^h / P_t \). The microfoundations of a Phillips Curve are standard, so we omit the derivation. The Phillips Curve is
\[
\pi_t = \beta \pi_{t+1} + \kappa (\hat{p}_t^h - \hat{p}_t),
\]
where \( \pi_t \) is inflation, \( \beta \) is the discount factor of price setting firms, and \( \kappa \) is the sensitivity of inflation to log real marginal costs. \( (\hat{p}_t^h - \hat{p}_t) \) is the deviation of price setting firms’ log real marginal costs from the steady state value.

For labor demand, we assume that changes nominal value added per worker follows an AR(1) process, that is
\[
\Delta D_t = \rho \Delta D_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2_{\epsilon})
\]
where \( D_t = A P_t^h \). Thus in this model, \( \epsilon_t \) captures shocks to nominal labor demand, such as monetary or fiscal shocks.

The equilibrium is a sequence \( \{v_t, u_t, w_t, P_t^h, \pi_t\}_{t=0}^{\infty} \) given nominal demand shocks \( \{\epsilon_t\}_{t=0}^{\infty} \), such that hiring firms maximize profits, there is free entry in vacancy creation, there is downward nominal wage rigidity, and price setting firms maximize profits.

Though the Phillips Curve is linearized, we solve the labor market block using the same global algorithm as in the main text. Thus the nonlinearities in our results come from downward wage rigidity in the labor market, and not from the behavior of price setting firms.
Figure 20: State Dependent Asymmetry with Nominal Rigidity

Notes: this graph plots the impulse response of unemployment with respect to positive and negative labor demand shocks, in two scenarios. In the first scenario, which is on the left hand side axis, the impulse response occurs when the economy is at the steady state. In the second scenario, which is on the left hand side axis, the impulse response occurs when the economy’s current labor demand is at its steady state value, but there was a contraction prior to the impulse response. The contraction is equal to one unconditional standard deviation of labor demand. For both scenarios, the solid line is the impulse response after a positive labor demand shock, and the dashed line is minus one times the impulse response after a negative shock. In each case, the impulse is a conditional standard deviation of labor demand.

F.2 Calibration

We calibrate \( \kappa \) and \( \tilde{\beta} \) using the median specifications in Table 5 of Mavroeidis, Plagborg-Møller, and Stock (2014), for the labor share specifications. All other calibrated parameters are the same as the model in the main text, our estimation strategy is also the same as in the main text.

F.3 Model Results

We simply conduct the same exercise as in Figure 11 of the main text, which reports the degree state dependence in the asymmetry of unemployment impulse responses. Figure 20 reports the result.

We plot the impulse response of unemployment to positive and negative labor demand shocks, at \( t = 0 \), from each scenario. In the first scenario, the response of unemployment is asymmetric; in the second scenario, the response of unemployment is asymmetric. On the
left hand axis, the figure plots the impulse response of unemployment to positive and negative shocks in scenario 1, whereby the model starts at the steady state. The solid line is the impulse response of unemployment after a positive shock. The dashed line is minus one times the impulse response of unemployment after a negative shock. Clearly, the impulse response after a negative shock is far bigger, roughly twice as large. On the right hand axis, the figure plots the impulse response of unemployment to positive and negative shocks in scenario 2, after a contraction in labor demand. Again, the solid line is the impulse response of unemployment to a positive shock, the dashed line is the impulse response of unemployment to a negative labor demand shock. The impulse response is symmetric.

Importantly, the quantitative magnitudes are similar in the model with nominal rigidity, to the model in main text. Thus adding nominal rigidity does not alter our basic conclusions.

G Time Series Evidence on State Dependent Asymmetry

We consider the following Jorda projection of unemployment on monetary policy shock:

\[
U_{t+h} - U_{t-1} = I_{t-1} \left( \alpha_h + \beta_h \varepsilon_t + \gamma_h I(\varepsilon_t > 0) \varepsilon_t \right) \\
+ (1 - I_{t-1}) \left( \tilde{\alpha}_h + \tilde{\beta}_h \varepsilon_t + \tilde{\gamma}_h I(\varepsilon_t > 0) \varepsilon_t \right) + u_t
\]

where \( U_t \) is quarterly national unemployment for 1969-2007; and \( \varepsilon_t \) is a monetary shock as in Romer and Romer (2004), extended to 2007 by Wieland and Yang (2016).

Then \( \beta_h \) is the IRF of unemployment to MP shock \( \gamma_h \) is asymmetry in the IRF of unemployment to monetary shocks. If \( \gamma_h > 0 \), then unemployment is more responsive to monetary contractions than expansions. We allow for state dependence, using a similar technique to Ramey and Zubairy (2018). In the regression, \( I_{t-1} = 1 \) if employment \( t < \max \{ \text{employment}_j \} \) \( j=1969,Q1 \), and \( I_{t-1} = 0 \) otherwise. Therefore the state is whether labor market is at its peak, or below its recent peak. We report the impulse responses below.

The figures show that when the labor market is below its previous peak, unemployment responds similarly to expansionary versus contractionary monetary shocks. When the labor market is below its previous peak, unemployment responds significantly more to negative than to positive shocks to monetary policy. Thus the dynamics of unemployment display state-dependent asymmetry.
Figure 21: Estimated Impulse Responses

Difference Between Positive and Negative Impulse Response, Labor Market At Peak

Change in Unemployment, pp

Quarters Since Shock

IRF for Monetary Contraction - IRF for Monetary Expansion

Note: 95% CI, Newey-West SEs

Difference Between Positive and Negative Impulse Response, Labor Market Below Peak

Change in Unemployment, pp

Quarters Since Shock

IRF for Monetary Contraction - IRF for Monetary Expansion

Note: 95% CI, Newey-West SEs