Downward Rigidity in the Wage for New Hires

Jonathon Hazell Bledi Taska*

Job Market Paper

Click HERE for the most recent version

December 6, 2019

Downward wage rigidity is central to many explanations of unemployment fluctuations. In benchmark models, the wage for new hires is particularly important, 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*—across successive vacancies posted by the same job title and establishment. We show that the wage for new hires is rigid downward but flexible 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 below. Second, when unemployment rises, wages do not fall—but wages do rise strongly as unemployment falls. We show that prior strategies, which study the *average* wage for new hires, cannot detect downward rigidity due to changing job composition. We then develop a tractable dynamic wage bargaining model with downward rigidity. We fit the model to our findings, and uncover state dependent asymmetry in unemployment dynamics. When there has been a contraction in the recent past, unemployment responds symmetrically to subsequent labor demand shocks; when there has recently been an expansion, unemployment is subsequently twice as sensitive to negative as to positive shocks.

*Hazell: Massachusetts Institute of Technology, Department of Economics (email: jhazell@mit.edu); Taska: Burning Glass Technologies. Hazell thanks Iván Werning, Daron Acemoglu, Jonathan Parker and Emi Nakamura for invaluable support and guidance. We also thank for their comments Marios Angeletos, Martin Beraja, Sydnee Caldwell, Tyler Cowen, Juliette Fournier, Daniel Greenwald, John Grigsby, Erik Hurst, Gwen Jing, Mazi Kazemi, Eben Lazarus, Chen Lian, Christina Patterson, Claudia Sahm, Pari Sastry, Anna Stansbury, Jón Steinsson and Emil Verner; as well as participants at the 2018 NBER Summer Institute, Monetary Economics, and the MIT Macro and Labor lunches. Hazell gratefully acknowledges the hospitality of the Becker-Friedman Institute at the University of Chicago, a doctoral fellowship from the Washington Center for Equitable Growth, and a Kennedy Summer Research Scholarship from the Kennedy Memorial Trust. This paper previously circulated under the title "Posted Wage Rigidity".

1 Introduction

Suppose there is downward wage rigidity—that is, wages do not fall during recessions. Economists have long argued that unemployment should then rise sharply, because the cost of labor remains high even as labor demand falls (Keynes, 1936). Downward wage rigidity for *new hires* is particularly important, because employment is a long term contract (Pissarides, 2009). So the present value of wages, which is closely tied to the wage for new hires, matters to workers and firms. Even if wages in continuing jobs change little, the present value of wages can still vary if the wage for new hires is flexible.

Job composition is a key challenge when studying the wage for new hires. Prior work often studies the average wage for new hires, averaging over all workers and jobs at a point in time, using survey data. Pissarides (2009) and Basu and House (2016) survey this work. If job composition varies over time, average wage changes reflect either changing job composition, or wage changes for individual jobs (Gertler and Trigari, 2009). As an example, consider an economy of high wage bankers and low wage baristas. Suppose the share of barista hires increases during recessions. Then average wages for new hires fall, even if wages fall for neither baristas nor bankers. Conversely, suppose the share of barista hires decreases during recessions. Then average wages will not fall, even if wages do fall for both barista and banker jobs. Estimates in the prior literature are often too imprecise to draw conclusions. For example, the point estimate in Haefke, Sonntag, and Van Rens (2013) suggests strong procyclicality, but the confidence interval includes zero cyclicality.[1]

There is evidence that wages are downwardly rigid for continuing workers (Grigsby, Hurst, and Yildirmaz, 2018). But continuing wage rigidity may reflect insurance provided to workers by firms (Beaudry and DiNardo, 1991). Firms need not extend the same insurance to new hires.

We study a dataset on the wage for new hires, from online vacancies, collected by Burning Glass Technologies. Our data has job and establishment level information on wages. Our paper makes two contributions. First, the wage for new hires is rigid downward, but strongly flexible upward. We isolate job- and establishment-level wage changes, to purge the effects of job composition. Second, we develop a tractable dynamic wage bargaining model with downward rigidity, and estimate the model. Our model reveals a new form of state dependence in the asymmetry of unemployment dynamics.

Our dataset contains wages on new vacancies, with job titles, establishment identifiers, and pay frequency, for 10% of all vacancies posted in the United States during 2010-2016. The dataset collects vacancies from the near-universe of online job boards and company websites.

[1]As we will discuss further, prior work attempts to control for job composition by, for example, including worker level observables or worker fixed effects in regressions. But residual job composition may be important.

Though not from a representative sample, our measure is a good proxy for the wage for new hires. We show that average wages in Burning Glass closely track state-by-quarter measures of the average wage for new hires from both survey and administrative data.[2]

But our dataset has a particular advantage, not available in prior datasets that measure the average wage for new hires. We can 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.[3] Consider a physical location of Starbucks, in Cambridge, Massachusetts, 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. Workers are typically hired once into a job. So worker-level data cannot easily track the wage across successive workers, hired into the same type of job.

There are two related benefits of job and establishment level data. First, by studying job level wages, we can purge the effects of job composition. Second, job- and establishment-level wages are particularly important for unemployment fluctuations. Standard labor search models, once extended to include establishments, capture the logic (Gertler and Trigari, 2009). In these models, aggregate hiring depends on whether establishments create jobs—which depends on establishments' profits from job creation. If the wage for new hires faced by an establishment does not fall during recessions, the establishment's profits from job creation fall. The establishment creates fewer jobs. In aggregate, unemployment rises.

We show that the wage for new hires is rigid downward, but is flexible upward. We have four findings. 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. It is well known continuing wages change infrequently and rise more often than fall (Grigsby, Hurst, and Yildirmaz, 2018). But plausible reasons why continuing wages change infrequently, such as implicit insurance by firms, need not apply to new hires. The result suggests mechanisms that impose parity between the wage of new hires and continuing workers, such as internal equity (Bewley, 2002).

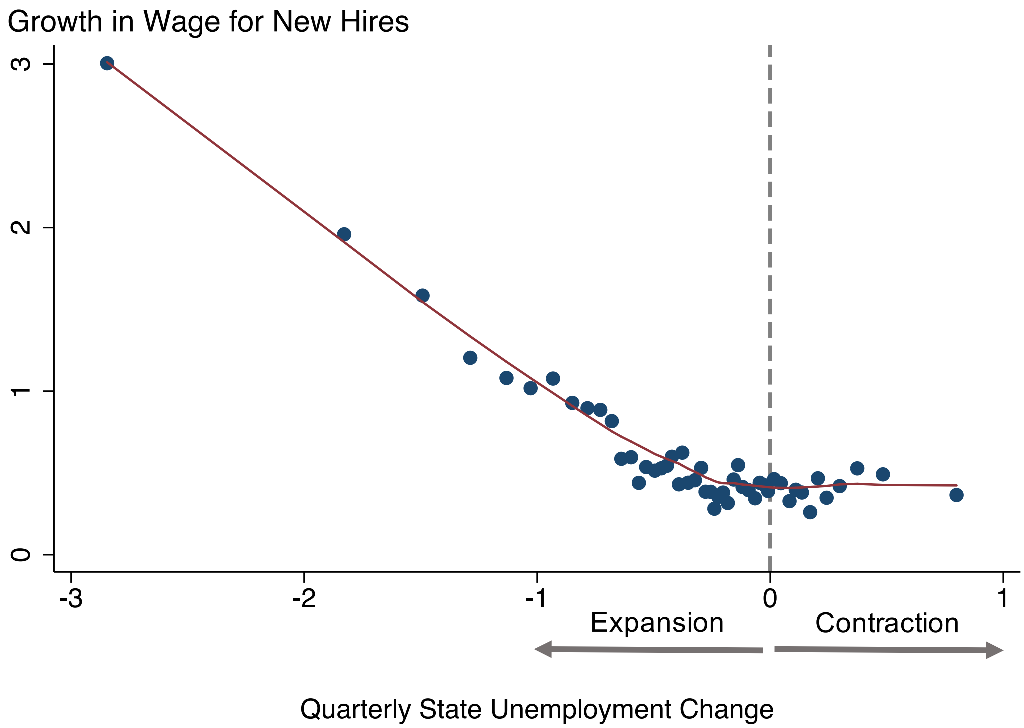
Second, at the job level, the wage for new hires rises during expansions but does not fall during contractions. Figure 1 illustrates the result. In the figure, the wage for new hires is averaged by job-quarter. On the y-axis is wage growth between two consecutive vacancies for the same job. On the x-axis is the growth in quarterly state level unemployment between the quarters in which the vacancies are posted.[4] As state unemployment decreases, the wage for new hires

[2] Posting vacancies on job boards or company websites is normally expensive, and vacancies are typically active for a month or less. We suspect these features discourage "stale" information in vacancies.

[3] Here, a "job" is a job title at an establishment.

[4] Since many jobs do not post in consecutive quarters, sometimes the fall in unemployment between postings

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.

rises strongly. As state unemployment increases, wages do not fall. Figure 1 isolates job-level wage growth for new hires. We remove variation from changing job composition, which might obscure downward wage rigidity, in order to focus on changes in the wage faced by establishments. We confirm the finding with regressions, and consider several robustness tests.

Third, we show that establishment wages—aggregating across jobs within the same establishment—rise when unemployment falls but do not fall when unemployment rises. So, a constraint at the job-level leads to downward rigidity in the wage faced by establishments, across all the jobs into which they hire.

Fourth, wage flexibility *upward* is state dependent. When there has been a regional contraction in the recent past, then subsequently, the wage for new hires responds little as regional unemployment falls. When there has been an regional expansion in the recent past, then subsequently, the wage for new hires responds strongly as regional unemployment falls. This state dependence is consistent with downward rigidity. Wages are "trapped too high" when there has

is relatively large.

been a contraction in the recent past, and a subsequent marginal increase in labor demand does not raise wages. After an expansion in the recent past, wages overcome the downward constraint.

However the *average* wage for new hires, the object of previous studies, shows no sign of downward rigidity—in contrast to our job- and establishment-level results. We examine the average wage for new hires in our dataset. The average wage does not respond differently to rises versus falls in unemployment. Similarly, measures of the average wage from worker-level survey data, used in Haefke, Sonntag, and Van Rens (2013) and Basu and House (2016), are not more rigid downward than upward.

We show that job composition obscures downward rigidity in average wages. Average wages aggregate across all types of jobs and establishments. Then average wage changes reflect either wage changes at the job level, or changes in job composition. We find that due to job composition, average wages have higher variance than job-level wages. In the data, the share of low wage jobs is volatile. When the share of low wage jobs changes, average wages also change. So, average wage changes have high variance due to job composition. Standard errors from regression estimates using average wages in Burning Glass are a factor of five larger than counterpart estimates using job-level wages. So, regressions using average wages have limited 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 three steps.

First, we develop a tractable dynamic wage bargaining protocol with downward rigidity. Our starting point is an alternate offer bargaining game as in Hall and Milgrom (2008), in which firms and workers alternate wage offers. But we then introduce downward wage rigidity, motivated by our new evidence. Neither workers nor firms can make a lower offer than the wage paid to previous workers. The constraints on wage offers introduce complexities relative to standard alternate offer games. But in our model, the bargaining solution is tractable. The equilibrium wage can be solved in a separate "block" from the other endogenous variables of the model, such as workers' value of unemployment. This result simplifies computation and lets us analytically characterize the equilibrium.

Second, we incorporate our wage bargaining protocol into an otherwise-standard labor search model, and estimate the model by indirect inference. We run the same regressions on simulated wages in the model as in real-world data, and then minimize the distance between the regression coefficients. Though parsimonious, the model matches several moments that the estimation does not explicitly target, including the dynamics of unemployment and continuing wages.[5] Moreover, downward rigidity lets us fit the time series pattern of slow wage growth

[5] The degree of wage rigidity in the data resolves the "unemployment volatility puzzle" of Shimer (2005).

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.[6]

Third, we show state dependent asymmetry in unemployment dynamics. Suppose there has been a contraction in the recent past. Subsequently, according to our model, unemployment dynamics are *symmetric*. Unemployment responds similarly to positive or negative labor demand shocks, subsequent to the contraction. Conversely, suppose there has been an expansion in the recent past. Subsequently, in our model, unemployment dynamics are *asymmetric*. Unemployment responds twice as much to negative labor demand shocks as to positive shocks, subsequent to the expansion. So, the asymmetry in unemployment dynamics is state dependent. Asymmetry emerges in the aftermath of expansions, but is not present in the aftermath of contractions. The key mechanism is the state dependence of wage dynamics created by downward rigidity. When there has been a contraction in the past, wages subsequently respond little to either positive or negative labor demand shocks. When there has been an expansion in the past, wages subsequently respond to positive shocks, but do not respond to negative shocks. We documented exactly this form of state dependence in our empirics. 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 positive and negative labor demand shocks. At the peak of booms, unemployment is around twice as sensitive to negative shocks.

1.1 Related Literature

Pissarides (2009) emphasizes that in benchmark labor search models, the wage for new hires is key for unemployment fluctuations. Since employment is a long term relationship, the present value of wages at the point of hiring matters. This present value is closely tied to the wage for a new hire. Wage changes for continuing workers then matter less for unemployment fluctuations (Barro, 1977).[7] If the wage for new hires is rigid, then unemployment is volatile over the business cycle (Hall, 2005b; Hagedorn and Manovskii, 2008; Hall and Milgrom, 2008; Gertler and Trigari, 2009).

The wage for new hires matters for a second, closely related, reason. In US data, unemployment fluctuations are primarily determined by hiring (Shimer, 2012).[8] The wage for new hires

[6] 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.

[7] Continuing wage rigidity is still 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. Equally, firms may moderate their wage increases to offset the effect of downward rigidity on unemployment (Elsby, 2009).

[8] See also Hall (2005a), Fujita and Ramey (2009) and Elsby, Michaels, and Solon (2009). The same result holds in

matters on this margin.

But evidence on wage rigidity for new hires is hard to interpret due to job composition. Bils (1985) studies the average wage for new hires, averaging over workers switching jobs or entering new jobs from unemployment, using survey data. This measure controls for worker observables and worker fixed effects, but averages over the jobs into which workers are hired. In Bils (1985) and several other papers, point estimates suggest the average wage for new hires is strongly procyclical, though standard errors are often large. Pissarides (2009) summarizes these results.[9] Gertler and Trigari (2009) emphasize the challenge of job composition. If the share of low wage jobs rises during recessions, then the average wage can fall, even if the wage faced by a given establishment does not fall. There is a "job composition bias" similar to omitted variable bias, imparting procyclicality into average wages.

Our work relates to three papers that study wage rigidity for new hires and correct for job composition. Gertler, Huckfeldt, and Trigari (2016) study wages for workers newly hired from unemployment, from survey data. The wage of workers hired from unemployment is likely less affected by job composition bias than the wage of workers switching jobs, and is weakly procyclical. Hagedorn and Manovskii (2013) construct a variable that, under plausible assumptions, controls for job composition bias. Adding this control lowers the the procyclicality of the average wage for new hires. Grigsby, Hurst, and Yildirmaz (2018) study the wage change for employment-to-employment job switchers, using high quality payroll data. They benchmark job switchers' wages against observably similar workers who are not switching jobs, to correct for composition bias. Grigsby et al find weak procyclicality after making this correction.

Our paper complements this prior work in three respects. First, we study wage changes between successive vacancies posted by the same job, to directly correct for job composition. Though prior work uses controls for job composition, the residual effects of composition may still matter. Second, we find that wages are rigid downward, but flexible upward. We seem to be the first to detect such asymmetries in the wage for new hires, in US data. Third, we argue that job composition raises the variance of average wages, making downward rigidity hard to detect. This concern is distinct from the issue of job composition bias.[10]

A large literature studies the consequence of downward rigidity for asymmetries in un-

most Anglo-Saxon economies, though not in the economies of peripheral Europe (Elsby, Hobijn, and Şahin, 2013). The pattern also continued over the Great Recession, especially after excluding separated workers who are then recalled (Fujita and Moscarini, 2017).

[9]Notable contributions include Shin (1994), Haefke, Sonntag, and Van Rens (2013), Kudlyak (2014) and Basu and House (2016).

[10]Two important papers study wage rigidity for new hires from outside the United States. Kaur (2019) studies wage rigidity for day laborers in rural India and detects an asymmetry—wages are rigid downward and flexible upward. Martins, Solon, and Thomas (2012) study Portuguese data, and construct a measure of the job-level from granular administrative wage data, with establishment and occupation information. Martins et al find that the wage for new hires is strongly procyclical.

employment. For example, Schmitt-Grohé and Uribe (2016) show that unemployment rises sharply during contractions and falls more slowly during expansions, due to downward wage rigidity. Dupraz, Nakamura, and Steinsson (2016) show that downward rigidity rationalize various important asymmetries in the time series of US unemployment.[11] We contribute to this literature in two ways. First, we provide evidence that wages for new hires are rigid downward but flexible upward, which supports the mechanism in these papers. Second, we argue that the degree of asymmetry in unemployment dynamics depends on whether there has been an expansion or contraction in the recent past.

Bewley (2002) conjectures that the wage for new hires inherits the rigidity of continuing workers' wages, due to internal equity concerns.[12] Continuing workers' wages are downwardly rigid and change infrequently.[13] We show that the wage for new hires inherits these properties, in line with the conjecture. Other theories suggest that wages should be rigid for continuing workers but for flexible for new hires.[14] So, a direct comparison of wage setting for new hires and continuing workers is helpful.

2 Data

We study an 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.[15]

The dataset covers approximately 10% of vacancies posted in the US, either online or offline (Carnevale, Jayasundera, and Repnikov, 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

[11]See also Akerlof, Dickens, and Perry (1996), Kim and Ruge-Murcia (2009), Kim and Ruge-Murcia (2011), Benigno and Ricci (2011), Daly and Hobijn (2014), Chodorow-Reich and Wieland (2017), Petrosky-Nadeau and Zhang (2013) and Petrosky-Nadeau, Zhang, and Kuehn (2018) for related nonlinearities in unemployment dynamics due to downward wage rigidity.

[12]See also Fang and Moscarini (2005), Menzio and Moen (2010) and Rudanko (2019) for versions of this conjecture.

[13]A non-exhaustive list of papers with this finding include Card and Hyslop (1997), Le Bihan, Montornès, and Heckel (2012), Barattieri, Basu, and Gottschalk (2014), Daly and Hobijn (2014), Sigurdsson and Sigurdardottir (2016), Kurmann and McEntarfer (2017), Mian, Sufi, and Verner (2017), Grigsby, Hurst, and Yildirmaz (2018), Kaur (2019), Jo (2019) and Makridis and Gittleman (2019). However, Elsby, Shin, and Solon (2016), Elsby and Solon (2018) and Jardim, Solon, and Vigdor (2019) argue the importance downward rigidity for continuing workers is overstated.

[14]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 (Eliaz and Spiegler, 2014). 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).

[15]A 6 digit SOC code is granular—at the detail of, for example, a high school Spanish teacher.

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 in wages (Bound and Krueger, 1991).

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 paid at a given frequency (e.g. annual or daily).

The dataset overweights certain occupations that disproportionately post online. Appendix Figure 2 plots the relative share of Burning Glass occupations versus the 2014-2016 Occupational Employment Statistics (OES). 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 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.2 explores in detail alternative ways of treating jobs that post a range, and finds that they do not make a difference to our key results.

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. Marinescu and Wolthoff (2016) show that the decision to include wages in vacancies is a time-invariant characteristic of certain types of firms. These considerations are likely not relevant for business cycles: in Appendix Table 1, we show that firms' decisions to include wages in 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 Quarterly Census of Employment and Wages (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. Moreover, in principle, wages posted on vacancies might not equal the wage paid at the start of the hire. 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 (CPS), 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, Sonntag, and Van Rens (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 avoid attenuation bias in the regression coefficients, due to measurement error in Burning Glass wages, we adapt the method of Angrist and Krueger (1995). 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. This procedure uncovers an unbiased estimate of the population coefficient from a regression of log CPS wages on log Burning Glass wages.

Table 2, Panel A, reports the regressions, and Appendix Figure 1 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 next compare Burning Glass wages to 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 (QWI), 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 QWI, 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.

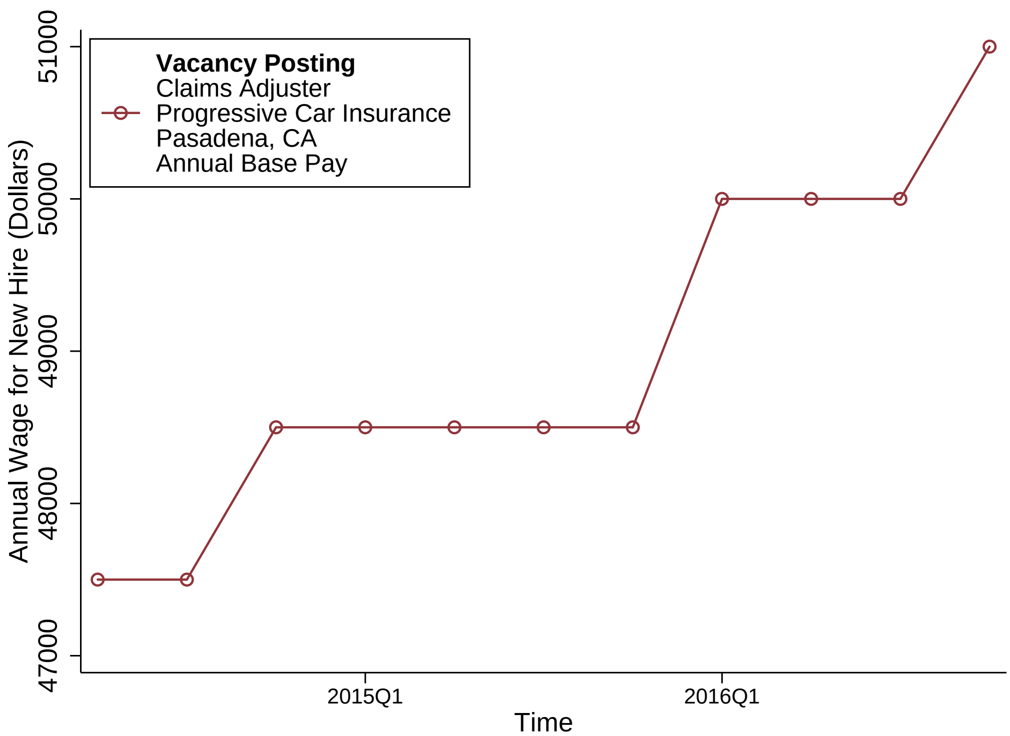
Table 2, Panel B, reports the regressions. The elasticity of new hire earnings with respect to Burning Glass wages is near, but above one. After one percent of growth in Burning Glass wages, QWI earnings for new hires grow by 1.25 percent. The larger movement in QWI earnings than in Burning Glass wages likely reflects a positive comovement between hours and wages in the QWI, so that QWI 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 2 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, for a representative sample of job-seekers, 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 when they are hired. 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.[16] 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.[17]

[16]See https://blog.proven.com/how-much-to-post-a-job.

[17]The duration of vacancies is similar to the mean vacancy duration reported in Davis, Faberman, and Haltiwanger (2013) from the BLS's JOLTS survey, of 20 days.

Figure 2: An Example of a Job



Notes: A job is a job-title by establishment by salary type by pay frequency unit, from Burning Glass. 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.

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.

2.2 Job and Establishment Data on the Wage for New Hires

Our dataset has a particular advantage not shared by prior data that measures the average wage for new hires. We can track the wage for new hires at 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 the wage for new hires faced by establishments.

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, California. The job title is claims adjuster. The salary is an annual wage, base pay. When the vacancy posts multiple times within the quarter, we take the average. 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.

Worker-level data cannot easily track job-level variation in the wage for new hires. Workers are typically hired once into a job. So worker data cannot easily track the wage across *successive* workers, hired into the same type of job.

Job- and establishment-level wage changes are particularly important for unemployment fluctuations. The logic 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).[18] In Gertler and Trigari's model, establishments either pay the same wage to workers hired in successive periods, or randomly receive an opportunity to reoptimize the wage. If the establishment's wage is fixed between periods, their hiring is sensitive to labor demand shocks—because firms' profits from job creation become sensitive to labor demand. In aggregate, because most establishments' wages are fixed for multiple periods at a time, hiring and unemployment are sensitive to labor demand. We study the wage for new hires faced by establishments, in line with these theories. 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, Huckfeldt, and Trigari (2016).

These models differ on the precise definition of the wage faced by establishments. In some models, such as Gertler, Huckfeldt, and Trigari (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 this latter set of models, there is a single type of job within each firm. In practice, the relative importance of job- versus establishment-level wages depends 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.[19]

In these models, average wages may differ from the wage faced by establishments, because

[18] See also Pissarides (2009), which emphasizes the importance of the wage for new hires in a model without establishments.

[19] 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 4.6.

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. But wage changes due to composition do not affect profits from job creation, so have little effect on hiring and unemployment fluctuations.

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.

3 Downward Constraints on Wage Setting in New Jobs

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. 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 for new hires. Wages are free to rise at the job level, but may not be able to fall.

3.1 Hazard Estimation of 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. In robustness exercises, we will reweight at a finely detailed 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 setting 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.[20] 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).

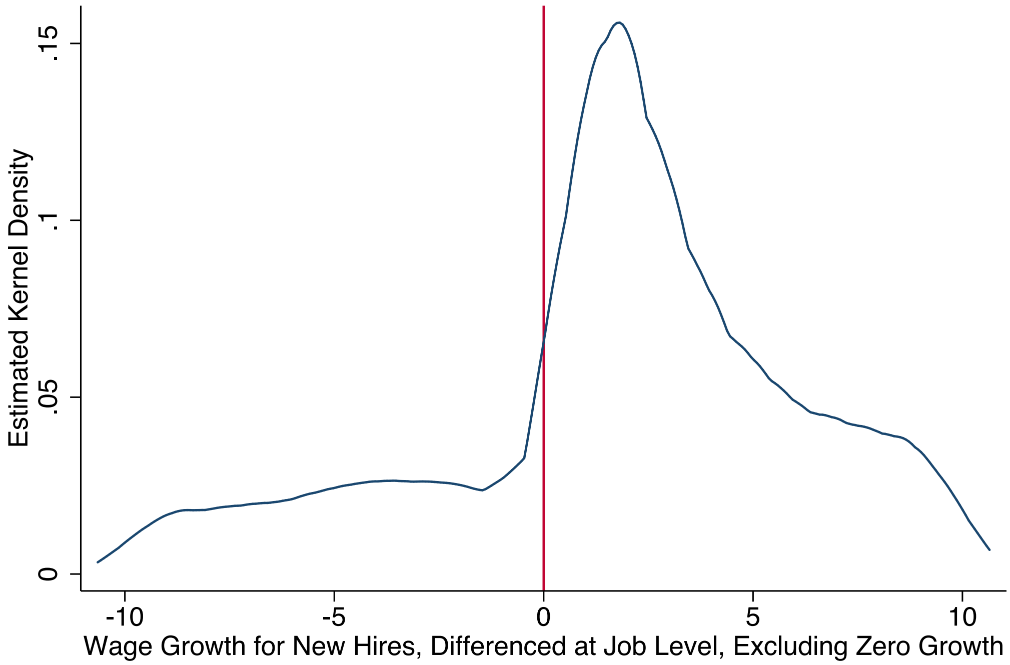
3.2 The Wage For New Hires Changes Infrequently at the Job Level

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

[20]We assume the 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 γ_{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 λ, which we estimate by maximum likelihood. The likelihood function is $L = \prod_i \prod_t \left(1 - e^{-\lambda\gamma_{it}}\right)^{I_{it}} \left(e^{-\lambda\gamma_{it}}\right)^{1-I_{it}}$. The probability of a 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 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, from Burning Glass. 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. The McCrary test tests the null hypothesis that the density function of wage changes is continuous at zero.

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.

Data tracking individual workers' wages cannot easily measure this statistic. Workers are typically hired once into a job. But the object of interest is the wage across *successive* workers hired into the same type of job.

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.

3.3 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.

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.

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.

3.4 Wage Increases Are Cyclically Sensitive, Wage Decreases Are Not

We now show that 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 labor 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 3.2.

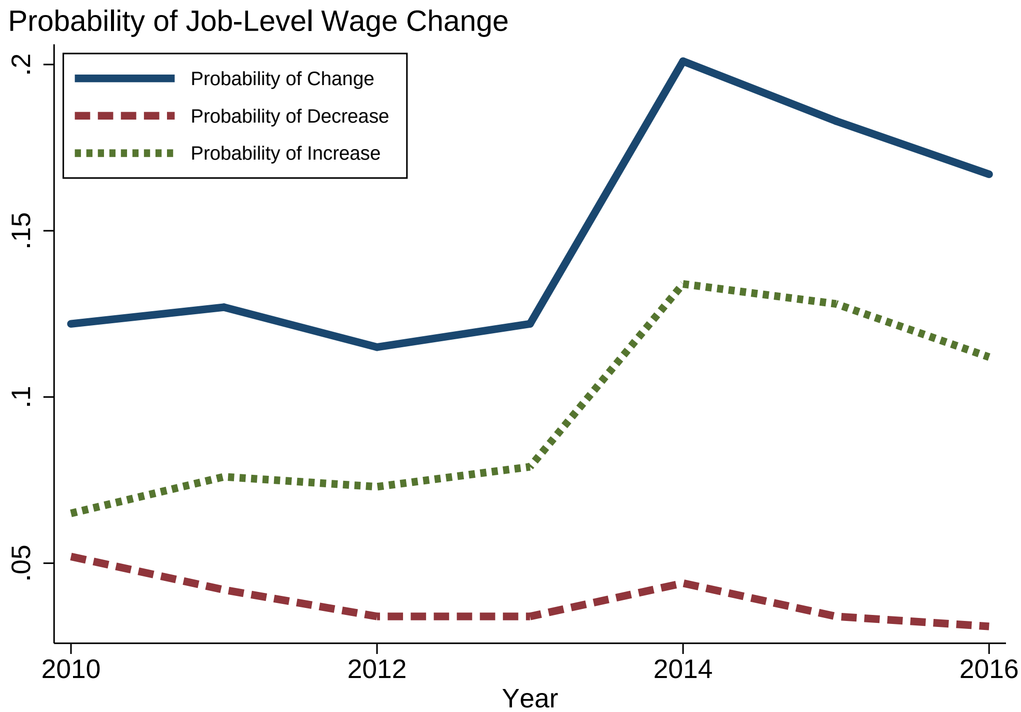
Figure 4 shows the results. As the labor market tightens over 2010-2016, the probability of wage change rises—as expected, given that wages rise over this period. However, the probability of wage change rises *entirely* because wage increases are more likely. Wage decreases are not more likely as the business cycle evolves. Thus wage increases for new hires are cyclically sensitive, and wage decreases are not.[21]

3.5 Wages For New Hires vs. Continuing 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. Workers in continuing employment—as opposed to workers newly hired into jobs—rarely experience wage changes.

[21] Figure 4 uses variation from only one business cycle expansion. In further support, Appendix Table 4 shows that the probability of increase is more cyclical than the probability of decrease, with respect to state business cycles. We calculate the probability of wage increase and decrease within each state-quarter. We regress these probabilities on the growth in employment for each state-quarter. The probability of wage increase comoves strongly with employment growth, the probability of decrease does not. See Jo (2019) for a related finding with continuing workers' wages.

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, using Burning Glass data.

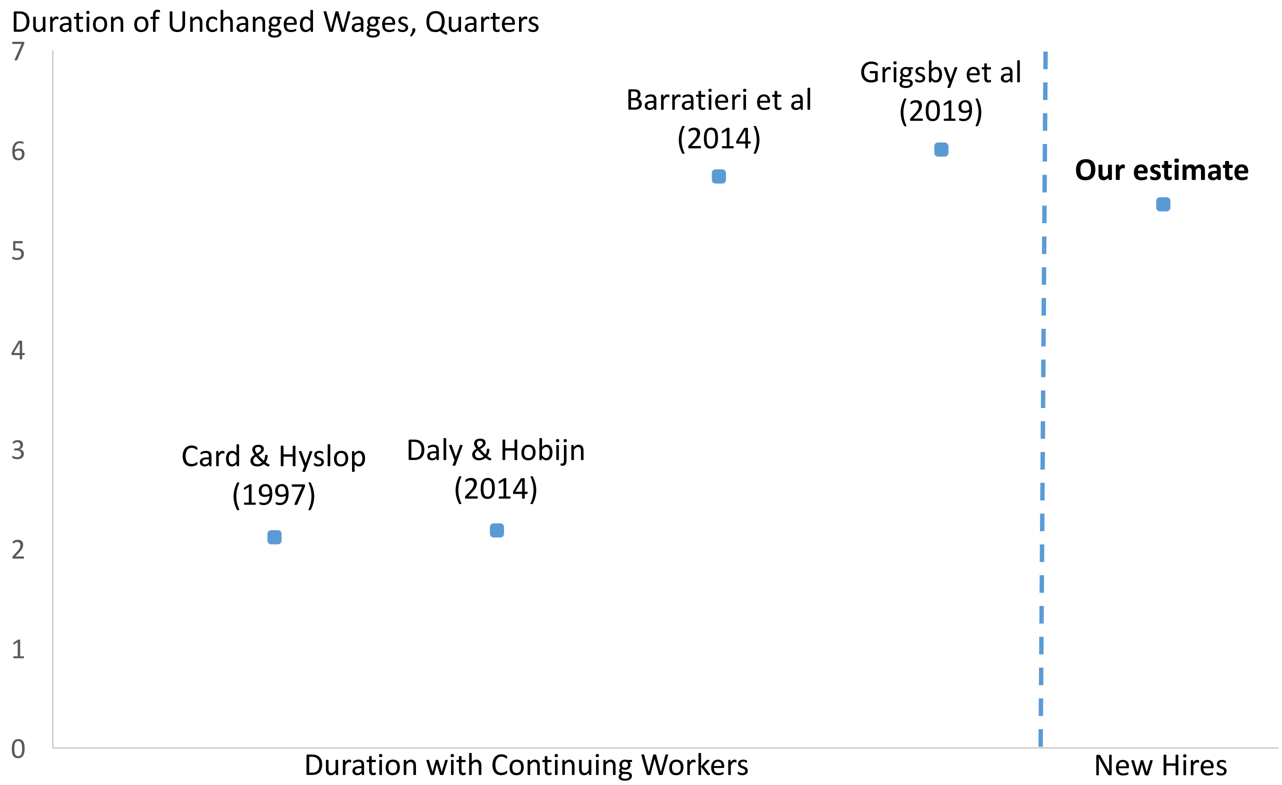
The duration for which wages do not change is similar, for new and continuing jobs. Figure 5 presents estimates of the duration that base wages are unchanged in continuing jobs. Two estimates are close to ours: the estimate of Grigsby, Hurst, and Yildirmaz (2018), which studies high quality payroll data; and the estimate of Barattieri, Basu, and Gottschalk (2014), which corrects for measurement error in survey wages.[22]

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, 2002). 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. As one example, implicit contracting models imply that continuing wages should be rigid downwards, while wages in new hires should be

[22] Other estimates are from survey data without correcting for measurement error, which biases downwards the estimated duration for which wages are unchanged.

Figure 5: Duration of Unchanged Wage for Continuing Workers and New Hires



Notes: this graph plots the implied duration for which wages are unchanged from four papers that study continuing wages using payroll and survey data, alongside our estimate for new hires wages using Burning Glass data.

flexible downwards (Harris and Holmstrom, 1982; Beaudry and DiNardo, 1991).[23] As a second example, continuing workers might have a reference point of their own past wage, and object to wage cuts because of morale. These considerations might matter less for new hires, who do not have a reference point of their own past wage. Thus wages for new hires could be flexible downward, even if continuing workers' wages were rigid downward (Eliaz and Spiegler, 2014).

4 Wage Cyclicality

This section asks whether the wage for new hires responds differently to business cycle contractions and expansions at the job level. We have three key results. First, across successive vacancies posted by the same job, the wage for new hires does not fall during contractions, but

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

does rise during expansions. Second, establishment wages—aggregating across jobs within the same establishment—do not fall contractions, but do rise during expansions. So, the downward constraint at the job level leads to downward rigidity in the wage faced by establishments, across all the jobs into which they hire. Third, wage flexibility *upward* is state dependent. The form of state dependence is consistent with downward rigidity.

4.1 Regional Unemployment Variation

In our regressions, we study the response of wages to unemployment, to measure wage cyclicality as in Bils (1985). We study regional business cycles, to avoid the problem of a 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 Quarterly Census of Employment and Wages (QCEW), to avoid attenuation bias.

States are a natural definition of a regional labor market. Since 2010, interstate migration has been relatively low, and mostly unrelated to cyclical considerations (Yagan, 2016; Beraja, Hurst, and Ospina, 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 labor 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.

4.2 Benchmark Specification

Our benchmark regression for measuring wage cyclicality, at the job level, is

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

w_{jst} is the nominal wage for a new hire 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. ΔU_{st} is the change in quarterly state level unemployment. γ_t is a time fixed effect. β and δ 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 instrument for ΔU_{st} and $I\left[\Delta U_{st} < 0\right] \times \Delta U_{st}$ with $\Delta \log \left(\text{employment}_{st}\right)$ and $I\left[\Delta \log \left(\text{employment}_{st}\right) < 0\right] \times \Delta \log \left(\text{employment}_{st}\right)$, where $\Delta \log \left(\text{employment}_{st}\right)$ is state-quarter employment growth from the QCEW.[24]

We study the same sample as in section 3, 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.

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

We turn to the first key empirical result of the section. Figure 1, previously shown in the introduction, illustrated that 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, β is not significantly different from zero, and indeed is slightly positive—thus the wage for new hires does not fall during contractions. Meanwhile δ is negative and statistically significant. Wages are more sensitive to expansions than contractions in unemployment, and rise during expansions. The results—both that β is near zero and δ 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.

Column (4) drops the $I\left[\Delta U_{st} < 0\right]\Delta U_{st}$ 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 instrumenting for state unemployment using a Bartik-style instrument based on states' regional exposure to the global oil price.[25] Again δ is negative and significant and β is insignificantly different from

[24] Appendix Table 9 reports the first stage regression projecting quarterly state unemployment changes onto employment growth. As expected, the two series are closely correlated.

[25] The first stage regression is $\Delta U_{st} = \sum_s \left[\beta_s \Delta \log\left(\text{oil price}_{t-1}\right) + \gamma_s I\left(\Delta \log\left(\text{oil price}_{t-1}\right) < 0\right) \Delta \log\left(\text{oil price}_{t-1}\right)\right] + \text{error}_{st}$, where α_s, β_s and γ_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 δ 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 cluster standard errors by both state and year in this regression, following the recommendation for inference in Bartik instruments

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, Finkelstein, and Notowidigdo (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 5 displays the oil price. Appendix Figures 3 and 4 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 Bureau of Labor Statistics' 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.[26] In all cases, the coefficient is 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 significant, again suggesting substantial nonlinearity.

Our Appendix contains numerous additional robustness checks. Appendix Table 5 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 6 shows the same result, using 2- and 3-digit industry by state variation. These regressions include state-by-time fixed effects, sweeping away state level labor supply shocks over this period, such as unemployment benefit extensions (Hagedorn, Karahan, Manovskii, and Mitman, 2013). Appendix Table 7 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 8 estimates our baseline regression for five broad occupations, and finds that downward wage rigidity is pervasive across all broad occupations.

by Adao, Kolesár, and Morales (2018).

[26] In the baseline, a job is a job title within an establishment at a given pay frequency (e.g. hourly or annual).

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 3 plots the share of vacancies in each state that experience rising state unemployment. Appendix Figure 4 plots the share of vacancies in each year that experience rising state unemployment.

4.3.1 Discussion of Job-Level Results

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

First, Mueller (2017) shows that the pool of unemployed workers tends to have a higher past wage during recessions. If workers with high past wages have high productivity, then during recessions the average unemployed worker has higher productivity. 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 wage posted in a vacancy and the 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. But 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 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.

4.4 Establishment-Level Specification and Result

We turn to the second key result of this section, on downward rigidity in establishment wages.

We start with an establishment level version of wage cyclicality regression. We study the regression

$$\Delta \log w_{et} = \alpha + \gamma_t + \beta \Delta U_{st} + \delta I \left[\Delta U_{st} < 0\right] \Delta U_{st} + \varepsilon_{et}. \tag{2}$$

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 vacancies at a location of Starbucks, between successive quarters. The variation in the job-level regression, from the previous section 4, 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, β is not significantly different from zero—thus the wage for new hires does not fall during contractions at the establishment level. Meanwhile δ 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 β is near zero and δ 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 $I\left[\Delta U_{st} < 0\right] \Delta U_{st}$ 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.[27]

4.5 Wage for New Hires and State Dependent Flexibility Upward

We turn to the third key result of this section, which points to downward wage rigidity. The wage for new hires displays state dependent flexibility *upward.* The form of state dependence is consistent with downward wage rigidity.

Let us explain the prediction of downward wage rigidity for state dependence. Suppose that

[27] In Appendix Section D.1 we ask whether establishments can alter the mix of jobs that they hire, in order to reduce the effects of downward wage rigidity. We find little evidence for such patterns.

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.[28]

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.

We estimate the state dependence of wage flexibility upward. We estimate the regression

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

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 Quarterly Census of Employment and Wages to deal with measurement error.

We restrict the sample only to observations for which $\Delta U_{st} < 0$. Therefore κ 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 κ is near to zero, then wages grow little as unemployment falls, in the aftermath of a previous contraction. If ν 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 ν 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 10 presents the results. Across all specifications, ν is large in magnitude and significantly negative. Therefore in the aftermath of expansions, the wage for new hires is more re-

[28]This simple model is similar to, amongst others, Schmitt-Grohé and Uribe (2016), Chodorow-Reich and Wieland (2017) and Dupraz, Nakamura, and Steinsson (2016).

sponsive to increases in labor demand. Wage flexibility upward is state dependent.

A corollary of our state dependence argument is that wages should have been inflexible upward in 2010, in the aftermath of the Great Recession. Wages should have become progressively more flexible upward over the course of the labor market recovery. We find evidence for precisely this phenomenon, in Appendix Section D.3.

4.6 Reallocation Between Establishments and Downward Wage Rigidity

So far, we have uncovered downward wage rigidity at the job and establishment level. We now consider whether reallocation between establishments might undo the effects of establishment level 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 of workers 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. 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. Nevertheless we investigate the concern.

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 4.4 and D.1, except for the outcome variable—which is the quarterly change in the state share of high wage vacancies.

Table 8 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.

5 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 (Haefke, Sonntag, and Van Rens, 2013; Basu and House, 2016). This section shows that due to job composition, average wages must have higher than job or establishment wages. So, regressions with average wages will have limited power to detect downward wage rigidity for new hires. We also explain a related issue: job composition might create a form of omitted variable bias, in regressions that use average wages.

First, we precisely define a 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 v_{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.[29] Previous researchers measure the *average* 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

[29]Recall that in our empirics, we define a "job" as a job title by establishment unit.

newly hired workers, and approximate the growth in the average wage for new hires by

$$\Delta\overline{\log w_{ist}} = \sum_i v_{ist} \log w_{ist}, \tag{3}$$

which is the change in average log wages.[30] Previous estimates using these data generally have large standard errors.

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

$$\underbrace{\Delta\overline{\log w_{st}}}_{\substack{\text{average}\\ \text{wage growth}}} \approx \overbrace{\sum_i v_{ist} \Delta \log w_{ist}}^{\substack{\text{job level}\\ \text{wage growth}}} + \underbrace{\sum_i \log w_{ist} \Delta v_{ist}}_{\substack{\text{wage growth due}\\ \text{to composition}}}. \tag{4}$$

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 right hand side of equation (4) is zero. If the share of low wage hires increases, wages change due to composition. The second term on the right hand side of equation (4) falls, so average wages fall.

From inspecting equation (4), we can see how job composition can raise the variance of average wages relative to job-level wages. Given downward rigidity, job-level wage growth $\Delta \log w_{ist}$ is small. So the first term on the right hand side of equation (4) has low variance. But suppose that the share of any given job type, v_{ist}, is volatile. Then the second term on the right hand side is large. So, average wage growth is volatile even if job-level wage growth has low variance. Intuitively, suppose that high- and low-wage job types hire intermittently, so high and low wage vacancies "churn" in and out of the data. Then in any given quarter, the share of low wage jobs may vary substantially. Average wages will fluctuate even if job-level wages change little.

Job composition might also create a form of omitted variable bias. Suppose that the share of low wage jobs rises during recessions. Then, from equation (4), average wages must *systematically* fall during recessions, even if job-level wages do not fall. Average wages for new hires might fall—even if wages do not fall at the job level. Thus average wages might seem flexible, despite rigidity at the job level. Regression estimates from average wages could suffer from omitted variable bias, as in the "composition bias" emphasized by Solon, Barsky, and Parker

[30] For practical reasons, researchers typically study the change in the average of log wages, instead of the change in the log of average wages. These papers typically control for variation in wages due to worker characteristics, including in some cases by using worker-level fixed effects.

(1994), Hagedorn and Manovskii (2013) and Gertler, Huckfeldt, and Trigari (2016). But in subsection 4.6, we 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. So, we do not focus on omitted variable bias due to job composition in this section.

We now explain how job composition affects inference, more formally. Our benchmark regression estimates downward rigidity using job level wage variation. That is, we study the population regression function

$$\Delta \log w_{ist} = \alpha + \gamma_t + \beta_{\text{Job Level}} \Delta U_{st} + \delta_{\text{Job Level}} I\left[\Delta U_{st} < 0\right] \Delta U_{st} + \varepsilon_{ist}, \tag{5}$$

where ε_{ist} has bounded variance σ^2_{ist}. We are interested in $V\left[\hat{\delta}_{\text{Benchmark}}\right]$, 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

$$\Delta \overline{\log w_{st}} = \bar{\alpha} + \bar{\gamma}_t + \beta_{\text{Average}} \Delta U_{st} + \delta_{\text{Average}} I\left[\Delta U_{st} < 0\right] \Delta U_{st} + \bar{\varepsilon}_{st}. \tag{6}$$

This regression is the analogue of our job-level regression, with average wages as the outcome variable. If estimates of δ_{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 δ_{Average}, which we term $V\left[\hat{\delta}_{\text{Average}}\right]$, 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 ΔU_{st}, then*

$$V\left[\hat{\delta}_{\textit{Average}} | \Delta U_{st}\right] > V\left[\hat{\delta}_{\textit{Job Level}} | \Delta U_{st}\right] \quad \textit{and} \quad V\left[\hat{\beta}_{\textit{Average}} | \Delta U_{st}\right] > V\left[\hat{\beta}_{\textit{Job Level}} | \Delta U_{st}\right]$$

We collect the proof of Proposition 1, and all our other propositions, in Appendix Section C. The proposition makes a simple point. From equation (3), the *only* difference between job-level and average wage changes comes from changing job composition. 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.[31]

[31] 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

In real-world data, 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.[32] We study quarter-by-state data for 2010-2016, as in our benchmark regression. We report the standard error of $\hat{\delta}_{\text{Average}}$. We contrast with the standard error of $\hat{\delta}_{\text{Benchmark}}$. In both cases, we cluster standard errors at the state level. This procedure consistently estimates the standard deviation of the estimators $\hat{\delta}_{\text{Average}}$ and $\hat{\delta}_{\text{Benchmark}}$, given that the regressor ΔU_{st} varies at the state level.[33]

Figure 6 reports the standard error of downward wage rigidity estimates, from job level and average wages. Table 9 reports the point estimates and standard errors. The difference in precision between the estimates using average and job level wages is enormous. Job composition does, indeed, inflate the variance of estimators of downward rigidity. The top row of Figure 6 reports the standard error of our job level estimate of downward wage rigidity, $\hat{\delta}_{\text{Benchmark}}$. The second row reports the standard error of $\hat{\delta}_{\text{Average}}$, the estimate of downward rigidity from average wages, with average wages for new hires from Burning Glass. The third row reports the standard error 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, Sonntag, and Van Rens (2013). In all the regressions that use average wages instead of job level wages, the standard error is far higher. Therefore the variance due to 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 standard error of $\hat{\delta}_{\text{Average}}$ is higher for average wages in the CPS, versus 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).[34]

The precision of the job-level estimates does not simply reflect a larger sample size in the re-

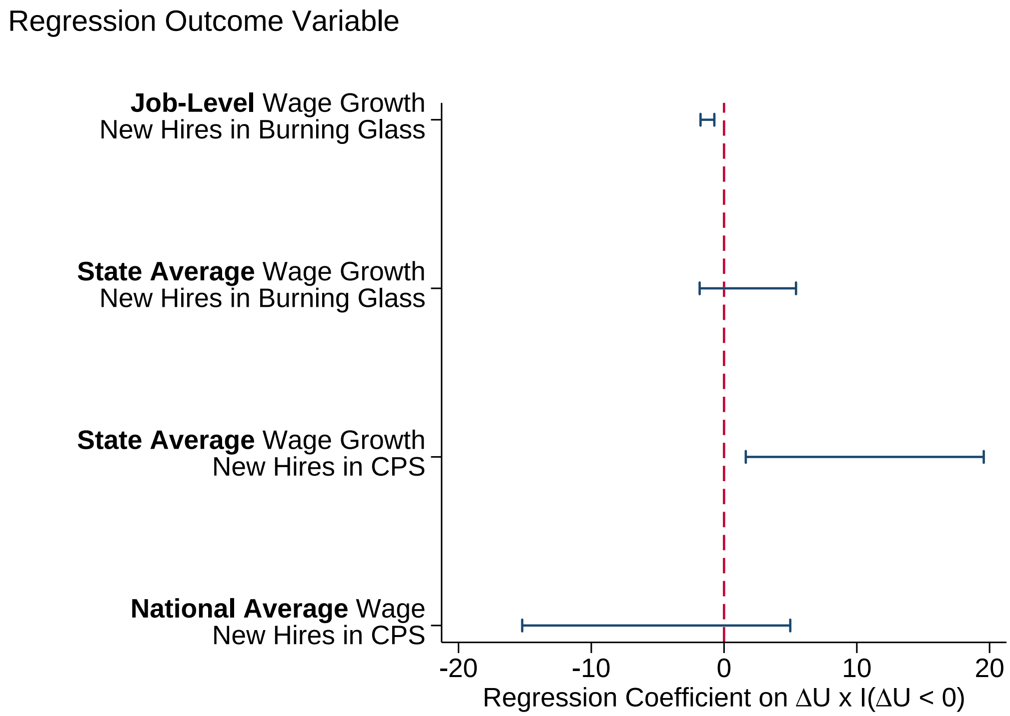
independent, consistent with the evidence of subsection 4.6.

[32]To construct the average wage for new hires in the CPS, we follow the procedure in Haefke, Sonntag, and Van Rens (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.

[33]Clustering at the state level follows econometric best practice (Abadie, Athey, Imbens, and Wooldridge, 2017). See Solon, Barsky, and Parker (1994) for alternative ways to construct standard errors.

[34]Table 9 also regresses another measure of wage growth for new hires, from average wages in the National Longitudinal Survey of Youth (NLSY), on national unemployment changes. The estimates are in column (6), the wage measure is from Basu and House (2016). The NLSY is a long panel, hence one can construct a measure of the average wage for new hires that controls for worker fixed effects. Estimates of downward wage rigidity remain imprecise.

Figure 6: Estimates of Downward Rigidity in Job Level and Average Wage for New Hires



The top row reports the estimate of δ, from regression (5), which estimates downward rigidity with job-level data on the wage for new hires from Burning Glass. The next three rows report various estimates of δ from regression (6), which estimates downward rigidity with average wages for new hires from Burning Glass. The second through fourth rows use, as the average wage measure, state-quarter average wages from Burning Glass, state-quarter average wages from the Current Population Survey, and national average wages from the Current Population Survey. See Table 9 for details.

gression 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.[35] Put differently, recall that we cluster standard errors in the benchmark regression at the state level, given that the regressor varies at the state level. So, holding fixed the number of states, more observations within the state may not lower the standard error.[36]

[35] To see this point formally, note that we can estimate $\hat{\delta}_{\text{Benchmark}}$ using *only* data aggregated at the state by quarter level. The benchmark regression equation (5) is numerically equivalent to the regression

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

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.

[36] Some papers studying wage rigidity for new hires consider regressions with worker-level panel data, of the form $w_{it} = \alpha + \beta U_t + \text{control}_{it} + \varepsilon_{it}$ where w_{it} is the wage for a newly hired worker and U_t is quarterly national unemployment. Occasionally papers cluster standard errors at the worker level. However, the regressor varies

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 limited power to detect downward wage rigidity, in either our dataset or worker-level survey data. By contrast, our job level estimates purge the variance associated with changing job composition. We argued in subsection 2.2 that wage changes at the job and establishment level are important for unemployment fluctuations, and wage changes due to composition may be less important.[37] Therefore average wages cannot detect downward rigidity even when it may matter for business cycles.

6 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.[38] Our argument proceeds in three steps. First, we introduce a new and tractable dynamic wage bargaining protocol, with downward rigidity, which we embed in an otherwise-standard labor search model. Second, we estimate the model with our new evidence. Third, we show an implication of downward rigidity, not recognized in prior work. In the model, the degree of asymmetry in unemployment dynamics is state dependent. When there has been a contraction, then subsequently the response of unemployment to labor demand is symmetric. When there has been an expansion, then subsequently unemployment is much more sensitive to negative than to positive shocks.

6.1 Outline of The Argument

Let us briefly outline the main mechanism and result.

We previously explained, with a simple model of downward wage rigidity, that wage flexibility upward should be state dependent. When there has been a large contraction, wages are "trapped too high" at their previous level prior to the contraction. Subsequently wages respond little to either positive or negative labor demand shocks. But when there has been a large expansion, wages reach their frictionless level. Subsequently, wages respond to positive labor

at the quarter level. So, clustering standard errors at the worker level understates the true standard error of the estimator, since there are many more workers than there are quarters. See Solon, Barsky, and Parker (1994), p. 13, for a lucid discussion of this issue.

[37] 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 4.6 do not suggest much reallocation of workers across establishments, at least over this sample period.

[38] 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 shocks, but not negative shocks. We found evidence for precisely this form of state dependence.

We will argue that, given the state dependence of wages, asymmetry in unemployment should also be state dependent. When there has been a contraction, the cost of labor is similarly insensitive to positive and negative labor demand shocks in the aftermath. So, unemployment should respond similarly to positive and negative shocks, subsequent to the contraction. When there has been an expansion, then subsequently the cost of labor rises after positive shocks, but does not fall after negative shocks. So, unemployment should respond much more to negative than to positive shocks in the aftermath of the expansion. We will see that this force is quantitatively powerful with the richer model of wage setting that we develop, when fit to our estimates.

6.2 Model Setup

We now develop a wage bargaining protocol with downward rigidity, which we embed in an otherwise-standard Diamond-Mortensen-Pissarides labor search model. We start with Hall and Milgrom's (2008) alternate offer bargaining protocol. We introduce downward rigidity into this model, and derive a tractable form for the equilibrium wage. Alternate offer bargaining is a natural starting point because it matches micro and macro facts that other protocols such as Nash bargaining miss.[39]

6.2.1 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 consume their wage in the periods that they are employed, and derive flow utility z from unemployment. Workers have discount factor $\beta^w \in (0,1)$ over future utility flows.

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

$$u_t = 1 - (1-s)\, l_{t-1}, \tag{7}$$

[39] For example, alternate offer bargaining is consistent with a low pass through of unemployment benefits into wages (Jäger, Schoefer, Young, and Zweimüller, 2018) and the macro volatility of wages and unemployment (Christiano, Eichenbaum, and Trabandt, 2016).

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 firms, with discount factor $\beta^f \in \left(\beta^w, 1\right)$. Firms 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

$$m_t = \frac{v_t u_t}{\left(v_t^\iota + u_t^\iota\right)^{\frac{1}{\iota}}} \quad \iota > 0.$$

The key state variable governing labor market dynamics is market tightness

$$\theta_t \equiv v_t / u_t. \tag{8}$$

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 $q_t = m_t / v_t = \left(1 + \theta_t^\iota\right)^{-\frac{1}{\iota}}$. The vacancy filling rate is decreasing in θ_t—in a tight labor market, firms cannot find workers easily. If the vacancy is not filled at the end of the period, it is destroyed.[40]

Workers can start working in the same period that they match with firms. The job finding rate of a worker is $f(\theta_t) = \left(1 + \theta_t^{-\iota}\right)^{-\frac{1}{\iota}}$. The job finding rate is increasing in θ_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

$$l_t = 1 - \left(1 - f(\theta_t)\right)\left(1 - (1-s)\, l_{t-1}\right). \tag{9}$$

6.2.2 Labor Demand

Again following the standard Diamond-Mortensen-Pissarides framework, unemployment fluctuations are driven by output per worker y_t, which follows an exogenous AR(1) process with mean value $\bar{y}$, that is

$$y_t - \bar{y} = \rho\left(y_{t-1} - \bar{y}\right) + \varepsilon_t \quad \varepsilon_t \sim N(0, \sigma^2). \tag{10}$$

y_t is a measure of labor demand. In the model ε_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, which could reflect monetary or fiscal shocks.[41]

[40] This assumption is a minor modification of the standard Diamond-Mortensen-Pissarides model, which implies that vacancies have no continuation value. Other versions of the Diamond-Mortensen-Pissarides model with wage rigidity, such as Hall (2005b), make similar assumptions.

[41] In appendix section F.2, we make this argument concrete by extending the model to include nominal rigidities and demand shocks. The model dynamics are similar.

6.2.3 Worker and Firm Value

Consider a worker-firm match that starts producing output at time t. For periods $t+j$ in which a match is not destroyed, the match produces output y_{t+j}, and pays wage w_t to the worker fixed over all periods of production. The firm receives flow profit $y_{t+j} - w_t$.[42]

Once a job starts producing output, its value to the firm, J_t, is the flow profit and the continuation value after deducting the risk of job destruction—that is

$$J_t(w_t) = y_t - w_t + \beta^f (1-s)\mathbb{E}_t J_{t+1}(w_t). \tag{11}$$

The value of an unfilled vacancy depends on the chance that a vacancy is filled, and the cost of posting vacancies. Then if K_t is the value of an unfilled vacancy, we have

$$K_t = -c + q(\theta_t) J_t(w_t), \tag{12}$$

which incorporates that vacancies have no continuation value.

Once production starts, the value of employment to worker, M_t, is the wage and the continuation value. If the job is destroyed, the worker must search for unemployment in the next period, which has value U_{t+1}, so the value of employment in a match that is producing output at time t is

$$M_t(w_t) = w_t + \beta^w \mathbb{E}_t [sU_{t+1} + (1-s) M_{t+1}(w_t)] \tag{13}$$

Finally, the value of unemployment to the worker at t depends on the probability of finding employment and the value of employment, as well as the worker's continuation value should she remain unemployed. Thus U_t satisfies

$$U_t = z + f(\theta_t) M_t(w_t) + \beta^w \mathbb{E}_t \left[\left(1 - f(\theta_t)\right) U_{t+1} \right]. \tag{14}$$

6.2.4 Bargaining Stage with Downward Wage Rigidity

We now introduce the bargaining stage of the model. We develop a tractable dynamic wage bargaining protocol with downward rigidity, which is our novel feature relative to the standard Diamond-Mortensen-Pissarides model. We will discipline the model with our evidence on downward rigidity.

Let us describe the model. Our starting point is the model of Hall and Milgrom (2008).There

[42] The timing of wage payments that we choose, with wages fixed throughout the match, is a convenient normalization. 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).

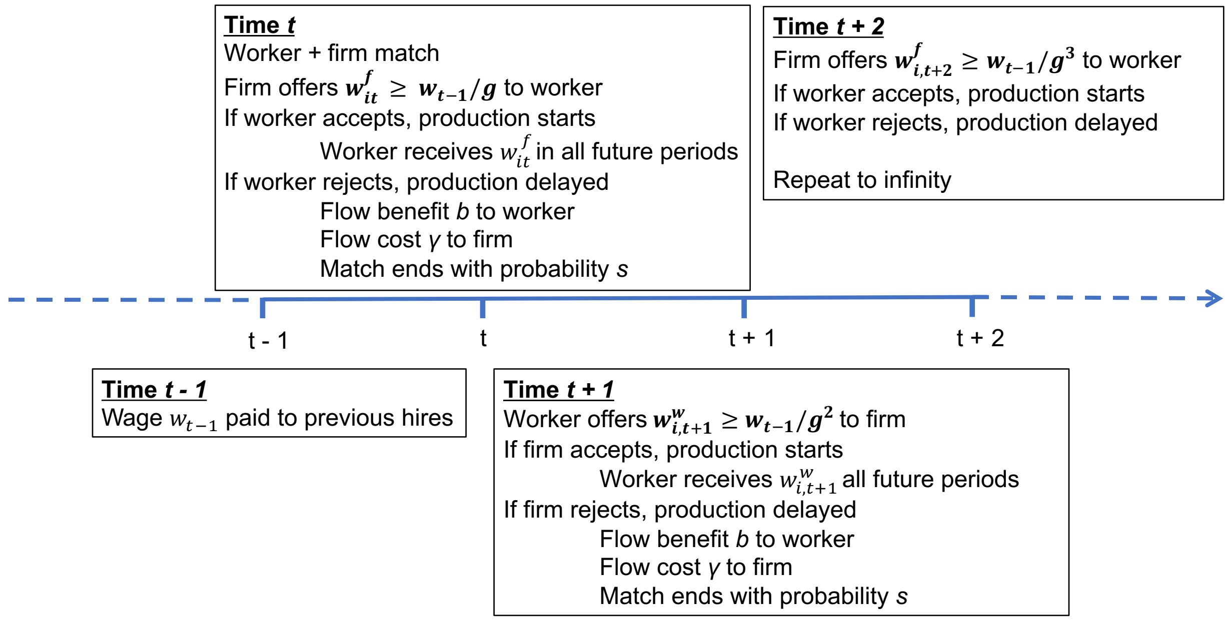
is alternate-offer bargaining over an infinite horizon. After worker and firm pair i match at time t, they bargain over wages. The firm makes the first wage offer, and then in each period $t+j$, the firm and worker alternate in making wage offers. The firm offers a wage $w^f_{i,t,j}$ and the worker offers a wage $w^w_{i,t,j}$ in the periods when each is proposing. After a proposer makes an offer, the respondent can either accept the offer, or reject and make a counter-offer. If the respondent agrees to the offer in period $t+j$, then the worker receives a fixed wage $w_{i,t,j}$ in all periods for which the match continues. If the respondent chooses to make a counter-offer, the game continues to the following period.[43] The firm suffers a cost $\gamma > 0$ and the worker enjoys a flow benefit z for each period of delay. During delay, there is a probability s that the match is exogenously destroyed. If the match is destroyed, the firm receives a payoff of zero, and the worker searches for new jobs, therefore receiving the value of unemployment. Workers' and firms' discount factors, β^w and β^f, can differ. This difference affects the relative cost of delay to firms and workers, and hence their bargaining power in our dynamic setting.

In line with our evidence, we introduce *downward wage rigidity* into the model. For all periods $t+j$, the firm's wage offer must satisfy $w^f_{i,t,j} \geq w_{t-1}/g^j$, a worker's offer must satisfy $w^w_{i,t,j} \geq w_{t-1}/g^j$. Neither firm nor worker can offer a wage much lower than w_{t-1}. w_{t-1} is the wage paid to new hires in $t-1$, which the worker-firm pair i take as given when they bargain. Since there is no heterogeneity, the wage at $t-1$ is the same for all new hires. The term g captures the effect of trend wage growth on the downward wage constraint. Our model does not directly feature trend wage growth. Instead, the downward constraint falls by a factor of g between successive periods. The effect is equivalent to trend wage growth of g, which would also reduce the effect of downward constraints on wages over time. In this sense, trend wage growth "greases the wheels" of the labor market. Figure 7 depicts the bargaining stage.

We use alternate-offer bargaining to capture two salient features of wage determination. First, bargaining may be dynamic, involving both wage offers by the firm and counter-offers by the worker. Suppose a worker and firm match, and the firm makes a wage offer to the worker. If the offer is unappealing, the worker's best option may not be to terminate bargaining and return to unemployment. After all, given search frictions, the worker has been fortunate to receive the chance of a job. Rather, the worker can reject the firm's offer, delay production, and make a wage counter-offer. The firm and worker experience costs from the delay—since production will start later, firms forgo profits and workers forgo wages. Anticipating the cost of delay, the

[43] We do not allow either workers or firms to voluntarily exit bargaining after it has started. Still, on the equilibrium path of our model, workers and firms will always have higher payoffs from bargaining, than their outside option should they choose to exit the bargain. Allowing either worker or firm to "opt out" of bargaining can lead to multiple equilibria, which are sensitive to the parameters of the model and the timing of when workers or firms can opt out (Osborne and Rubinstein, 1990). So, the bargaining problem becomes intractable. In a different setting, where firms can bargain sequentially with multiple workers, Shaked and Sutton (1984) do obtain uniqueness when the firm can opt out of bargaining with a given worker.

Figure 7: Bargaining Stage with Downward Wage Rigidity



firm should initially make a more appealing wage offer.

Second, our bargaining protocol features downward rigidity. Firms cannot always make low wage offers to workers, even if the worker finds it optimal to accept such a wage, nor may workers always propose low wage offers. The downward constraint on wage setting, which we previously documented in our empirics, prevents such offers.[44]

We make four additional comments about our wage bargaining protocol. First, the probability that the match is exogenously destroyed before bargaining has finished, s, is the same as the probability that the job is destroyed after bargaining finishes. This modification of Hall & Milgrom's (2008) model will yield a tractable solution to the bargaining game, and builds on an insight from Ljungqvist and Sargent (2017) in a setting without uncertainty or downward wage rigidity.

Second, given the dynamic nature of the wage bargain, downward rigidity matters for firms' offers even in states when labor demand is high and past wages are low. Suppose, in the present, that the downward constraint is slack. In the future, labor demand may be low and the downward constraint may bind. Workers' counter-offers will be higher due to the constraint. The firm, anticipating these higher counter-offers in the future, will change its own offers in the present.

Third, agents also account for the uncertainty that arises from delaying acceptance of an

[44] In ongoing work, we investigate the reasons for the downward constraint on wage setting. For example, the downward constraint might reflect an internal equity constraint within the firm, whereby firms cannot pay new hires less than existing workers (Bewley, 2002).

offer, given the dynamic environment. Finally, we reiterate that after bargaining starts, though firms and workers can reject offers and make counter-offers, they cannot "opt out" of bargaining.

6.2.5 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

$$v_t \geq 0, K_t \geq 0, v_t K_t = 0 \tag{15}$$

for all t. When labor productivity rises, job creation becomes more profitable. Firms create many vacancies and the labor market tightens until the value of vacancy creation K_t is zero. If the downward wage constraint binds and labor demand falls sufficiently far, then job creation may not be profitable because wages are too high relative to output per worker. Then firms do not create vacancies, and $v_t = 0$ by the free entry condition.

An equilibrium is a collection of stochastic processes $\{l_t, v_t, \theta_t, u_t, w_{it}\}_{t=0}^{\infty}$ that satisfy the following conditions.

- The law of motion for unemployment (7) holds.
- The definition of labor market tightness (8) holds.
- The Bellman equations for the value of an unfilled vacancy (12), the value of a job producing output (11), the value of employment and unemployment to a worker (13) and (14) are satisfied.
- The free entry condition (15) is satisfied.
- w_{it} comes from a subgame perfect equilibrium of the bargaining stage in subsection 6.2.4 for all worker-firm pairs i matching in period t.
- The equilibrium is conditional on initial employment l_{-1}, initial wage w_{-1}, and an AR(1) process (10) for labor demand y_t.

6.3 Characterizing the Equilibrium of the Model

We now characterize the equilibrium of the economy and show it is tractable.

We start by deriving the equations that characterize the subgame perfect equilibrium of the wage bargaining stage. If the subgame perfect equilibrium of the wage bargaining stage is unique, then the value of rejecting an offer is uniquely defined. The respondent accepts an offer if and only if it is better than the continuation payoff. Hence in each period there is a some lowest wage offer than the respondent will accept. That is, in each period that the firm makes an offer, there is a lowest wage that the worker will accept. In each period that the worker makes an offer, there is a highest wage that the firm will accept. Then the firm will optimally offer the lowest wage that is acceptable to the worker, unless the downward constraint on wage offers binds for the firm. The worker offers the lowest wage that is acceptable to the firm, unless the downward constraint binds. In equilibrium, the worker will then accept the first offer made by the firm.

We can then describe the wage offers $w^f_{i,t,j}$ and $w^w_{i,t,j}$, by the firm and the worker in the subgame perfect equilibrium of the bargaining stage. The lowest wage acceptable to the worker, $\tilde{w}^f_{i,t,j}$, when contemplating a wage offer in period $t+j$ by the firm, is

$$M_{t+j}\left(\tilde{w}^f_{i,t,j}\right) = z + \beta^w \mathbb{E}_{t+j}\left[(1-s)\, M_{t+j+1}\left(w^w_{i,t,j+1}\right) + sU_{t+j+1}\right]. \tag{16}$$

At the lowest acceptable wage offered by the firm, the worker is indifferent between being employed at the firm's offered wage, $\tilde{w}^f_{i,t,j}$, and making a counter-offer $w^w_{i,t,j+1}$ in the next period. If the worker does reject the firm's offer, the value of the worker's counter-offer accounts for the flow benefit of delay z and the risk s that the match is destroyed, so that worker must search for new work. The firm therefore offers the wage that is the maximum of either the lowest wage acceptable to the worker, or the wage dictated by the downward constraint on wage offers. That is, the firm offers the wage

$$w^f_{i,t,j} = \max\left[\tilde{w}^f_{i,t,j}, w_{t-1}/g^{j+1}\right]. \tag{17}$$

The lowest wage acceptable to the firm, when contemplating a wage offer $\tilde{w}^w_{t,j}$ in period $t+j$ by the worker, is

$$J_{t+j}\left(\tilde{w}^w_{i,t,j}\right) = -\gamma + \beta^f\,(1-s)\,\mathbb{E}_{t+j}\, J_{t+j+1}\left(\tilde{w}^f_{i,t,j+1}\right). \tag{18}$$

At the lowest acceptable wage offered by the worker, the firm is indifferent between the value of starting production at the worker's offered wage, $J_{t+j}\left(\tilde{w}^w_{i,t,j}\right)$, and making a counter-offer in the next period. If the firm rejects the worker's offer, the value of the firm's counter-offer accounts for the flow cost of delay γ, and the risk s that the match is destroyed—in which case the firm receives a continuation payoff of zero. The worker therefore offers the maximum of lowest wage acceptable to the firm, or the wage dictated by the downward constraint, that is

$$w^w_{i,t,j} = \max\left[\tilde{w}^w_{i,t,j}, w_{t-1}/g^{j+1}\right]. \tag{19}$$

We assume the regularity condition that for all $t+j$, $\left(1-\tilde{\beta}^f\right)\left(y_{t+j}+\gamma\right) \geq \left(1-\tilde{\beta}^w\right) z$ and $w_{t-1}/g \leq$

$y_{t+j}+\gamma$. In all our simulations, we verify that the condition does indeed hold at all points in the state space. This assumption ensures uniqueness of the subgame perfect equilibrium of the bargaining stage. For what follows, we define $\tilde{\beta}^w \equiv \beta^w(1-s)$ and $\tilde{\beta}^f \equiv \beta^f(1-s)$. Equations (16)-(18) then let us characterize the subgame perfect equilibrium of the wage bargaining stage, and then the equilibrium of the economy.

Proposition 2. *(Characterizing bargaining stage).*

1. *There exists a unique subgame perfect equilibrium of the wage bargaining stage. In period $t+j$, the worker accepts any wage of at least $w^f_{i,t,j}$ offered by the firm, and the firm accepts at any wage of at most $w^w_{i,t,j}$ offered by the worker, where $w^f_{i,t,j}$ and $w^w_{i,t,j}$ satisfy equations (16)-(19). So, the worker accepts the firm's first offer on the equilibrium path of the bargaining stage.*

2. *On the equilibrium path, the wage is $w_{it}=w_t \equiv w(y_t, w_{t-1}/g)$, where $w(\cdot,\cdot)$ is defined by the functional equation*

$$w(y_t, w_{t-1}/g) =$$
$$\max\left[\left(1-\tilde{\beta}^w\right)z+\left(1-\tilde{\beta}^f\right)\tilde{\beta}^w\left(\rho y_t+(1-\rho)\bar{y}\right)+\tilde{\beta}^w\left(1-\tilde{\beta}^f\right)\gamma+\tilde{\beta}^f\tilde{\beta}^w\mathbb{E}_t\left[w(y_{t+2}, w_{t-1}/g^3)\right], w_{t-1}/g\right]. \tag{20}$$

Corollary. *(Characterizing equilibrium of economy). The equilibrium of the economy is unique.*

We make four comments about the equilibrium characterization. First, the subgame perfect equilibrium of the wage bargaining stage is unique. The downward constraint on wage bargaining prevents either workers or firms from making low wage offers. This nonlinearity makes the game more complicated than other alternate-offer bargaining settings, such as Rubinstein (1982) or Hall and Milgrom (2008). Nevertheless, existence and uniqueness of the bargaining stage obtain. The wage is same for all workers hired in a given time period.

Second, the equilibrium wage is more rigid downward than upward. The current wage w_t cannot fall below w_{t-1}/g—that is, current wages are constrained from beneath by past wages. Meanwhile, wages are free to adjust upward.

Third, given a unique policy function for wages, we can show that the equilibrium of the economy, as well as the bargaining stage, is unique. Uniqueness is well known in the benchmark Diamond-Mortensen-Pissarides model with Nash-bargained wages (Pissarides, 2000). Our environment is complicated by dynamic bargaining and downward wage rigidity.

Fourth, and most novel to our setting, the equilibrium wage is *block recursive* in y_t and w_{t-1}. As a result, the equilibrium is tractable. From equation (20), one can solve for the equilibrium wage with information on only the past wage, current labor demand, and exogenous parameters. So, one can calculate the wage in a separate "block", prior to solving for the other endogenous variables of the model. In particular, the value of unemployment does not affect the equilibrium wage.

The block recursive result may be surprising. In the canonical Nash wage bargaining protocol, workers' threat point is to return to unemployment. So, workers' bargaining power and their wages depend on the value of unemployment. In turn, the value of unemployment relates to whether workers can find another job in the future, which depends on equilibrium forces.

But in our alternate offer bargaining model, the value of unemployment does *not* matter for wage bargaining, which leads to block recursion. Let us explain the intuition. Recall that with alternate offers, workers' bargaining power comes from refusing firms' offers and making counter-offers. So, workers' cost of delay relative to firms, governs their bargaining power. If workers want to finish bargaining quickly, they will accept a low wage—if they are prepared to "wait out" firms, they get a higher wage. Workers' cost of delay depends on workers' impatience and firms' costs of forgoing production, which are unrelated to the value of unemployment. Crucially, workers' threat point is to reject and make a counteroffer, not to return to unemployment—in contrast to Nash bargaining. So, the value of unemployment does not matter for bargaining. This feature of bargaining seems realistic. After all, workers have been fortunate to match with firms and escape the pool of the unemployed. It seems plausible that, if workers receive an unfavorable offer, they would prefer to make a counter-offer than to return to unemployment.[45][46]

Our tractable characterization of the equilibrium wage, equation (20), has two principal benefits. First, it is analytically helpful, letting us prove uniqueness of both the subgame perfect equilibrium of the bargaining stage and the equilibrium of the economy. In the equilibrium of our model, the worker's value of unemployment is a nonlinear function of labor demand and both past and current wages, depending on the current and future likelihood of finding jobs. If, in turn, the value of unemployment were to affect current wages, there would be nonlinear "feedback" between the value of unemployment and wages. Equilibria of either the wage

[45]Though Hall and Milgrom (2008) do provide intuition along similar lines, they do not analytically derive a block recursion. In a steady state environment without downward rigidity, Ljungqvist and Sargent (2017) derived the independence of wages from the value of unemployment in Hall and Milgrom's model. We exploit Ljungqvist and Sargent's insight in a dynamic setting with downward wage rigidity.

[46]Mathematically, a higher value of unemployment does raises workers' payoffs in each round of bargaining. But changes in U_{t+j} do not affect the *difference* between workers payoffs in different rounds of bargaining, which is the cost of delay. Equation (16) encodes this logic. On the equilibrium path, and absent downward wage rigidity, the firm offers a wage such that workers' payoff in t and $t+1$ is the same. Both sides of equation (16) depend positively on U_{t+j}, since worker's value of employment E_t accounts for the value of future unemployment. But higher U_{t+j} affects workers' payoffs in t and $t+1$ by the same amount, so U_{t+j} "cancels out" of both sides of equation (16). We assume that a match is equally likely to end before or after bargaining concludes. This assumption generates the "cancelling out" result.

bargaining stage or the full economy would be complicated. Neither existence nor uniqueness would be guaranteed.

Second, our characterization facilitates computation and estimation of the model. Given the block recursion, one can solve for wages in a separate "block" that depends only on exogenous parameters, and then solve the rest of the model. One needs not keep track of endogenous variables such as workers' value of unemployment, or market tightness, to solve for wages.

This insight may be helpful in settings more complicated than our representative model. For example, Nash wage bargaining creates complications in models of random search with worker or firm heterogeneity (Elsby and Michaels, 2013; Acemoglu and Hawkins, 2014). Due to Nash bargaining, wages depend on the value of unemployment. Given heterogenous firms, the value of unemployment is a high dimensional object. So, in equilibrium, wages are also a high dimensional object, which may be hard to characterize or compute out of steady state. By severing the link between wages and the value of unemployment, alternate offer bargaining makes the equilibrium form for wages tractable. For computational tractability, other models with random search make assumptions to suppress the dependence of wages on the value of unemployment.[47] As a by product, these assumptions eliminate worker bargaining power. In our model, wages do not depend on the value of unemployment, offering similar tractability. Nevertheless workers still engage in dynamic bargaining, which yields qualitatively different insights as we discuss below.[48]

We now derive an expression for the "frictionless wage"—that is, the equilibrium wage if the downward constraint does not bind in any states. The expression for the frictionless wage will motivate how we bring the model to the data, and also sharpen the implications of our wage bargaining protocol that differ with previous work.

Proposition 3. *(Frictionless wage). When $g \to \infty$, so the downward wage rigidity constraint never binds, the wage is*

$$w_t^{frictionless} = \frac{\left(1-\tilde{\beta}^w\right)z + \left(1-\tilde{\beta}^f\right)\tilde{\beta}^w \bar{y} + \tilde{\beta}^w\left(1-\tilde{\beta}^f\right)\gamma}{1-\tilde{\beta}^f\tilde{\beta}^w} + \frac{\left(1-\tilde{\beta}^f\right)\tilde{\beta}^w\rho}{1-\tilde{\beta}^f\tilde{\beta}^w\rho^2}\left(y_t - \bar{y}\right). \tag{21}$$

When the downward constraint does not bind, then equation (21) is the wage. The wage is then a linear function of labor demand y_t. Two terms matter for the frictionless wage. First, there is the "pass through" of output per worker into wages—that is, the coefficient on y_t. Sec-

[47] For example, Dupraz, Nakamura, and Steinsson (2016) assume a constant pass through of output per worker into wages; Cooper, Haltiwanger, and Willis (2007) and Gavazza, Mongey, and Violante (2018) assume firms make take-it-or-leave-it wage offers to workers.

[48] Models with wage posting and directed search also yield block recursive wage policy functions (e.g. Menzio and Shi, 2011; Schaal, 2017). The environment and form of block recursion in these models is different from what our paper studies.

ond, there is a constant term that affects the level of wages.

We make two additional comments. First, we will estimate the parameters governing wage pass through using our new data. Equation (21) shows that, alongside other parameters, $\tilde{\beta}^w$ and $\tilde{\beta}^f$ govern the pass through of labor demand into the frictionless wage. When $\tilde{\beta}^w$ is high relative to $\tilde{\beta}^f$, workers are patient. Workers are willing to bear the costs of delay associated with bargaining, and should receive a higher share of the surplus from bargaining. Thus the passthrough of output per worker into wages is greater. $\tilde{\beta}^w$ and $\tilde{\beta}^f$ are natural parameters to estimate when we discipline the model with data on wage flexibility for new hires.

Second, equation (21) highlights a plausible feature of wage bargaining: the persistence of labor demand should matter for wage pass through. The pass through of labor demand into wages is higher when ρ is high and labor demand is autocorrelated. Intuitively, with persistent labor demand, current changes in y_t associate with greater changes in the present value of y_t. Workers bargain over this present value. Models with a constant pass through of output per worker into wages will miss this feature.

We briefly explain the solution method. We exploit the contraction defined in equation (20) to solve for the wage policy function, via function iteration. Then, with a wage policy function in hand, we solve the rest of the model with a global algorithm similar to Petrosky-Nadeau and Zhang (2013), which accounts for the occasionally binding constraint associated with the free entry condition (15).

6.4 Estimating the Model

We now pin down the key parameters of the model with our new evidence on downward wage rigidity for new hires.

We estimate β^w, which pins down the pass through of labor demand into the frictionless wage, by indirect inference. Since β^w and β^f are not separately identified, we fix the value of the firm's weekly discount factor at $\beta^f = 0.97^{\frac{1}{12}}$.[49] To estimate β^w, we simulate the model at weekly frequency. We aggregate the data from the model to quarterly frequency, and run regression equation (34) on the simulated data. We minimize the distance between the regression coefficient from the simulated data, and the coefficient in 2015 from regression equation (34). In the model and the data, this regression coefficient measures the extent to which wages are flexible upward in the aftermath of a persistent labor market expansion.

Our discussion of the identification of β^w is heuristic, because we jointly estimate β^w alongside three other model parameters. γ, the firm's flow cost of delay, and z, the worker's flow benefit from delay, are not separately identified. We normalize $z = 0$ and then choose γ to target

[49]The value of the firm's discount factor is lower than the typical macro calibration. The model can then potentially accommodate a wide range of values for wage pass through, which is important for estimation.

mean postwar US unemployment. We choose the autocorrelation of the labor demand shock ε_t, to match the first autocorrelation of log value added, filtered as in Hamilton (2018). We choose the standard deviation of the labor demand shock to match the standard deviation of Hamilton-filtered log value added. Table 11 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 12 reports these parameters. 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. These previous three parameters are the same as Hagedorn and Manovskii (2008). We set trend real wage growth, g, equal to an annual rate of 1%—between the zero composition-adjusted trend real wage growth for 1988-2008 estimated Acemoglu and Autor (2011), and the 2% growth in output per worker over the same period.

6.5 Validating the Model with Un-targeted Moments

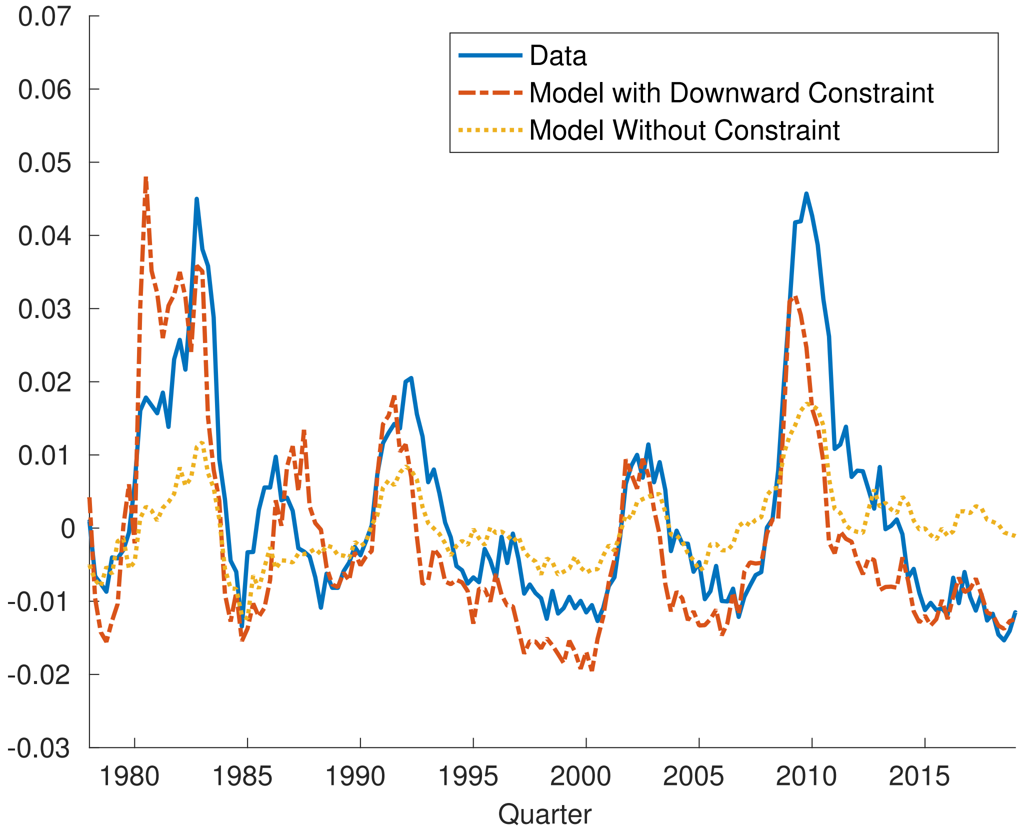
We now validate the model against various moments that the estimation does not explicitly target. The model successfully matches key features of both unemployment and wage dynamics.

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 ε_t, such that 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 ε_t such that the model-generated and real-world data match exactly. Appendix Figure 6 reports model-generated and real-world filtered output, which by the nature of the exercise match exactly.

We then validate the model against two 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 8 reports this result. The match is close. Visually, the model is able to replicate the persistence, volatility, and skewness of unemployment dynamics. Table 13 confirms this message by calculating these moments in the model and data, showing that they are similar. Importantly, though unemployment fluctuations are asymmetric in US data, output fluctuations are relatively symmetric (McKay and Reis, 2008). 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.

As a simple way of showing how downward rigidity affects the fit of the model, Figure 8 also

Figure 8: Unemployment in the US Times Series



Notes: the solid line is model generated unemployment simulated from the model, and then aggregated to quarterly frequency and Hamilton-filtered. We compare to Hamilton-filtered quarterly national unemployment for 1988-2018, from the BLS, which is is the thickly dashed line. We also report unemployment simulated from the model after switching off the downward wage constraint, which is the thinly dashed line.

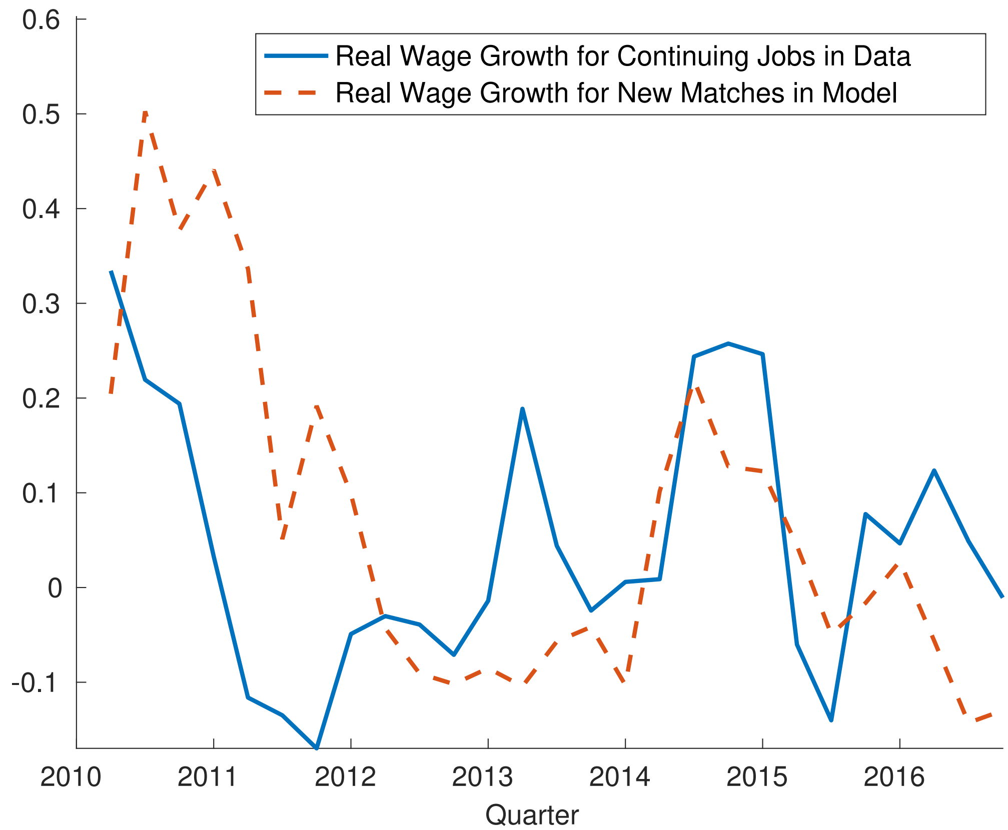
simulates unemployment in a counterfactual in which the wage is always equal to its frictionless value, and the downward constraint on wage setting is "switched off". The fit deteriorates, and the skewness of model-generated unemployment falls. Thus downward wage rigidity helps to rationalize the dynamics of unemployment.[50] Therefore the standard labor search model, when matched against our new evidence on downward wage rigidity, can replicate US unemployment dynamics.[51]

Second, we show that the model does a good job of matching *continuing* real wage growth over 2010-2016. Figure 9 reports this result. We plot wage growth for continuing jobs in the US time series, and compare with the wage for new hires in the model. The match is close, despite the noisiness of high frequency wage measures. Recall that, in section 3, we found similar

[50]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".

[51]This finding mirrors the results in Dupraz, Nakamura, and Steinsson (2016), who also show that downward wage rigidity leads US unemployment to display "plucking" behavior.

Figure 9: Wage Growth in the Model and Data



Notes: quarterly continuing real wage growth is from the BLS's Employment Cost Index deflated by the Consumer Price Index excluding energy and food. We compare to quarterly real wage growth simulated and then time-aggregated in the model.

wage setting patterns for new hires and continuing jobs. The results of Figure 9 point in the same direction. Importantly, the measure of wage growth for continuing jobs, from the BLS's Employment Cost Index, adjusts for job composition analogously to our measure of the wage for new hires.[52] Our model potentially helps to explain the puzzle of "missing wage growth" before 2015 (see, e.g. Atlanta Fed, 2014). In the model as in the data, wage growth is low during 2012-2014, and then increases in 2015. In the model, this pattern partly reflects the increasing flexibility of wages with respect to positive labor demand shocks after 2010.

6.6 Model Result: State Dependent Asymmetry

Armed with a model that can match wage and unemployment dynamics, we now show our main quantitative result: state dependent asymmetry. When there has been a contraction, unemployment responds similarly to positive and negative labor demand shocks in the aftermath.

[52] Specifically, the Employment Cost Index tracks wage growth for the same job over time, for a sample of continuing jobs, and then takes the average.

When there has been an expansion, unemployment is subsequently twice as sensitive to negative as to positive shocks to labor demand.

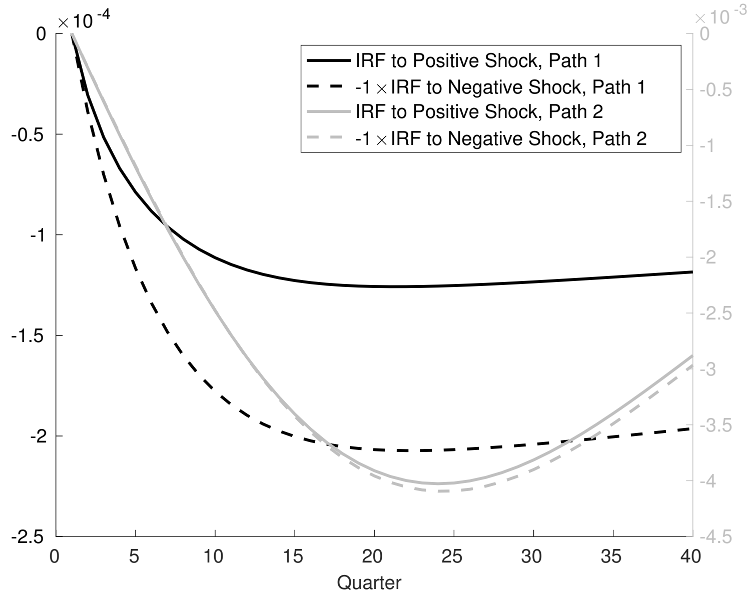
We consider two scenarios in the model. We study the impulse response of unemployment to positive and negative labor demand shocks at $t = 0$. We consider different paths for labor demand prior to $t = 0$. Appendix Figure 7 plots these paths. On path 1, we assume the economy is at steady state. On path 2, 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 two unconditional standard deviations. Thus the state that differs is not current labor demand, which is fixed across the two paths. Instead, these paths isolate the impact of *prior* contractions or expansions in labor demand, on the *current* degree of asymmetry in the impulse response of unemployment.

Figure 10 plots the impulse response of unemployment to positive and negative labor demand shocks, at $t = 0$, from each scenario. On path 1, the response of unemployment is asymmetric; on path 2, the response of unemployment is symmetric. On the left hand axis, the figure plots the impulse response of unemployment to positive and negative shocks on path 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 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 on path 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.

State dependence of wage rigidity to positive shocks is key to the result. Figure 10 also depicts the impulse response of wages. On path 1, 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. On path 2, 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. Note that in Figure 10, the impulse response on path 2 is zero to both positive and negative labor demand shocks. 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 documented precisely this form of state dependent wage flexibility in 4.5.

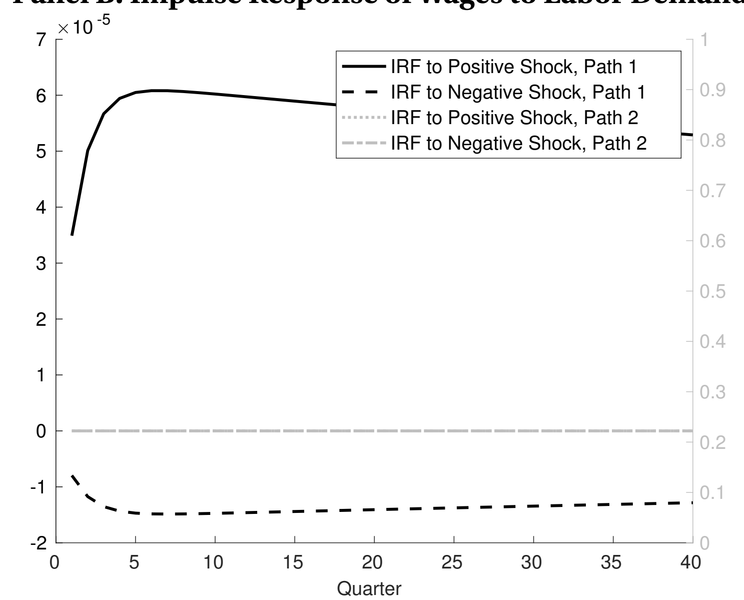
Figure 10

Panel A: Impulse Response of Unemployment to Labor Demand



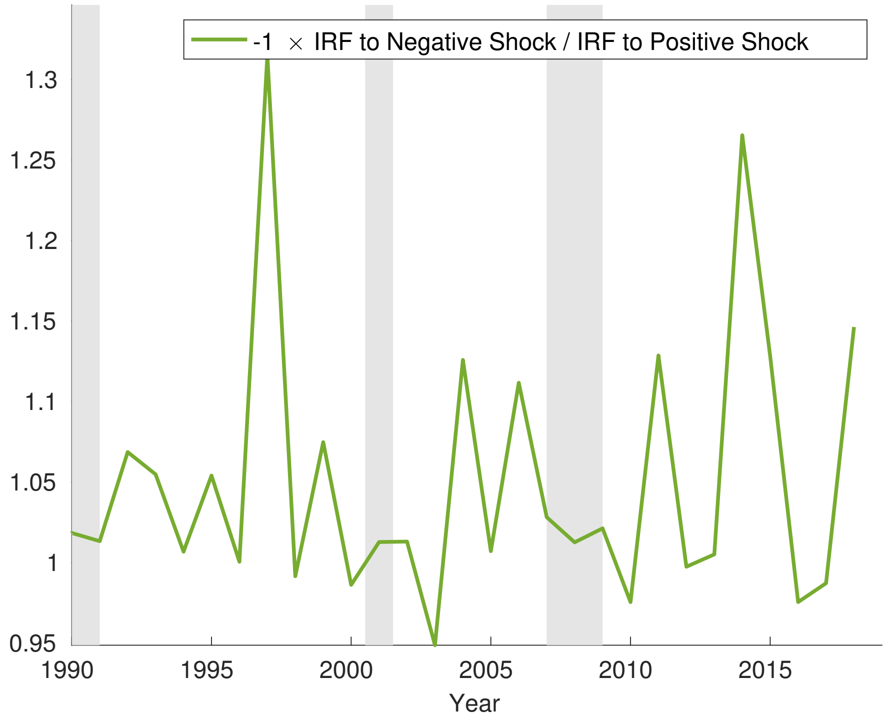
Notes: this graph plots the impulse response of unemployment with respect to positive and negative labor demand shocks, in two scenarios. In the first scenario (left axis) the impulse response occurs when the economy is at the steady state, on Path 1 of Appendix Figure 7. In the second scenario (right 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, on Path 2 of Appendix Figure 7. The contraction is equal to two unconditional standard deviations of labor demand. The impulse is 0.1 conditional standard deviations of labor demand.

Panel B: Impulse Response of Wages to Labor Demand



Notes: this graph plots the impulse response of wages with respect to positive and negative labor demand shocks, in two scenarios. The IRFs on Path 2 to positive and negative shocks are the same, and hence they overlap in the figure.

Figure 11: Asymmetry in Impulse Response of Unemployment Over Time



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 0.1 conditional standard deviations of labor demand.

We now show that the degree of state dependence varies substantially over time. Figure 11 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 recessions 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 1990 and 1993, unemployment was similarly sensitive to positive and negative shocks. At the peak of the labor market in 1996, unemployment was 40% more sensitive to negative shocks to labor demand. Again, the relevance of *past* contractions or expansions to *current* unemployment dynamics is clear in Figure 11. The effect of downward rigidity—which creates symmetric unemployment dynamics—matters not only during recessions, but also during the early part of recoveries. Only during the late part of recoveries, when labor demand has risen so that downward constraints are no longer binding, do pronounced asymmetries emerge.

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.[53] This evidence is in line with our model's prediction of state dependent asymmetry.

6.7 Caveats to the Model

We close with some important caveats to our model, and its link to our empirical exercise.

First, we model downward rigidity in real and not nominal wages, for two reasons. Firstly, the evidence of Appendix Table 7 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.2 extends our model to account for inflation, in two different ways. First, we allow for positive trend inflation, in subsection F.1, which unwinds the downward constraint on wage setting more rapidly. Second, we introduce a Phillips Curve, to endogenize inflation, in subsection F.2. We re-estimate both models. Neither feature modifies our quantitative conclusions.

Second, our model features wage bargaining and random search. In our bargaining model, we will see that workers accept the first offer made by firms in equilibrium. In the data we observe the wage attached to vacancies. So, through the lens of the model, the wage on vacancies is the firm's first wage offer. Our model also has random search—workers cannot choose which types of jobs they apply for. But wage bargaining and random search may not accurately describe labor markets. Alternatively, the labor market might feature posted wages and directed search. Firms might post wages, and commit to paying these wages without allowing workers to bargain. Workers might direct their search towards jobs that they prefer. In directed search models with posted wages, firms can use wages to attract workers and fill vacancies more quickly (e.g. Kaas and Kircher, 2015). One might worry that our wage rigidity estimate has a different interpretation in this class of models. Instead, drawing on results from (Moen, 1997), we derive an equivalence between our model and an alternative with directed search and wage posting. So, our conclusions about the effect of downward rigidity on unemployment fluctuations, from the model in the main text, apply equally to a model with wage posting and directed search. We present this equivalence in Appendix subsection F.3. In practice, US labor markets feature both posted and bargained wages, and both random and directed search (Hall and Krueger, 2012).

Third, our model features a single type of job. Again, we make this choice on the grounds

[53]In the model of the main text, we do not have nominal rigidities, and hence no role for monetary shocks. However, in Appendix Section F.2 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.

of parsimony. Nevertheless, Appendix Section F.1 extends our model to allow for multiple job types. There is a continuum of jobs. There are aggregate labor demand shocks, and also idiosyncratic shocks that affect output per worker in each type of job. Wages are downwardly rigid for each type of job. Otherwise the model is similar to the main text. We re-estimate the model, and again find similar quantitative conclusions.

Fourth, 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 were 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.[54]

7 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 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. When there has been a contraction, then unemployment responds similarly to positive and negative shocks in the aftermath. When there has been an expansion, unemployment is afterwards as much as twice as sensitive to positive shocks.

[54] 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. The formal argument is available on request.

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

ABADIE, A., S. ATHEY, G. W. IMBENS, AND J. WOOLDRIDGE (2017): "When Should You Adjust Standard Errors for Clustering?," Discussion paper, National Bureau of Economic Research.

ACEMOGLU, D., AND D. AUTOR (2011): "Skills, tasks and technologies: Implications for employment and earnings," in *Handbook of labor economics*, vol. 4, pp. 1043–1171. Elsevier.

ACEMOGLU, D., A. FINKELSTEIN, AND M. J. NOTOWIDIGDO (2013): "Income and health spending: Evidence from oil price shocks," *Review of Economics and Statistics*, 95(4), 1079–1095.

ACEMOGLU, D., AND W. B. HAWKINS (2014): "Search with multi-worker firms," *Theoretical Economics*, 9(3), 583–628.

ADAO, R., M. KOLESÁR, AND E. MORALES (2018): "Shift-share designs: Theory and inference," Discussion paper, National Bureau of Economic Research.

AKERLOF, G., W. DICKENS, AND G. PERRY (1996): "The Macroeconomics of Low Inflation," *Brookings Papers on Economics Activity*.

ALLCOTT, H., AND D. KENISTON (2017): "Dutch disease or agglomeration? The local economic effects of natural resource booms in modern America," *The Review of Economic Studies*, 85(2), 695–731.

ANGRIST, J. D., AND A. B. KRUEGER (1995): "Split-sample instrumental variables estimates of the return to schooling," *Journal of Business & Economic Statistics*, 13(2), 225–235.

BARATTIERI, A., S. BASU, AND P. GOTTSCHALK (2014): "Some evidence on the importance of sticky wages," *American Economic Journal: Macroeconomics*, 6(1), 70–101.

BARLEVY, G. (2002): "The sullying effect of recessions," *The Review of Economic Studies*, 69(1), 65–96.

BARRO, R. J. (1977): "Long-term contracting, sticky prices, and monetary policy," *Journal of Monetary Economics*, 3(3), 305–316.

BASU, S., AND C. L. HOUSE (2016): "Allocative and Remitted Wages: New Facts and Challenges for Keynesian Models," in *Handbook of Macroeconomics*, vol. 2, pp. 297–354. Elsevier.

BEAUDRY, P., AND J. DINARDO (1991): "The effect of implicit contracts on the movement of wages over the business cycle: Evidence from micro data," *Journal of Political Economy*, 99(4), 665–688.

BENIGNO, P., AND L. A. RICCI (2011): “The inflation-output trade-off with downward wage rigidities,” *American Economic Review*, 101(4), 1436–66.

BERAJA, M., E. HURST, AND J. OSPINA (2016): “The aggregate implications of regional business cycles,” Discussion paper, National Bureau of Economic Research.

BEWLEY, T. F. (2002): *Why wages don’t fall during a recession*. Harvard University Press.

BILS, M., Y. CHANG, AND S.-B. KIM (2014): “How sticky wages in existing jobs can affect hiring,” Discussion paper, National Bureau of Economic Research.

BILS, M. J. (1985): “Real wages over the business cycle: evidence from panel data,” *Journal of Political economy*, 93(4), 666–689.

BLANCHARD, O., AND J. GALI (2010): “Labor markets and monetary policy: A New Keynesian model with unemployment,” *American economic journal: macroeconomics*, 2(2), 1–30.

BOUND, J., AND A. B. KRUEGER (1991): “The extent of measurement error in longitudinal earnings data: Do two wrongs make a right?,” *Journal of Labor Economics*, 9(1), 1–24.

CAJNER, T., AND D. RATNER (2016): “A Cautionary Note on the Help Wanted Online Data,” *FEDS Notes, Board of Governors of the Federal Reserve System https://www. federalreserve. gov/econresdata/notes/feds-notes/2016/acautionary-note-on-the-help-wanted-online-data-20160623. html*.

CAMPBELL III, C. M., AND K. S. KAMLANI (1997): “The reasons for wage rigidity: evidence from a survey of firms,” *The Quarterly Journal of Economics*, 112(3), 759–789.

CARD, D., AND D. HYSLOP (1997): “Does inflation" grease the wheels of the labor market"?,” in *Reducing inflation: Motivation and strategy*, pp. 71–122. University of Chicago Press.

CARNEVALE, A. P., T. JAYASUNDERA, AND D. REPNIKOV (2014): “Understanding online job ads data,” *Georgetown University, Center on Education and the Workforce, Technical Report (April)*.

CHODOROW-REICH, G., AND J. WIELAND (2017): “Secular labor reallocation and business cycles,” Discussion paper, National Bureau of Economic Research.

CHRISTIANO, L. J., M. S. EICHENBAUM, AND M. TRABANDT (2016): “Unemployment and business cycles,” *Econometrica*, 84(4), 1523–1569.

COOPER, R., J. HALTIWANGER, AND J. L. WILLIS (2007): “Search frictions: Matching aggregate and establishment observations,” *Journal of Monetary Economics*, 54, 56–78.

DALY, M. C., AND B. HOBIJN (2014): "Downward nominal wage rigidities bend the Phillips curve," *Journal of Money, Credit and Banking*, 46(S2), 51–93.

DAVIS, S. J., R. J. FABERMAN, AND J. C. HALTIWANGER (2013): "The establishment-level behavior of vacancies and hiring," *The Quarterly Journal of Economics*, 128(2), 581–622.

DUPRAZ, S., E. NAKAMURA, AND J. STEINSSON (2016): "A plucking model of business cycles," Discussion paper, mimeo.

ELIAZ, K., AND R. SPIEGLER (2014): "Reference dependence and labor market fluctuations," *NBER macroeconomics annual*, 28(1), 159–200.

ELSBY, M. W. (2009): "Evaluating the economic significance of downward nominal wage rigidity," *Journal of Monetary Economics*, 56(2), 154–169.

ELSBY, M. W., B. HOBIJN, AND A. ŞAHIN (2013): "Unemployment dynamics in the OECD," *Review of Economics and Statistics*, 95(2), 530–548.

ELSBY, M. W., AND R. MICHAELS (2013): "Marginal jobs, heterogeneous firms, and unemployment flows," *American Economic Journal: Macroeconomics*, 5(1), 1–48.

ELSBY, M. W., R. MICHAELS, AND G. SOLON (2009): "The ins and outs of cyclical unemployment," *American Economic Journal: Macroeconomics*, 1(1), 84–110.

ELSBY, M. W., D. SHIN, AND G. SOLON (2016): "Wage adjustment in the Great Recession and other downturns: Evidence from the United States and Great Britain," *Journal of Labor Economics*, 34(S1), S249–S291.

ELSBY, M. W., AND G. SOLON (2018): "How Prevalent Is Downward Rigidity in Nominal Wages? International Evidence from Payroll Records and Pay Slips," Discussion paper, National Bureau of Economic Research.

FANG, H., AND G. MOSCARINI (2005): "Morale hazard," *Journal of Monetary Economics*, 52(4), 749–777.

FUJITA, S., AND G. MOSCARINI (2017): "Recall and unemployment," *American Economic Review*, 107(12), 3875–3916.

FUJITA, S., AND G. RAMEY (2009): "The cyclicality of separation and job finding rates," *International Economic Review*, 50(2), 415–430.

GAVAZZA, A., S. MONGEY, AND G. L. VIOLANTE (2018): "Aggregate recruiting intensity," *American Economic Review*, 108(8), 2088–2127.

GERTLER, M., C. HUCKFELDT, AND A. TRIGARI (2016): "Unemployment fluctuations, match quality, and the wage cyclicality of new hires," Discussion paper, National Bureau of Economic Research.

GERTLER, M., L. SALA, AND A. TRIGARI (2008): "An estimated monetary DSGE model with unemployment and staggered nominal wage bargaining," *Journal of Money, Credit and Banking*, 40(8), 1713–1764.

GERTLER, M., AND A. TRIGARI (2009): "Unemployment fluctuations with staggered Nash wage bargaining," *Journal of political Economy*, 117(1), 38–86.

GRIGSBY, J., E. HURST, AND A. YILDIRMAZ (2018): "Aggregate Nominal Wage Adjustments: New Evidence from Administrative Payroll Data," *Working paper*.

HAEFKE, C., M. SONNTAG, AND T. VAN RENS (2013): "Wage rigidity and job creation," *Journal of monetary economics*, 60(8), 887–899.

HAGEDORN, M., F. KARAHAN, I. MANOVSKII, AND K. MITMAN (2013): "Unemployment benefits and unemployment in the great recession: the role of macro effects," Discussion paper, National Bureau of Economic Research.

HAGEDORN, M., AND I. MANOVSKII (2008): "The cyclical behavior of equilibrium unemployment and vacancies revisited," *American Economic Review*, 98(4), 1692–1706.

——— (2013): "Job selection and wages over the business cycle," *American Economic Review*, 103(2), 771–803.

HALL, R. E. (2005a): "Employment efficiency and sticky wages: Evidence from flows in the labor market," *Review of Economics and statistics*, 87(3), 397–407.

——— (2005b): "Employment fluctuations with equilibrium wage stickiness," *American economic review*, 95(1), 50–65.

HALL, R. E., AND A. B. KRUEGER (2012): "Evidence on the incidence of wage posting, wage bargaining, and on-the-job search," *American Economic Journal: Macroeconomics*, 4(4), 56–67.

HALL, R. E., AND P. R. MILGROM (2008): "The limited influence of unemployment on the wage bargain," *American economic review*, 98(4), 1653–74.

HAMILTON, J. D. (2018): "Why you should never use the Hodrick-Prescott filter," *Review of Economics and Statistics*, 100(5), 831–843.

HARRIS, M., AND B. HOLMSTROM (1982): "A theory of wage dynamics," *The Review of Economic Studies*, 49(3), 315–333.

HECKMAN, J., AND B. SINGER (1984): "A method for minimizing the impact of distributional assumptions in econometric models for duration data," *Econometrica: Journal of the Econometric Society*, pp. 271–320.

HERSHBEIN, B., AND L. B. KAHN (2016): "Do recessions accelerate routine-biased technological change? Evidence from vacancy postings," Discussion paper, National Bureau of Economic Research.

JÄGER, S., B. SCHOEFER, S. G. YOUNG, AND J. ZWEIMÜLLER (2018): "Wages and the Value of Nonemployment," Discussion paper, National Bureau of Economic Research.

JARDIM, E. S., G. SOLON, AND J. L. VIGDOR (2019): "How Prevalent Is Downward Rigidity in Nominal Wages? Evidence from Payroll Records in Washington State," Discussion paper, National Bureau of Economic Research.

JO, Y. J. (2019): "Downward nominal wage rigidity in the United States," Discussion paper, Technical report, Columbia University.

KAAS, L., AND P. KIRCHER (2015): "Efficient firm dynamics in a frictional labor market," *American Economic Review*, 105(10), 3030–60.

KAUR, S. (2019): "Nominal wage rigidity in village labor markets," *American Economic Review*, 109(10), 3585–3616.

KEYNES, J. M. (1936): *The general theory of employment, interest, and money*. Springer.

KIM, J., AND F. J. RUGE-MURCIA (2009): "How much inflation is necessary to grease the wheels?," *Journal of Monetary Economics*, 56(3), 365–377.

——— (2011): "Monetary policy when wages are downwardly rigid: Friedman meets Tobin," *Journal of Economic Dynamics and Control*, 35(12), 2064–2077.

KLENOW, P. J., AND O. KRYVTSOV (2008): "State-dependent or time-dependent pricing: Does it matter for recent US inflation?," *The Quarterly Journal of Economics*, 123(3), 863–904.

KUDLYAK, M. (2014): "The cyclicality of the user cost of labor," *Journal of Monetary Economics*, 68, 53–67.

KURMANN, A., AND E. MCENTARFER (2017): "Downward Wage Rigidity in the United States: New Evidence from Administrative Data," .

LE BIHAN, H., J. MONTORNÈS, AND T. HECKEL (2012): "Sticky wages: evidence from quarterly microeconomic data," *American Economic Journal: Macroeconomics*, 4(3), 1–32.

LJUNGQVIST, L., AND T. J. SARGENT (2017): "The fundamental surplus," *American Economic Review*, 107(9), 2630–65.

MAKRIDIS, C., AND M. GITTLEMAN (2019): "On the Cyclicality of Real Wages and Employment: New Evidence and Stylized Facts from Performance Pay and Fixed Wage Jobs," *Available at SSRN 3017034*.

MARINESCU, I., AND R. WOLTHOFF (2016): "Opening the black box of the matching function: The power of words," Discussion paper, National Bureau of Economic Research.

MARTINS, P. S., G. SOLON, AND J. P. THOMAS (2012): "Measuring what employers do about entry wages over the business cycle: A new approach," *American Economic Journal: Macroeconomics*, 4(4), 36–55.

MAVROEIDIS, S., M. PLAGBORG-MØLLER, AND J. H. STOCK (2014): "Empirical evidence on inflation expectations in the New Keynesian Phillips Curve," *Journal of Economic Literature*, 52(1), 124–88.

MCKAY, A., AND R. REIS (2008): "The brevity and violence of contractions and expansions," *Journal of Monetary Economics*, 55(4), 738–751.

MENZIO, G., AND E. R. MOEN (2010): "Worker replacement," *Journal of Monetary Economics*, 57(6), 623–636.

MENZIO, G., AND S. SHI (2011): "Efficient search on the job and the business cycle," *Journal of Political Economy*, 119(3), 468–510.

MIAN, A., A. SUFI, AND E. VERNER (2017): "How do credit supply shocks affect the real economy? Evidence from the United States in the 1980s," Discussion paper, National Bureau of Economic Research.

MICHAILLAT, P. (2012): "Do matching frictions explain unemployment? Not in bad times," *American Economic Review*, 102(4), 1721–50.

MOEN, E. R. (1997): "Competitive search equilibrium," *Journal of political Economy*, 105(2), 385–411.

MORTENSEN, D. T., AND C. A. PISSARIDES (1994): "Job creation and job destruction in the theory of unemployment," *The review of economic studies*, 61(3), 397–415.

MUELLER, A. I. (2017): "Separations, Sorting, and Cyclical Unemployment," *American Economic Review*, 107(7), 2081–2107.

NAKAMURA, E., AND J. STEINSSON (2008): "Five facts about prices: A reevaluation of menu cost models," *The Quarterly Journal of Economics*, 123(4), 1415–1464.

NAKAMURA, E., AND J. STEINSSON (2014): "Fiscal stimulus in a monetary union: Evidence from US regions," *American Economic Review*, 104(3), 753–92.

OF ATLANTA, F. R. B. (2014): "Wage Growth A Missing Piece of the Full Employment Puzzle," *https://www.frbatlanta.org/about/publications/annual-reports/2014/wage-growth-missing.aspx*.

OSBORNE, M. J., AND A. RUBINSTEIN (1990): *Bargaining and markets*. Academic press.

PETROSKY-NADEAU, N., AND L. ZHANG (2013): "Solving the DMP model accurately," Discussion paper, National Bureau of Economic Research.

PETROSKY-NADEAU, N., L. ZHANG, AND L.-A. KUEHN (2018): "Endogenous disasters," *American Economic Review*, 108(8), 2212–45.

PISSARIDES, C. A. (2000): *Equilibrium unemployment theory*. MIT press.

——— (2009): "The unemployment volatility puzzle: Is wage stickiness the answer?," *Econometrica*, 77(5), 1339–1369.

RAMEY, V. A., AND S. ZUBAIRY (2018): "Government spending multipliers in good times and in bad: evidence from US historical data," *Journal of Political Economy*, 126(2), 850–901.

ROMER, C. D., AND D. H. ROMER (2004): "A new measure of monetary shocks: Derivation and implications," *American Economic Review*, 94(4), 1055–1084.

RUBINSTEIN, A. (1982): "Perfect equilibrium in a bargaining model," *Econometrica: Journal of the Econometric Society*, pp. 97–109.

RUDANKO, L. (2019): "Firm wages in a frictional labor market," .

SCHAAL, E. (2017): "Uncertainty and unemployment," *Econometrica*, 85(6), 1675–1721.

SCHMITT-GROHÉ, S., AND M. URIBE (2016): "Downward nominal wage rigidity, currency pegs, and involuntary unemployment," *Journal of Political Economy*, 124(5), 1466–1514.

SCHOEFER, B. (2015): "The financial channel of wage rigidity," Ph.D. thesis, Harvard University.

SHAKED, A., AND J. SUTTON (1984): “Involuntary unemployment as a perfect equilibrium in a bargaining model,” *Econometrica: Journal of the Econometric Society*, pp. 1351–1364.

SHIMER, R. (2005): “The cyclical behavior of equilibrium unemployment and vacancies,” *American economic review*, 95(1), 25–49.

——— (2012): “Reassessing the ins and outs of unemployment,” *Review of Economic Dynamics*, 15(2), 127–148.

SHIN, D. (1994): “Cyclicality of real wages among young men,” *Economics Letters*, 46(2), 137–142.

SIGURDSSON, J., AND R. SIGURDARDOTTIR (2016): “Time-dependent or state-dependent wage-setting? Evidence from periods of macroeconomic instability,” *Journal of Monetary Economics*, 78, 50–66.

SOLON, G., R. BARSKY, AND J. A. PARKER (1994): “Measuring the cyclicality of real wages: how important is composition bias?,” *The quarterly journal of economics*, 109(1), 1–25.

WIELAND, J. F., AND M.-J. YANG (2016): “Financial dampening,” Discussion paper, National Bureau of Economic Research.

YAGAN, D. (2016): “Is the great recession really over? longitudinal evidence of enduring employment impacts,” *Unpublished Manuscript*.

8 Tables

Table 1: Summary Statistics

	Min	Max	Average
Posts Per State	4799	3012689	421412
Posts Per Quarter	279252	1278327	782622
Posts Per State-Quarter	49	190582	15050
Posts Per 6 Digit SOC Code	1	1925439	25500
Total Posts	21913422		
Share Missing Job Title	.57		
Share Missing Establishment Code	.57		
Share of 6 digit SOC occupations covered	.99		
Share posting wage range	.44		
Average width of range	.077		

Pay Categories:

	Base Pay	Bonus	Total Pay	**Total**
Annual	3962172	530169	3648138	8234372
Daily	330899	306405	857674	1520389
Hourly	6067618	376666	3918815	10397359
Monthly	380414	438023	743509	1577650
Weekly	80038	22368	68401	183652
Total	10821141	1673631	9236537	21913422

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. The share of 6 digit SOC occupations covered, is defined as the share of 6 digit occupations in the 2014-2016 Occupational Employment Statistics (OES) that post in Burning Glass, weighted by OES employment.

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					
	(1)	(2)	(3)	(4)	(5)	(6)
Independent Variable:						
Log Burning Glass Wage,	0.970***	1.034***	0.715***			
All Vacancies	(0.174)	(0.252)	(0.108)			
Log Burning Glass Wage,				0.957***	1.017***	0.706***
Vacancies with Job Code only				(0.171)	(0.246)	(0.106)

Panel B:	Log QWI New Hire Earnings, by State-Quarter					
	(1)	(2)	(3)	(4)	(5)	(6)
Independent Variable:						
Log Burning Glass Wage,	1.246***	1.184***	1.007***			
All Vacancies	(0.203)	(0.347)	(0.140)			
Log Burning Glass Wage,				1.234***	1.168***	0.997***
Vacancies with Job Code only				(0.201)	(0.341)	(0.139)
State Effects	N	Y	N	N	Y	N
Time Effects	N	N	Y	N	N	Y
Number of Observations	1428	1428	1428	1428	1428	1428
State Clusters	52	52	52	52	52	52

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

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

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

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

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

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

Dependent Variable:	Quarterly Job-Level Growth in Wage for New Hires				
	(1)	(2)	(3)	(4)	(5)
Independent Variable:					
ΔU_{st}	-0.0517	0.152	0.0454	-0.946***	0.367
	(0.256)	(0.308)	(0.249)	(0.102)	(0.892)
$\Delta U_{st} \times I(\Delta U_{st} < 0)$	-1.255***	-1.413***	-1.309***		-2.397*
	(0.265)	(0.371)	(0.246)		(1.029)
Job-Level Difference	Y	Y	Y	Y	Y
Time Effect	Y	Y	Y	Y	Y
State Trend	N	Y	N	N	N
OES Weight	N	N	Y	N	N
Oil Shock IV	N	N	N	N	Y
N	1566182	1566182	1511642	1566182	1566182
State Clusters	52	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 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 $\Delta U_{st} = \sum_s \left[\beta_s \Delta \log\left(\text{oil price}_{t-1}\right) + \gamma_s I\left(\Delta \log\left(\text{oil price}_{t-1}\right) < 0\right) \Delta \log\left(\text{oil price}_{t-1}\right)\right] + \text{error}_{st}$, 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

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

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

Dependent Variable:	Quarterly Establishment-Level Growth in Wage for New Hires			
	(1)	(2)	(3)	(4)
Independent Variable:				
ΔU_{st}	0.00392	-0.268	-0.0431	-0.909***
	(0.313)	(0.353)	(0.341)	(0.0737)
$\Delta U_{st} \times I(\Delta U_{st} < 0)$	-1.082**	-0.785$^+$	-1.021*	
	(0.382)	(0.427)	(0.414)	
$(\Delta U_{st})^2$				
Establishment-Level Difference	Y	Y	Y	Y
Time Effect	Y	Y	Y	Y
State Trend	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. 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 State Share in High Wage Vacancies on Unemployment

Panel A:	Quarterly Change in State Share of High Wage Vacancies			
	(1)	(2)	(3)	(4)
ΔU_{st}	-0.654	-1.040	4.815	-0.0414
	(0.831)	(1.286)	(2.677)	(0.393)
$\Delta U_{st} \times I(\Delta U_{st} < 0)$	0.982	1.549	-3.537	
	(1.270)	(1.927)	(5.138)	
State Difference	Y	Y	Y	Y
Time Effect	Y	Y	Y	Y
State Trend	N	Y	N	N
QCEW Weight	N	N	Y	N
N	1404	1404	1404	1404
State Clusters	51	51	51	51

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 9: Estimates of Downward Wage Rigidity from Pooled and Worker-Level Wages

Dependent Variable:	Quarterly Growth in Pooled State Wages, BG		Quarterly Growth in State Wage for New Hires, CPS		Quarterly Growth in National Wage for New Hires	
					CPS	NLSY
	(1)	(2)	(3)	(4)	(5)	(6)
Independent Variable:						
ΔUnemployment	0.788	0.671	-5.748	-8.141	3.770	-1.779
	(1.048)	(1.579)	(4.359)	(5.903)	(3.468)	(3.172)
ΔUnemployment ×	1.182	1.424	10.59*	13.78	-5.108	2.935
$I\left(\Delta\text{Unemployment} < 0\right)$	(1.338)	(2.149)	(4.560)	(6.886)	(5.151)	(4.311)
State Difference	Y	Y	Y	Y	Y	Y
Time Effect	Y	Y	Y	Y	N	N
State Trend	N	Y	N	Y	N	N
Hagedorn and Manovskii (2013)	N	N	N	N	N	Y
Cumulative Tightness Control						
N	1377	1377	1377	1377	83	83
State Clusters	51	51	51	51	-	-

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 workers newly hired from unemployment. 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, Sonntag, and Van Rens (2013). The wage series partials out wage variation due to worker-specific observable characteristics, namely gender, race, marital status, education and a fourth order polynomial in experience. 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.
In the the sixth column, the dependent variable is the quarterly percentage growth in the national mean wage for newly hired workers. This wage series is for 1984-2006, and is measured from the National Longitudinal Survey of Youth. This specification also controls for job composition using cumulative tightness, as in Hagedorn and Manovskii (2013). The wage series for new hires is from the National Longitudinal Youth Survey, and is from Basu and House (2016). The wage series partials out wage variation due to worker-specific fixed effects, and age. 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 10: Wage Rigidity After Contractions and Expansions

Dependent Variable:	Quarterly Job-Level Growth in Wage for New Hires		
	(1)	(2)	(3)
Independent Variables:			
ΔU_{st}	-0.557**	-0.486**	-0.621***
	(0.184)	(0.168)	(0.0555)
$\Delta U_{st} \times$	-0.727***	-0.744***	-0.646***
$I\left(U_{s,t-1} - U_{s,t-13} < 0\right)$	(0.138)	(0.130)	(0.0561)
Job-Level Difference	Y	Y	Y
Time Effects	Y	Y	Y
State Trend	N	Y	N
State ×Quarter-of-Year Effects	N	N	Y
Number of Observations	1089785	1089785	1089785
State Clusters	52	52	52

Notes: We estimate the regression

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

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 11: Estimated Parameters and Moments in Model and Data

	Autocorr$[\log VA]$	$SD[\log VA]$	Mean u	Regression Coefficient
Data	0.908	0.0329	0.0575	-0.94
Model	0.889	0.0329	0.0575	-0.939

Parameter	Autocorr $[\varepsilon_t]$	$SD\,[\varepsilon_t]$	γ	$\tilde{\beta}^w$
Estimate	0.996	0.00194	0.144	0.998

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. In the data, the regression coefficient is β_{2015} from regression equation (34). In the model, the regression coefficient is a regression of wage growth on unemployment changes, only for negative unemployment changes, after a persistent expansion. We simulate the same moments in the model and the data, and minimize the distance between them, to estimate the parameters, Autocorr $[\varepsilon_t]$, $SD\,[\varepsilon_t]$, γ and $\tilde{\beta}^w$.

Table 12: Model Calibration

Parameter	Value
β^f	$0.97^{\frac{1}{12}}$
s	0.0081
ι	0.407
c	0.58
g	$1.01^{\frac{1}{52}}$

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. $g$is trend wage growth.

Table 13: Moments of Unemployment Dynamics in Model and Data

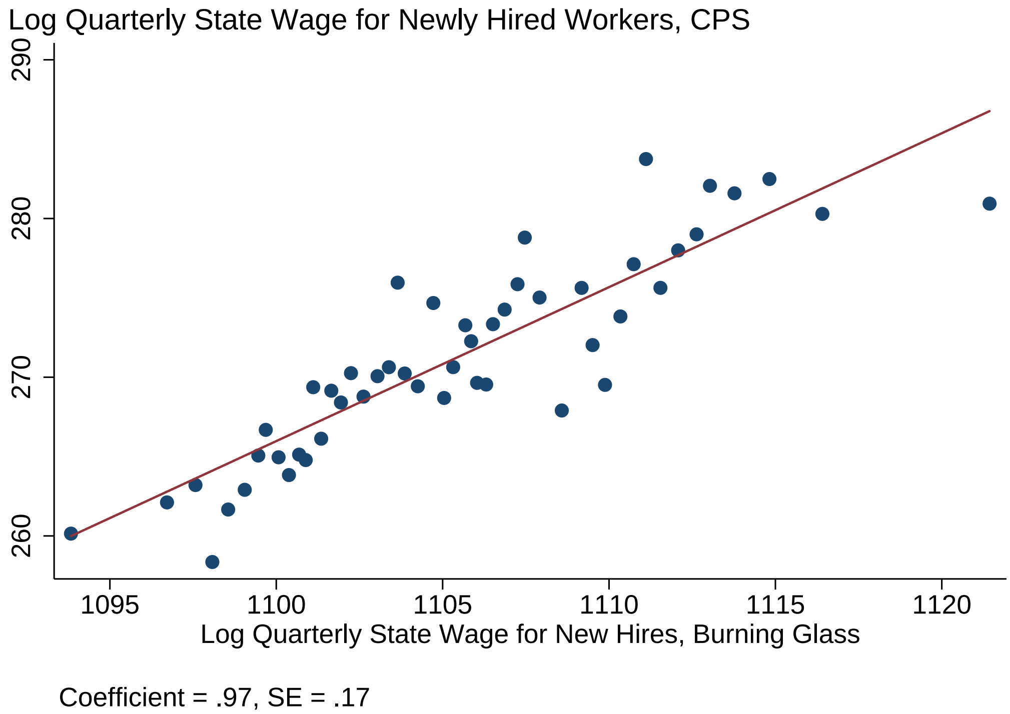
	Model	Data
First Autocorrelation	0.917	0.919
Standard Deviation	0.0232	0.0142
Skewness	0.794	0.904

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

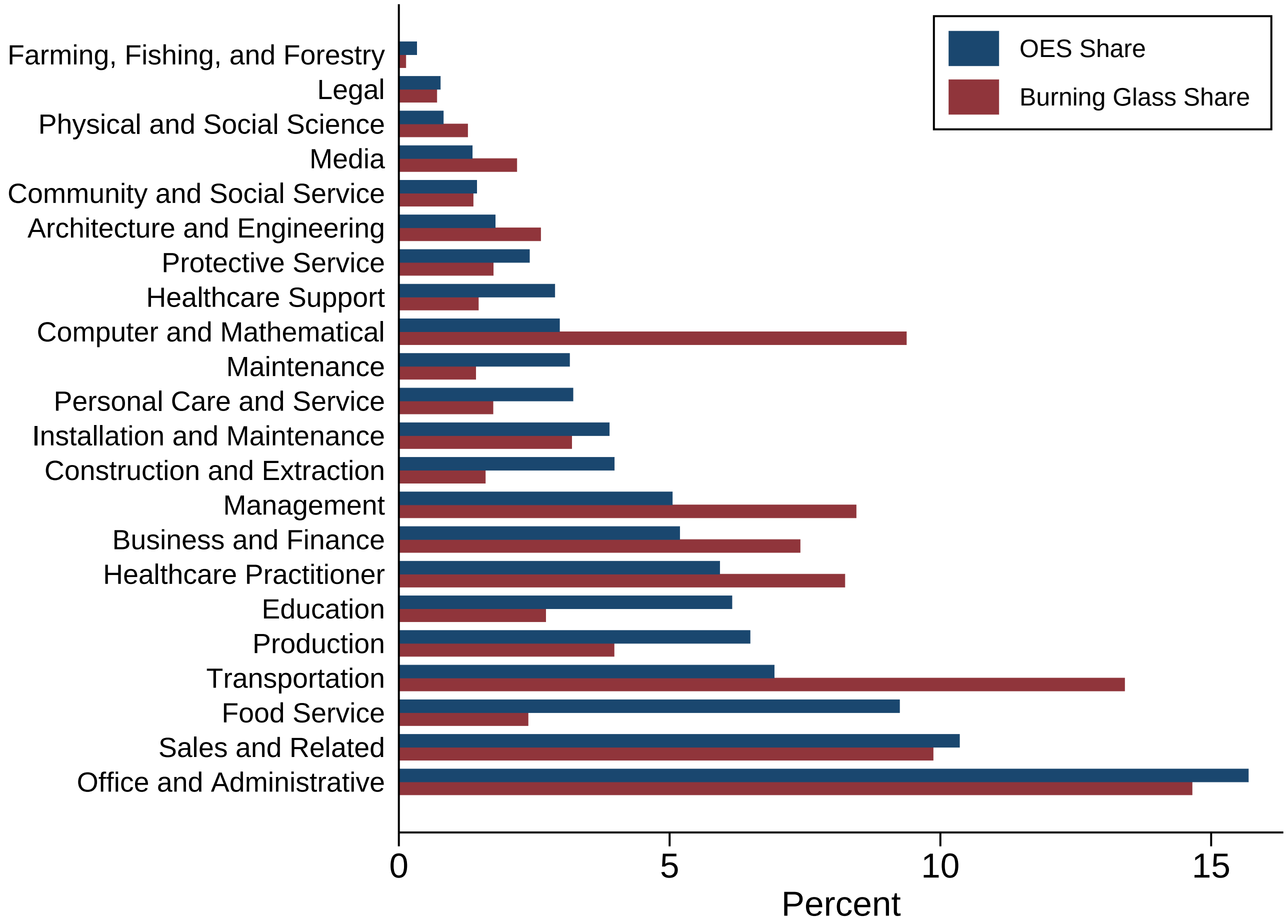
A Additional Figures

Figure 1: Binned Scatter of State-Quarter Wages for New Hires, in the CPS and Burning Glass



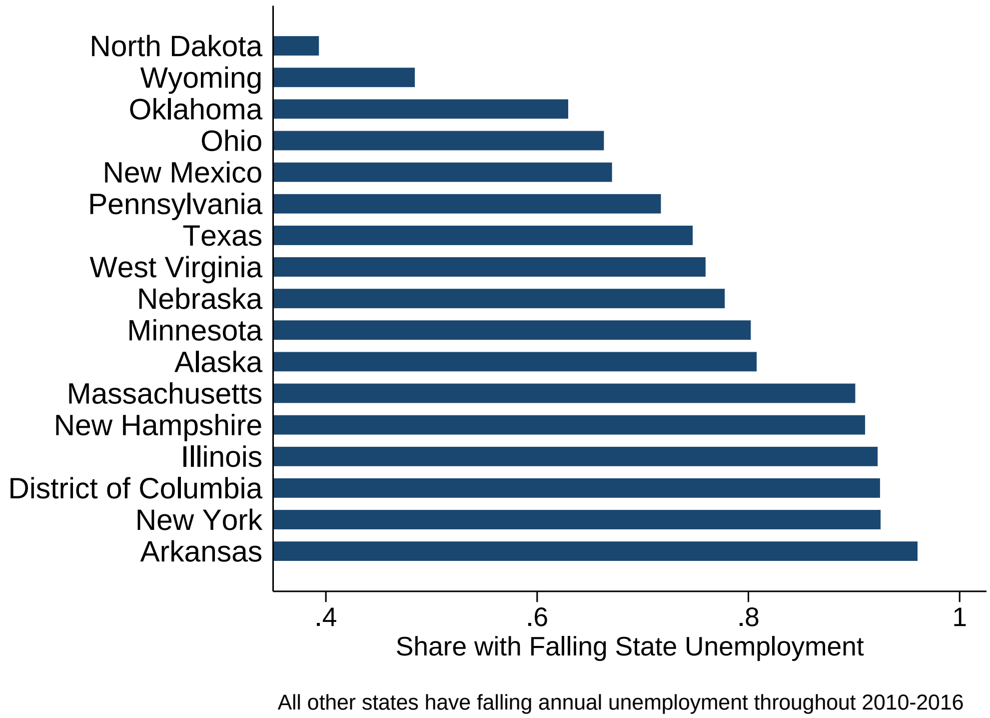
Notes: the y axis variable is the log of hours-weighted mean state-quarter wage for newly hired workers, from the 2010-2016 CPS. The x axis variable is the log of mean state-quarter wages for new hires, from the 2010-2016 Burning Glass data. The graph plots the weighted mean value of the y variable, 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.

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



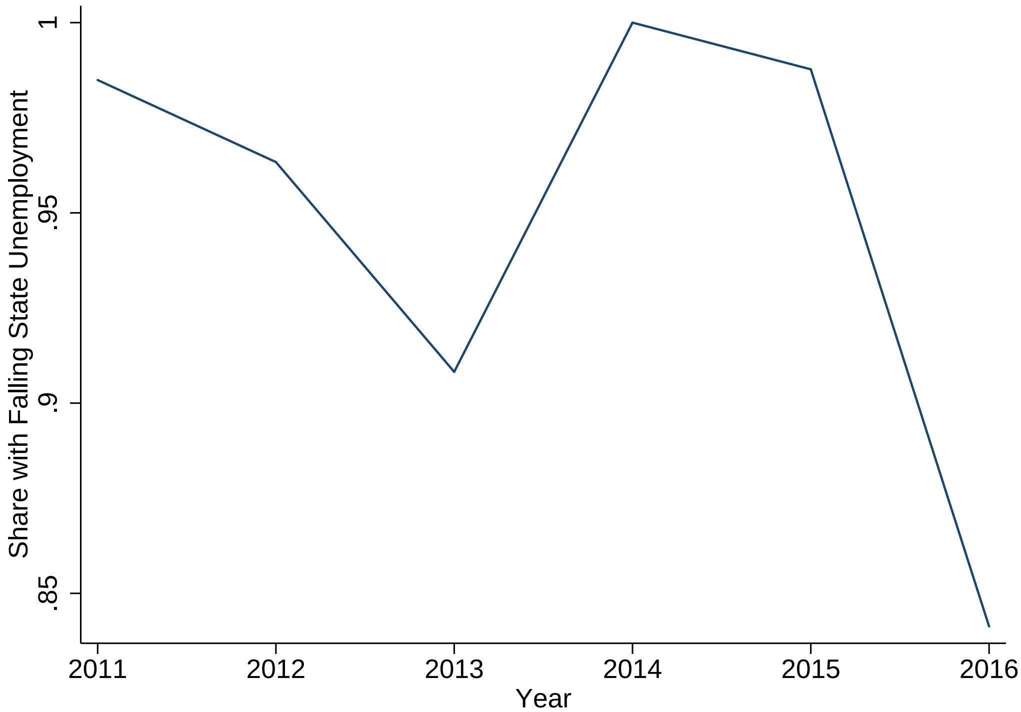
Notes: In Burning Glass, the data is 2010-2016; in the OES, the data is 2014-2016. In both datasets, the comparison is at the 2 digit SOC level, and excludes military.

Figure 3: Share of Wage Growth Observations in Each State with Falling Unemployment



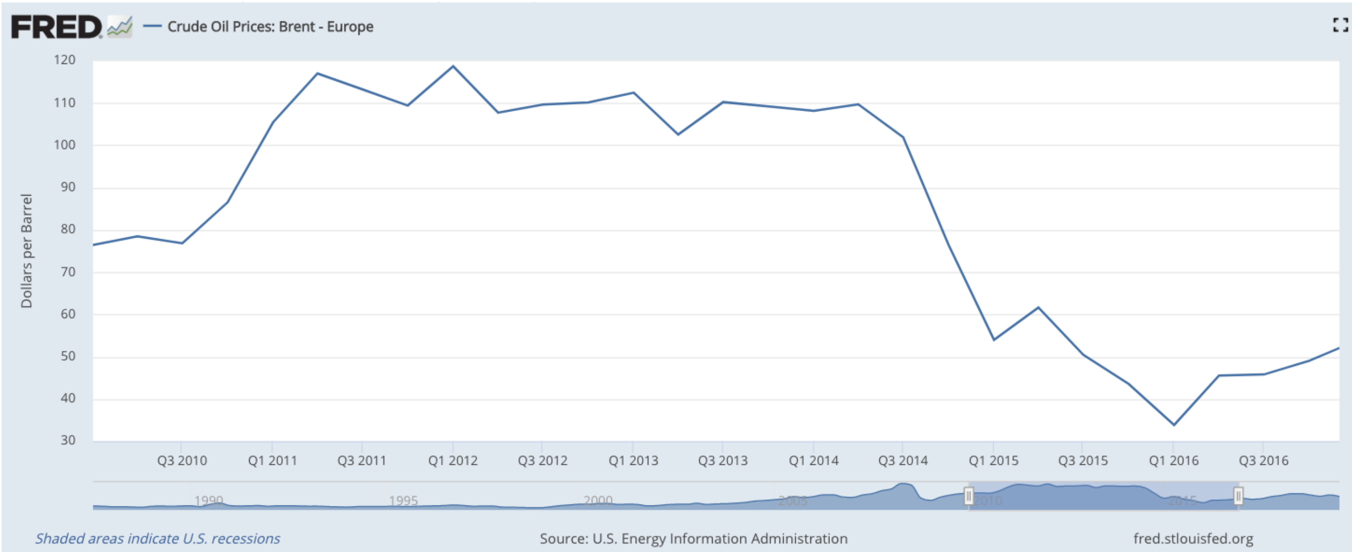
Notes: this graph plots the share of wage growth observations in each state, for which annual state unemployment is falling during the year of the wage posting, for the state in which the vacancy is posted. Log wages are differenced by job. The time period is 2010-2016. Unemployment is from the LAUS.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

Figure 4: Share of Wage Growth Observations in Each Year with Falling Unemployment



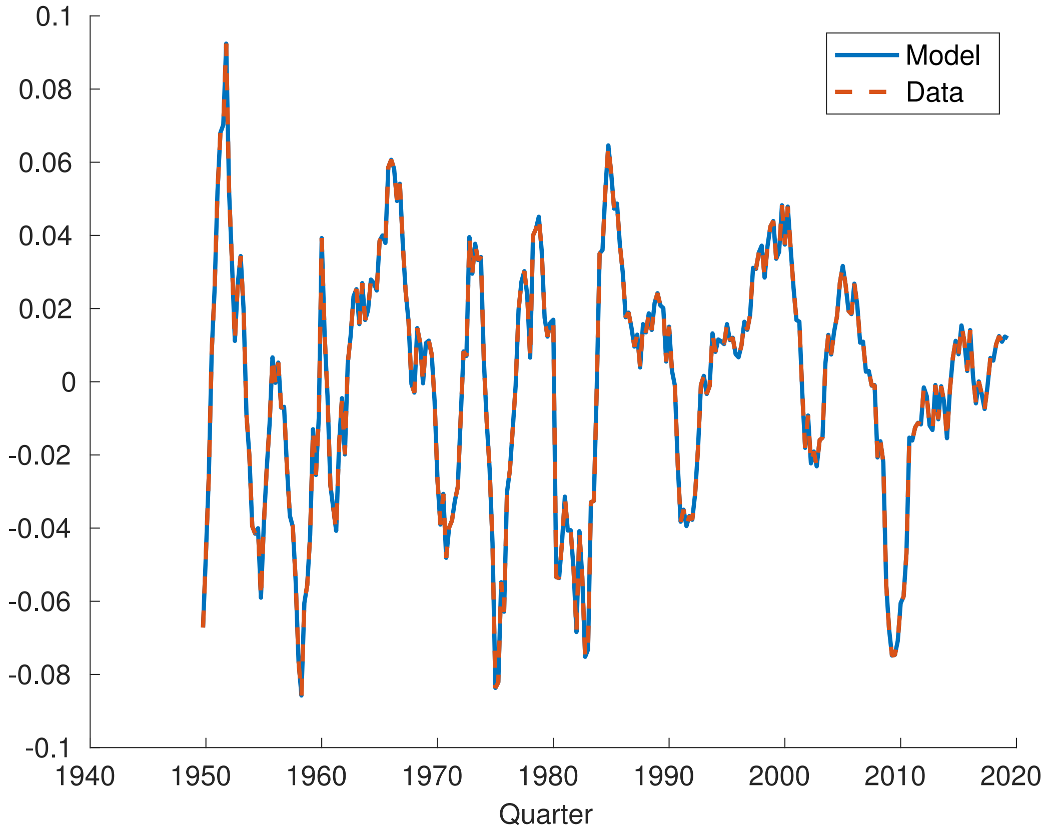
Notes: this graph plots the share of wage growth observations in each year, for which annual state unemployment is falling during the year of the wage posting, for the state in which the vacancy is posted. Log wages are differenced by job. The time period is 2010-2016. Unemployment is from the LAUS.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

Figure 5: Quarterly Global Oil Prices



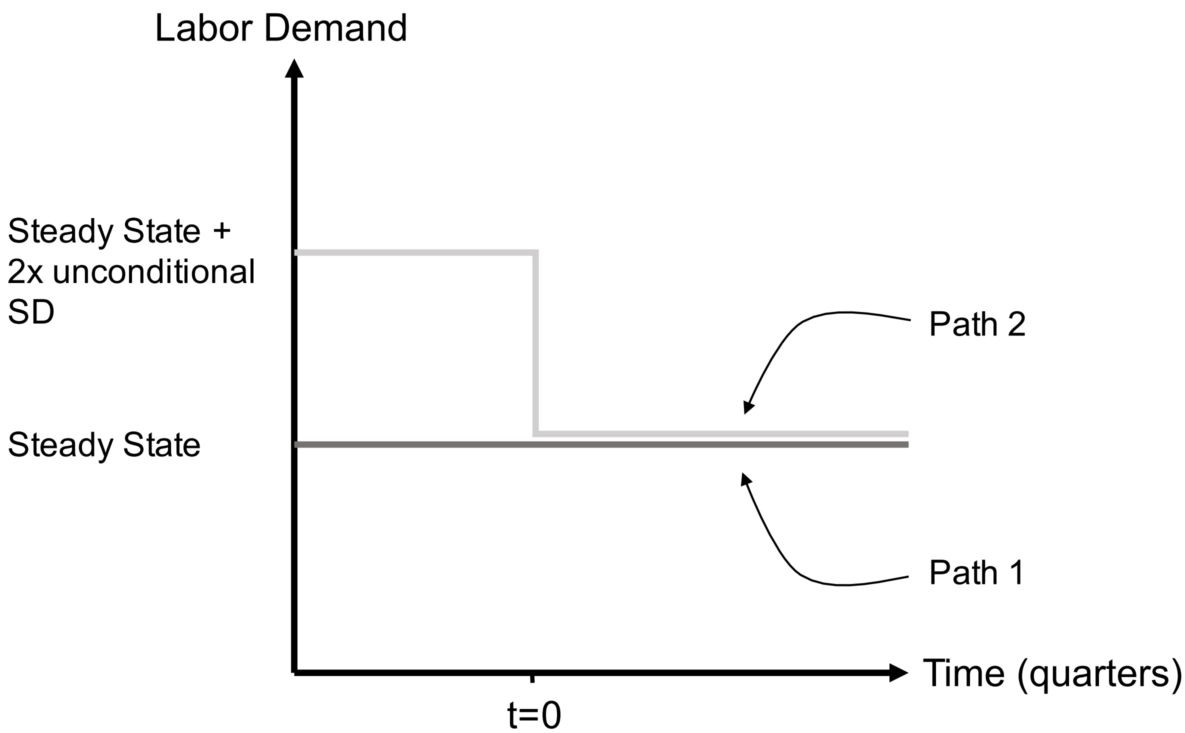
Notes: this figure plots the quarterly average oil price for 2010 to 2016, using the Brent Crude measure.

Figure 6: Hamilton-Filtered Log Output in Model and Data



Notes: we feed a sequence of labor demand shocks ε_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 ε_t such that filtered output in the model matches the data exactly.

Figure 7: Paths for Labor Demand in Model Scenarios



B Additional Tables

Table 1: Cyclicality of Whether Firms Include Wages In Vacancies

Dependent Variable:	Change in Share of State Vacancies with Wage			
	(1)	(2)	(3)	(4)
Quarterly State	0.0102	0.00746		
Unemployment Change	(0.0136)	(0.0214)		
Annual State			0.00304	-0.0111
Unemployment Change			(0.00542)	(0.0139)
State Difference	Y	Y	Y	Y
Time Effects	Y	Y	Y	Y
State Trend	N	Y	N	Y
Number of Observations	1377	1377	306	306
State Clusters	52	52	52	52

Notes: the dependent variable is the change in percentage points 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 percentage points 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.

Table 2: Comparison of Burning Glass Wages with Occupation Wages and City Earnings

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

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

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 3: Annual Job-Level Statistics On Wage for New Hires

	Unweighted	OES Weights	QCEW Weights	High Wage Jobs
Probability of Job-Level Wage Change	0.405	0.418	0.402	0.418
Probability of Job-Level Wage Decrease	0.088	0.095	0.09	0.087
Probability of Job-Level Wage Increase	0.304	0.305	0.3	0.31
Implied Duration for which Job-Level Wages Are Unchanged (Years)	1.841	1.836	1.875	1.841

Notes: a job is an establishment by region by job title by salary type by pay frequency observation. 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 4: Cyclicality of the Probability of Quarterly Wage Change for New Hires

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

Notes: the probability of a 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 5: Job-Level Growth in Wage for New Hires and Industry Labor Demand Growth

Panel A:	Quarterly Job-Level Growth in Wage for New Hires			
	(1)	(2)	(3)	(4)
$\Delta \log\left(\text{employment}_{it}\right)$	-0.00416	-0.00188	-0.00632	0.00571**
	(0.00301)	(0.00321)	(0.00348)	(0.00206)
$\Delta \log\left(\text{employment}_{it}\right)$	0.0180***	0.0157***	0.0249***	
$\times I\left(\Delta \log\left(\text{employment}_{it}\right) > 0\right)$	(0.00425)	(0.00440)	(0.00525)	
Time Effects	Y	Y	Y	Y
Industry Trend	N	Y	N	N
Seasonally Adjusted	N	N	Y	N
Number of observations	791270	791269	791270	791270
Industry clusters	75	75	75	75

Panel B:	Annual Job-Level Growth in Wage for New Hires		
	(1)	(2)	(3)
$\Delta \log\left(\text{labor productivity}_{it}\right)$	-0.126	-0.122	-0.0125
	(0.0693)	(0.0921)	(0.0465)
$\Delta \log\left(\text{labor productivity}_{it}\right)$	0.210 +	0.244 +	
$\times I\left(\Delta \log\left(\text{labor productivity}_{it}\right) > 0\right)$	(0.108)	(0.137)	
Time Effects	Y	Y	Y
Industry Trend	N	Y	N
Number of observations	135977	135976	135977
Industry clusters	49	49	49

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 6: Job-Level Growth in Wage for New Hires and State-Industry Employment Growth

Dependent Variable:	Quarterly Job-Level Growth in Wage for New Hires			
	State by 2 digit Industry		State by 3 digit Industry	
$\Delta \log\left(\text{employment}_{ist}\right)$	-0.00313**	-0.00248*	-0.00276*	-0.00196
	(0.00118)	(0.00122)	(0.00131)	(0.00126)
$\Delta \log\left(\text{employment}_{ist}\right)$	0.0147***	0.0125***	0.0115***	0.00958***
$\times I\left(\Delta \log\left(\text{employment}_{ist}\right) > 0\right)$	(0.00193)	(0.00199)	(0.00193)	(0.00186)
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 7: Job-Level Growth in Wage for New Hires and City Employment Growth

	Quarterly Job-Level Growth in Wage for New Hires					
	Nominal			Real		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log\left(\text{employment}_{mt}\right)$	0.118	0.120	-0.679*	0.172**	0.172**	-0.900*
	(0.0601)	(0.0684)	(0.317)	(0.0620)	(0.0562)	(0.333)
$\Delta \log\left(\text{employment}_{mt}\right)$	0.225**	0.227*	1.098**	0.264***	0.270**	1.484***
$\times I\left(\Delta \log\left(\text{employment}_{mt}\right) > 0\right)$	(0.0708)	(0.0832)	(0.314)	(0.0690)	(0.0762)	(0.335)
Job-Level Difference	Y	Y	Y	Y	Y	Y
Time Effects	Y	Y	Y	Y	Y	Y
City Trend	N	Y	N	N	Y	N
Seasonally Adjusted	N	N	Y	N	N	Y
Number of observations	581862	581862	581862	580713	580713	580713

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 8: Downward Wage Rigidity by Occupation group

Dependent Variable:	Quarterly Job-Level Growth in Wage for New Hires				
Occupation Group:	Management	Services	Sales	Construction	Production
$\Delta U_{st} \times I(\Delta U_{st} < 0)$	-1.177**	-1.410***	-0.983*	-1.043*	-1.552***
	(0.348)	(0.310)	(0.447)	(0.433)	(0.321)
Number of Observations	568307	195274	342738	75637	329647

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 9: First Stage of Quarterly State Unemployment Change on Employment Growth

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

Notes: the dependent variable is the quarterly change in state level unemployment, from the 2010-2016 LAUS, 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.

C Proofs

C.1 Proof of Proposition 1

Summing regression equation (5) over i yields

$$\sum_i v_{ist}\Delta \log w_{ist} = \alpha + \gamma_t + \beta \Delta U_{st} + \delta_{\text{Benchmark}} I\left[\Delta U_{st} < 0\right] \Delta U_{st} + \varepsilon_{st} \tag{22}$$

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

$$\sum_i v_{ist}\Delta \log w_{ist} + \sum_i \log w_{ist}\Delta v_{ist} = \bar{\alpha} + \bar{\gamma}_t + \bar{\beta}\Delta U_{st} + \delta_{\text{Average}} I\left[\Delta U_{st} < 0\right] \Delta U_{st} + \bar{\varepsilon}_{st}. \tag{23}$$

For notational simplicity, we can rewrite equation (22) as

$$y_{st} = \mathbf{x}_{st}^{'}\mathbf{b} + \varepsilon_{st}$$

and equation (23) as

$$y_{st} + u_{st} = \mathbf{x}_{st}^{'}\bar{\mathbf{b}} + \bar{\varepsilon}_{st}$$

where

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

$\mathbf{x}_{st}^{'}\mathbf{b}$ and $\mathbf{x}_{st}^{'}\bar{\mathbf{b}}$ collect the covariates and coefficients in regressions 22) and (23) respectively. The OLS estimator of $\mathbf{b}$, which we term $\hat{\mathbf{b}}$, is

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

The variance of $\hat{\mathbf{b}}$ conditional on $\mathbf{x}_{st}$ is

$$\begin{aligned}
V\left[\hat{\mathbf{b}}|\mathbf{x}_{st}\right] &= V\left[\left(\frac{1}{ST}\sum_{s,t}\mathbf{x}_{st}\mathbf{x}_{st}'\right)^{-1}\left(\frac{1}{ST}\sum_{s,t}\mathbf{x}_{st}y_{st}\right)|\mathbf{x}_{st}\right] \\
&= \left(\frac{1}{ST}\sum_{s,t}\mathbf{x}_{st}\mathbf{x}_{st}'\right)^{-1}\frac{1}{(ST)^2}V\left[\left(\sum_{s,t}\mathbf{x}_{st}y_{st}\right)|\mathbf{x}_{st}\right]\left(\frac{1}{ST}\sum_{s,t}\mathbf{x}_{st}\mathbf{x}_{st}'\right)^{-1}
\end{aligned}$$

Table 10: Regression of Establishment Share in High Wage Occupations on Unemployment

	Quarterly Change in Share of Establishment Vacancies					
	in High Wage Occupations		with High Wages		in High Wage Occupations, by Broad Occupation Group	
ΔU_{st}	0.158	0.922	-0.0296	-0.0031	0.00881	-0.0728
	(0.370)	(0.642)	(0.0358)	(0.0577)	(0.338)	(0.333)
$\Delta U_{st} \times I(\Delta U_{st} < 0)$	0.167	-0.158	0.0537	0.0173	0.509	0.772
	(0.441)	(0.735)	(0.0369)	(.0648)	(0.351)	(0.341)
Establishment Difference	Y	Y	Y	Y	Y	Y
Time Effect	Y	Y	Y	Y	Y	Y
Size Weighted	N	Y	N	Y	N	Y
N	1770257	1770257	1883361	1883361	2388716	2388716
State Clusters	52	52	52	52	52	52

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.

The OLS estimator of $\bar{\mathbf{b}}$, which we term $\hat{\bar{\mathbf{b}}}$, is

$$\hat{\bar{\mathbf{b}}} = \left(\frac{1}{ST}\sum_{s,t}\mathbf{x}_{st}\mathbf{x}_{st}'\right)^{-1}\left(\frac{1}{ST}\sum_{s,t}\mathbf{x}_{st}\left(y_{st}+u_{st}\right)\right).$$

Then the variance of $\hat{\bar{\mathbf{b}}}$ conditional on $\mathbf{x}_{st}$ is

$$V\left[\hat{\bar{\mathbf{b}}}|\mathbf{x}_{st}\right] = V\left[\hat{\mathbf{b}}|\mathbf{x}_{st}\right] + \left(\frac{1}{ST}\sum_{s,t}\mathbf{x}_{st}\mathbf{x}_{st}'\right)^{-1}\frac{1}{(ST)^2}V\left[\sum_{s,t}\mathbf{x}_{st}u_{st}|\mathbf{x}_{st}\right]\left(\frac{1}{ST}\sum_{s,t}\mathbf{x}_{st}\mathbf{x}_{st}'\right)^{-1} \tag{24}$$

The second term in equation (24) is a matrix with strictly positive entries on its leading diagonal for $S,T<\infty$. Hence every entry on the leading diagonal of $V\left[\hat{\bar{\mathbf{b}}}|\mathbf{x}_{st}\right]$ is greater than the corresponding entry on the leading diagonal of $V\left[\hat{\mathbf{b}}|\mathbf{x}_{st}\right]$.

C.2 Proof of Proposition 2

We show that there is a unique subgame perfect equilibrium that satisfies equations (16)-(18).

In a subgame perfect equilibrium, in any history, there is some lowest wage that the firm can offer at its next move, above which the worker will always accept the offer. We term this wage the *worker's reservation wage.* Similarly, we suppose that the *firm's reservation wage* is the highest wage below which a firm will accept any offer by a worker. Let $\underline{w}^w_{t,j+1}$ be the infimum across subgame perfect equilibria of the firm's reservation wage, for each history at $t+j+1$, during which the worker makes an offer. Let $\underline{w}^f_{t,j}$ be the infimum across subgame perfect equilibria of the worker's reservation wage, for each history at $t+j$, during which the firm makes an offer. Then $\underline{w}^f_{t,j}$ and $\underline{w}^w_{t,j+1}$ are the best possible equilibrium bargaining outcomes for the firm in periods $t+j$ and $t+j+1$.

We conjecture a subgame perfect equilibrium at $t+j+1$, in which the worker offers $\underline{w}^w_{t,j+1}$ and the firm accepts. Hence, we can construct a subgame perfect equilibrium at $t+j$ in which, if the firm's offer is rejected, the worker proposes $\underline{w}^w_{t,j+1}$ in the next round of bargaining and the firm accepts. Equation (16) can be solved for $w^f_{t,j}$ and written as $w^f_{t,j} = \Phi_{1,t+j}\left(w^w_{t,j+1}\right)$. For any history at $t+j$, in our constructed equilibrium, the worker will accept any wage $w^f_{t,j} \geq \Phi_{1,t+j}\left(\underline{w}^w_{t,j+1}\right)$, that is, the worker will accept any wage with higher value than their continuation payoff in the subgame starting at $t+j+1$ in our constructed equilibrium. Hence the employer offers the lowest wage that the worker will accept at $t+j$, subject to the downward constraint, so the firm offers a wage $\max\left[\Phi_{1,t+j}\left(\underline{w}^w_{t,j+1}\right), w_{t-1}/g^{j+1}\right]$, which is the worker's reservation wage according to our definition. So, by we must have

$$\underline{w}^f_{t,j} = \max\left[\Phi_{1,t+j}\left(\underline{w}^w_{t,j+1}\right), w_{t-1}/g^{j+1}\right]. \quad (25)$$

In the constructed equilibrium, the firm offers $\underline{w}^f_{t,j}$, the worker accepts any wage greater than $\underline{w}^f_{t,j}$, and rejects any lesser wage.

There is no one-shot deviation for either the firm or worker at time $t+j$. If the firm offers a higher wage than $\underline{w}^f_{t,j}$, the worker still accepts, but the firm receives lower payoff. If the downward constraint does not bind for the firm, and the firm offers a lower wage than $\underline{w}^f_{t,j}$ then the worker rejects. The firm receives $\underline{w}^w_{t,j+1}$ in the next period. Lemma C.5 verifies that this latter option has lower value to the firm. If the downward constraint binds on the firm's wage offer and the worker rejects, the worker receives a lower value in the next period. If the downward constraint does not bind on the firm's wage offer and the worker rejects, the worker receives the same value in the next period.

So, we can construct a perfect equilibrium of a subgame starting at $t+j-1$, in which the aforementioned continuation equilibrium is played whenever the worker's offer is rejected at $t+j-1$. In this constructed equilibrium, the firm's reservation wage at $t+j-1$ must be $\underline{w}^w_{t,j-1}$ as previously defined. For each history at $t+j-1$, equation (18) can be solved for $w^w_{t,j-1}$ and written as $w^w_{t,j-1} = \Phi_{2,t+j-1}\left(w^f_{t,j}\right)$. So, in our constructed equilibrium, at $t+j$ $\underline{w}^w_{t,j-1} \leq \Phi_{2,t+j-1}\left(\underline{w}^f_{t,j}\right)$. That is, the firm's reservation wage at $t+j-1$ cannot be more than the wage for which the firm is indifferent between accepting the offer, or rejecting and making a counter-offer. The worker optimally offers the highest wage that the firm will accept, subject to the downward constraint, so

$$\underline{w}^w_{t,j-1} = \Phi_{2,t+j-1}\left(\underline{w}^f_{t,j}\right) \quad (26)$$

is the firm's reservation wage at $t+j-1$. But given the downward constraint, the worker must offer

$$w^w_{t,j-1} = \max\left[\underline{w}^w_{t,j-1}, w_{t-1}/g^{j+1}\right].$$

Lemma C.4 shows that in the constructed equilibrium, the downward constraint never binds, so

$$w^w_{t,j-1} = \underline{w}^w_{t,j-1}.$$

In the constructed equilibrium, the worker then offers $\underline{w}^w_{t,j-1}$, the firm accepts any wage less than $\underline{w}^w_{t,j-1}$ and rejects any greater wage.

There is no one-shot deviation for either the firm or the worker at time $t+j-1$. If firm rejects when worker offers $\underline{w}^w_{t,j-1}$, they receive a payoff to which they are indifferent in the next period.

If the worker offers a lesser wage than $\underline{w}^{w}_{t,j-1}$, then the firm still accepts and the worker is less well off. If the worker offers a greater wage than $\underline{w}^{w}_{t,j-1}$, the firm rejects and counter-offers $\underline{w}^{f}_{t,j}$ in the next period, which the worker accepts. Lemma C.5 verifies that the worker's continuation payoff is lower than their payoff from offering $\underline{w}^{w}_{t,j-1}$.

So, we have constructed a subgame perfect equilibrium of the bargaining stage that starts at t, given by the sequence of random variables $\left\{\underline{w}^{f}_{t,0}, \underline{w}^{w}_{t,1}, \ldots\right\}$, which satisfies equations (26) and (25), which are equivalent to equations (16)-(18) in the main text.

Now, let $\overline{w}^{w}_{t,j+1}$ be the supremum across subgame perfect equilibria of the firm's reservation wage, for each history at $t+j+1$, during which the worker makes an offer. Let $\overline{w}^{f}_{t,j}$ be the supremum across subgame perfect equilibria of the worker's reservation wage, for each history at $t+j$, during which the firm makes an offer. By analogous logic, we can construct a subgame perfect equilibrium of the bargaining stage that starts at t, given by the sequence of random variables $\left\{\overline{w}^{f}_{t,0}, \overline{w}^{w}_{t,1}, \ldots\right\}$, which also satisfies equations (16) and (18) in the main text.

We will now show that given w_{t-1} and a process for y_t , there exists a unique sequence $\{w^{f}_{t}, w^{w}_{t+1}, \ldots\}$ satisfying equations (16)-(18). Uniqueness implies that $\left\{\underline{w}^{f}_{t,0}, \underline{w}^{w}_{t,1}, \ldots\right\} = \left\{\overline{w}^{f}_{t,0}, \overline{w}^{w}_{t,1}, \ldots\right\}$, and that both sequences exist. The infimum and supremum of the sequence of reservation wages exist and and are equal. So, the subgame perfect equilibrium of the bargaining stage must exist and be unique. Provided that the assumptions in the proposition hold, no other subgame perfect equilibria can exist.

Solving equation (13) forward yields

$$M_t(w_t) = w_t + \beta^w \mathbb{E}_t \left[sU_{t+1} + (1-s) M_{t+1}(w_t)\right]$$

$$\implies M_t(w_t) = \frac{w_t}{1-\beta^w(1-s)} + \left[1-\beta^w(1-s)\mathscr{L}^{-1}\right]^{-1} \beta^w s \mathbb{E}_t U_{t+1} \tag{27}$$

where $\mathscr{L}$ is the lag operator. Substituting equation (27) into equation (16) yields

$$M_{t+j}\left(\tilde{w}^{f}_{t,j}\right) = z + \beta^w \mathbb{E}_{t+j}\left[(1-s) E_{t+j+1}\left(w^{w}_{t,j+1}\right) + sU_{t+j+1}\right]$$

$$\implies \tilde{w}^{f}_{t,j} = \left(1-\beta^w(1-s)\right) z + \beta^w (1-s)\mathbb{E}_{t+j}\, w^{w}_{t,j+1}. \tag{28}$$

From equation (11) we have

$$J_t(w_t) = y_t - w_t + \beta^f (1-s)\mathbb{E}_t J_{t+1}(w_t)$$

$$\implies J_t(w_t) = \left[1-\beta^f(1-s)\mathscr{L}^{-1}\right]^{-1} y_t - \frac{w_t}{1-\beta^f(1-s)}. \tag{29}$$

Then substituting equation (29) into equation (18) yields

$$\left[1-\beta^f(1-s)\mathscr{L}^{-1}\right]^{-1} y_{t+j} - \frac{w^w_{t,j}}{1-\beta^f(1-s)} = -\gamma + \beta^f(1-s)\mathbb{E}_{t+j}\left[\left[1-\beta^f(1-s)\mathscr{L}^{-1}\right]^{-1} y_{t+j+1} - \frac{w^f_{t,j+1}}{1-\beta^f(1-s)}\right]$$

$$\implies w^w_{t,j+1} = \left(1-\beta^f(1-s)\right) y_{t+j+1} + \gamma\left(1-\beta^f(1-s)\right) + \beta^f(1-s)\mathbb{E}_{t+j+1}\left[w^f_{t,j+2}\right]. \tag{30}$$

Substituting equations (17), (30) and (28) together yields

$$\begin{aligned} w^f_{t,j} &= \max\left[\left(1-\beta^w(1-s)\right)z + \beta^w(1-s)\mathbb{E}_{t+j}\, w^w_{t,j+1}, w_{t-1}/g^{j+1}\right] \\ &= \max\left[\left(1-\tilde{\beta}^w\right)z + \left(1-\tilde{\beta}^f\right)\tilde{\beta}^w\left(\rho y_{t+j} + (1-\rho)\bar{y}\right) + \tilde{\beta}^w\left(1-\tilde{\beta}^f\right)\gamma + \tilde{\beta}^f\tilde{\beta}^w\,\mathbb{E}_{t+j}\, w^f_{t,j+2}, w_{t-1}/g^{j+1}\right]. \end{aligned} \tag{31}$$

Since $w^f_{t,j}$ is bounded and y_{t+j} is Markovian, the unique solution to equation (31) is a function $w^f(y_{t+j}, w_{t-1}/g^{j+1})$ and wage $w^f_{t,j} = w^f(y_{t+j}, w_{t-1}/g^{j+1})$, where $w^f(y_{t+j}, w_{t-1}/g^{j+1})$ is defined by the functional equation

$$w^f(y_{t+j}, w_{t-1}/g^{j+1}) = \max\left[\left(1-\tilde{\beta}^w\right)z + \left(1-\tilde{\beta}^f\right)\tilde{\beta}^w\left(\rho y_{t+j} + (1-\rho)\bar{y}\right) + \tilde{\beta}^w\left(1-\tilde{\beta}^f\right)\gamma + \tilde{\beta}^f\tilde{\beta}^w\,\mathbb{E}\left[w^f(y_{t+j+2}, w_{t-1}/g^{j+3})|y_{t+j}\right], w_{t-1}/g^{j+1}\right]. \tag{32}$$

Equation (32) implies a contraction, so $w^f\left(y_{t+j}, w_{t-1}/g^{j+1}\right)$ exists and is unique. Finally, we show uniqueness of the equilibrium of the economy. We can solve forward equation (11) to yield

$$\begin{aligned} J_t &= \mathbb{E}_t \sum_{j=0}^{\infty} \tilde{\beta}^j\left(y_{t+j} - w_t\right) \\ &= \frac{y_t - \bar{y}}{1-\rho\tilde{\beta}} + \frac{\bar{y} - w(y_t, w_{t-1})}{1-\tilde{\beta}}. \end{aligned}$$

Solving equation (12) when $K_t = 0$ yields

$$J_t = \frac{c}{q(\theta_t)}.$$

Thus

$$\frac{y_t - \bar{y}}{1-\rho\tilde{\beta}} + \frac{\bar{y} - w(y_t, w_{t-1})}{1-\tilde{\beta}} = \frac{c}{q(\theta_t)}, \tag{33}$$

and θ_t is uniquely determined by y_t, w_{t-1} when $K_t = 0$. Finally, for values of y_t, w_{t-1} such that there is no admissible solution for θ_t in equation (33), then constraint (15) must bind and $V_t = 0$. Thus the equilibrium of the economy is unique.

C.3 Proof of Proposition 3

When $g \to \infty$ we have

$$
\begin{aligned}
w_t^{frictionless} &= \left(1-\tilde{\beta}^w\right) z + \left(1-\tilde{\beta}^f\right) \tilde{\beta}^w \left(\rho y_t + (1-\rho)\,\bar{y}\right) + \tilde{\beta}^w \left(1-\tilde{\beta}^f\right) \gamma + \tilde{\beta}^f \tilde{\beta}^w \mathbb{E}_t \left[w_{t+2}^{frictionless} \right] \\
&= \frac{\left(1-\tilde{\beta}^w\right) z + \left(1-\tilde{\beta}^f\right) \tilde{\beta}^w \bar{y} + \tilde{\beta}^w \left(1-\tilde{\beta}^f\right) \gamma}{1-\tilde{\beta}^f \tilde{\beta}^w} + \frac{\left(1-\tilde{\beta}^f\right) \tilde{\beta}^w \rho}{1-\tilde{\beta}^f \tilde{\beta}^w \rho^2} \left(y_t - \bar{y}\right).
\end{aligned}
$$

C.4 Lemma

This lemma establishes that

$$\underline{w}^w_{t,j-1} \geq w_{t-1}/g^{j+1}$$

and so

$$w^w_{t,j-1} = \underline{w}^w_{t,j-1}.$$

It is sufficient to show $\underline{w}^w_{t,j-1} \geq w_{t-1}/g$. From equation (30) we have

$$
\begin{aligned}
\Phi_{2,t+j-1}(\underline{w}^f_{t,j}) &= \left(1-\beta^f(1-s)\right) y_{t+j-1} + \gamma \left(1-\beta^f(1-s)\right) + \beta^f(1-s)\,\mathbb{E}_{t+j-1}\, \underline{w}^f_{t,j} \\
&= \left(1-\beta^f(1-s)\right) y_{t+j-1} + \gamma \left(1-\beta^f(1-s)\right) + \beta^f(1-s)\,\mathbb{E}_{t+j-1} \max\left[\Phi_{1,t+j}\left(\underline{w}^w_{t,j+1}\right), w_{t-1}/g\right] \\
&\geq \left(1-\beta^f(1-s)\right) y_{t+j-1} + \gamma \left(1-\beta^f(1-s)\right) + \beta^f(1-s)\, w_{t-1}/g
\end{aligned}
$$

where the second line substitutes in equation (25). So a sufficient condition is

$$
\begin{aligned}
&\left(1-\beta^f(1-s)\right) y_{t+j-1} + \gamma \left(1-\beta^f(1-s)\right) + \beta^f(1-s)\, w_{t-1}/g \geq w_{t-1}/g \\
\iff &\left[1-\beta^f(1-s)\right] w_{t-1}/g \leq \left(1-\beta^f(1-s)\right) y_{t+j-1} + \gamma \left(1-\beta^f(1-s)\right) \\
\iff &w_{t-1}/g \leq y_{t+j-1} + \gamma
\end{aligned}
$$

which is the assumption at the start of Proposition (2).

C.5 Lemma

In the first part, we establish that the value to the firm of $\underline{w}^f_{t,j}$ is higher than the value to the firm of $\underline{w}^w_{t,j+1}$. Recall that the downward constraint cannot bind. Otherwise the firm would not be able to make the lower wage offer and be rejected. So we have

$$\underline{w}^f_{t,j} = \Phi_{1,t+j}\left(\underline{w}^w_{t,j+1}\right).$$

The wage at which the firm is indifferent between $\underline{w}^{w}_{t,j+1}$ and receiving a wage today is $\Phi_{2,t+j}(\underline{w}^{w}_{t,j+1})$. It suffices to show that $\Phi_{1,t+j}\left(\underline{w}^{w}_{t,j+1}\right) \leq \Phi_{2,t+j}(\underline{w}^{w}_{t,j+1})$. That is, $\underline{w}^{f}_{t,j}$ is lower than the firm's value from rejecting and receiving $\underline{w}^{w}_{t,j+1}$ tomorrow.

From equations (28) and (30) we have

$$\Phi_{2,t+j}\left(\underline{w}^{f}_{t,j+1}\right) = \left(1-\beta^{f}(1-s)\right) y_{t+j} + \gamma\left(1-\beta^{f}(1-s)\right) + \beta^{f}(1-s)\,\mathbb{E}_{t+j}\,\underline{w}^{f}_{t,j+1}$$

$$\Phi_{1,t+1}\left(\underline{w}^{f}_{t,j+1}\right) = \left(1-\beta^{w}(1-s)\right) z + \beta^{w}(1-s)\,\mathbb{E}_{t+j}\,\underline{w}^{f}_{t,j+1}.$$

So, we require

$$\left(1-\beta^{f}(1-s)\right) y_{t+j} + \gamma\left(1-\beta^{f}(1-s)\right) + \beta^{f}(1-s)\,\mathbb{E}_{t+j}\,\underline{w}^{f}_{t,j+1}$$

$$\geq \left(1-\beta^{w}(1-s)\right) z + \beta^{w}(1-s)\,\mathbb{E}_{t+j}\,\underline{w}^{f}_{t,j+1}.$$

Since $\beta^{w} \leq \beta^{f}$ a sufficient condition is

$$\left(1-\tilde{\beta}^{f}\right)\left(y_{t+j}+\gamma\right) \geq \left(1-\tilde{\beta}^{w}\right) z,$$

which is the assumption at the start of proposition (2).

In the second part of the lemma, we establish that the value to the worker of $\underline{w}^{w}_{t,j-1}$ is greater than the value of $\underline{w}^{f}_{t,j}$. We have

$$\underline{w}^{w}_{t,j-1} = \Phi_{2,t+j-1}\left(\underline{w}^{f}_{t,j}\right),$$

so by identical logic to the first part of the lemma, it suffices to show $\Phi_{1,t+j}\left(\underline{w}^{w}_{t,j+1}\right) \leq \Phi_{2,t+j}(\underline{w}^{w}_{t,j+1})$.

D Additional Empirics

D.1 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 wage faced by the establishment might fall during contractions, and partially offset the effect of downward wage rigidity.

This concern supposes that establishments can easily substitute between high and low wage workers. In practice, low and high wage jobs might be very different, preventing such substitution.

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.

Appendix Table (10) 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.

D.2 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 11 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 cyclicality.

Table 11: Wage Cyclicality in Occupations with High vs. Low Share Posting Wage Ranges

Dependent Variable:	Log Wage, CPS, Newly Hired Workers
Independent Variables:	
Quarterly Unemployment	-1.019
	(1.11)
Quarterly Unemployment ×	1.120
High Share Posting Wage Ranges	(0.82)
Annual Unemployment	-1.131
	(1.19)
Annual Unemployment ×	1.174
High Share Posting Wage Ranges	(0.83)
Time Effect	Y
State Effect	Y
Number of Observations	67327

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.

D.3 Wage Flexibility Upward Over Time

We estimate the regression

$$\Delta \log w_{jst} = \alpha_y + \gamma_t + \beta_y \Delta U_{st} + \varepsilon_{jst}, \tag{34}$$

for $y \in \{2010, \ldots, 2016\}$, and again restrict the sample to observations where $\Delta U_{st} < 0$. That is, we estimate the regression for every year y. β_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 β_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.

Table 12: Regression of Wage Growth on State Unemployment Declines

Dependent Variable:	Job-Level Growth in Wage for New Hires			Establishment-Level Growth in Wage for New Hires
	(1)	(2)	(3)	(4)
Independent Variables:				
ΔU_{st}	-0.208	-0.219	-0.362*	0.0261
	(0.167)	(0.180)	(0.156)	(0.493)
$\Delta U_{st} \times I(\text{Year} = 2011)$	-0.0330	0.0305	0.0416	-0.691
	(0.240)	(0.218)	(0.209)	(0.786)
$\Delta U_{st} \times I(\text{Year} = 2012)$	-0.462*	-0.379	-0.312	-0.850
	(0.221)	(0.238)	(0.230)	(0.720)
$\Delta U_{st} \times I(\text{Year} = 2013)$	-0.415	-0.360	-0.278	-0.964
	(0.244)	(0.232)	(0.216)	(0.506)
$\Delta U_{st} \times I(\text{Year} = 2014)$	-0.451*	-0.406*	-0.314	-1.045
	(0.193)	(0.185)	(0.174)	(0.540)
$\Delta U_{st} \times I(\text{Year} = 2015)$	-1.014***	-0.935***	-0.812***	-1.216*
	(0.184)	(0.190)	(0.173)	(0.516)
$\Delta U_{st} \times I(\text{Year} = 2016)$	-1.746***	-1.664***	-1.524***	-1.253*
	(0.176)	(0.184)	(0.174)	(0.474)
Time Effects	Y	Y	Y	Y
State Effects	N	Y	N	N
State × Quarter-of-Year Effects	N	N	Y	N
Number of Observations	1090035	1089914	1090035	1279369
State Clusters	52	52	52	52

Notes: we estimate the regression

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

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.

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.

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

$$y_t = (1-\rho) + \rho y_{t-1} + \varepsilon_t \quad \varepsilon_t \sim N(0,\sigma^2). \tag{35}$$

y_t is a measure of labor demand.[55] There is a unit measure of homogeneous workers, who are either employed and producing output y_t, 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.

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

$$w_{Ht} = \max\left[w_{H,t-1}, \phi_H y_t^{\gamma}\right] \tag{36}$$

[55] 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.

$$w_{Lt} = \max\left[w_{L,t-1}, \phi_L y_t^{\gamma}\right] \tag{37}$$

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 ϕ_i and γ.

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 ω 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 $t-1$.[56] 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

$$u_{it} = \frac{1}{2} - (1-\omega)(1-s)\, l_{i,t-1}, \tag{38}$$

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 $n_{it} = M(u_{it}, v_{it}) = \Psi u_{it}^{\alpha} v_{it}^{1-\alpha}, \alpha \in (0,1)$.The key state variable governing each labor market is labor market tightness

$$\theta_{it} \equiv v_{it}/u_{it}. \tag{39}$$

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 $q(\theta_{it}) = \Psi\theta_{it}^{-\alpha}$. The vacancy filling rate is decreasing in θ_{it}—in a tight labor market, firms cannot

[56]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 θ_{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

$$l_{it} = \frac{1}{2} - \left(1 - f(\theta_{it})\right)\left(\frac{1}{2} - (1-\omega)(1-s)\, l_{i,t-1}\right). \tag{40}$$

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

$$K_{it} = -c + q(\theta_{it}) J_{it,t} + \beta\left(1 - q(\theta_{it})\right)\mathbb{E}_t K_{i,t+1}. \tag{41}$$

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

$$J_{i,t,t+j} = y_{t+j} - w_{it} + \beta\left[(1-s)(1-\omega)\mathbb{E}_{t+j} J_{i,t,t+j+1} + [1-(1-s)(1-\omega)]\mathbb{E}_{t+j} K_{i,t+j+1}\right] \tag{42}$$

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

$$K_{it} \geq 0 \quad v_{it} \geq 0 \tag{43}$$

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 (38), the definition of labor market tightness

(39), wage setting equations (36) and (37), the Bellman equations for the value of an unfilled vacancy (41) and the value of a filled vacancy (42), and the free entry condition (43). The equilibrium is conditional on initial employment $l_{i,-1}$ for each job type and the AR(1) process (35) for y_t.

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

$$\frac{\Delta \log u_t}{\Delta \log y_t} = -A + B \frac{\overbrace{\mu \Delta \log w_{Ht} + (1-\mu) \Delta \log w_{Lt}}^{\textit{average job-level wage growth}}}{\Delta \log y_t} \tag{44}$$

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 μ.

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

The left hand side of equation (44) 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 (36) and (37). A and B capture other time-invariant factors affecting the sensitivity of unemployment to shocks.

Equation (44) 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

$$\Delta [\nu_{Ht} w_{Ht} + (1-\nu_{Ht}) w_{Lt}] \approx [\nu_{Ht} \Delta w_{Ht} + (1-\nu_{Ht}) \Delta w_{Lt}] + (w_{Ht} - w_{Lt}) \Delta \nu_{Ht}. \tag{45}$$

The term in the square brackets on the right hand side of equation (45) represents job level wage changes, and affects unemployment fluctuations by equation (44). The second term represents changes in average wages due to shifting composition between high and low wage jobs, as represented by the $\Delta\nu_{Ht}$ term. $\Delta\nu_{Ht}$ does not enter the right hand side of equation (44). 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 $\mu\Delta\log w_{Ht} + \left(1-\mu\right)\Delta\log w_{Lt}$ pins down unemployment fluctuations.

F Model Extensions

This section presents three extensions of our baseline model. The first model includes positive trend inflation and idiosyncratic labor demand shocks. The second model features nominal wage rigidity and a Phillips Curve in goods markets. The third model features directed search and wage posting. The conclusions from all three models are similar to our main results.

F.1 Model with Trend Inflation and Idiosyncratic Shocks

In this section, we introduce two features missing from our baseline model. Neither alter our quantitative conclusions. First, we allow for multiple job types, with idiosyncratic labor demand shocks for each type of job. Second, we allow for positive trend inflation.

F.1.1 Model Setup

Time is discrete and infinite. There is a unit measure of job types $i \in [0,1]$. Output per worker for a job type, y_{it}, is the sum of two exogenous AR(1) processes, which stand for idiosyncratic and aggregate labor demand.

So, output per worker is

$$y_{it} = 1 + x_t + z_{it} \tag{46}$$

$$z_{it} = \rho_z z_{i,t-1} + \varepsilon_{zt} \quad \varepsilon_{zt} \sim N(0,\sigma_z^2)$$

$$x_t = \rho_x x_{t-1} + \varepsilon_{xt} \quad \varepsilon_{xt} \sim N(0,\sigma_x^2).$$

As in the main text, y_t is a measure of labor demand. There is a unit measure of homogeneous workers, who are either employed and producing output y_t, 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.

Wage Setting: Downward Rigidity and Job Types. Workers search for employment in a job type i 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 hires in job type i satisfies

$$P_t w_{it} = \max[\overbrace{P_t w^*_{it}}^{\substack{\text{frictionless}\\ \text{nominal}\\ \text{wage}}}, \underbrace{P_{t-1} w_{i,t-1}}_{\substack{\text{prior nominal}\\ \text{wage}}}] \tag{47}$$

$$w^*_{it} = b + \phi_x x_t + \phi_z z_{it}$$

This specification of wage setting has three implications. First, wages are set differently for each type of job. Second, we allow the pass through of idiosyncratic and aggregate labor demand shocks, x_t and z_{it}, into wages, differ according to the value of the coefficients ϕ_x and ϕ_z. Third, there is downward wage rigidity in *nominal* wages. Current nominal wages $P_t w_{it}$ cannot fall below their previous nominal value $P_{t-1} w_{i,t-1}$. However, if the nominal constraint does not bind, real wages are at their frictionless value w^*_{it}. Wages are free to rise in response to positive shocks, provided that the downward constraint does not bind. We can usefully rearrange equation (47) as

$$w_{it} = \max\left[w^*_{it}, \frac{w_{i,t-1}}{\Pi_t}\right],$$

where $\Pi_t \equiv P_t / P_{t-1}$. So, the downward constraint on nominal wages will matter less for real wages if gross inflation Π_t is high. Inflation "greases the wheels" of the labor market.

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 ω 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 $t-1$. Worker's search is not directed across higher or lower wage jobs—consistent with our empirical results[57]. 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

$$u_{it} = 1 - (1-\omega)(1-s)\, l_{i,t-1}, \tag{48}$$

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 $(1-\omega)(1-s)\, l_{i,t-1}$ workers remain employed from the previous period. Aggregate unemployment is $u_t = \int_0^1 u_{it} di$.

[57]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.

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 $n_{it} = M(u_{it}, v_{it}) = \Psi u_{it}^{\alpha} v_{it}^{1-\alpha}, \alpha \in (0,1)$.The key state variable governing each labor market is labor market tightness

$$\theta_{it} \equiv v_{it}/u_{it}. \tag{49}$$

The per-period cost of posting vacancies is $c > 0$.

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 $y_{i,t+j}$, and pays job-type-specific wage w_{it} to the worker. The firm receives flow profit $y_{i,t+j} - w_{it}$.

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

$$K_{it} = -c + q(\theta_{it}) J_{it,t} + \beta \left(1 - q(\theta_{it})\right) \mathbb{E}_t K_{i,t+1}. \tag{50}$$

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

$$J_{i,t,t+j} = y_{t+j} - w_{it} + \beta \left[(1-s)(1-\omega) \mathbb{E}_{t+j} J_{i,t,t+j+1} + [1-(1-s)(1-\omega)] \mathbb{E}_{t+j} K_{i,t+j+1} \right] \tag{51}$$

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

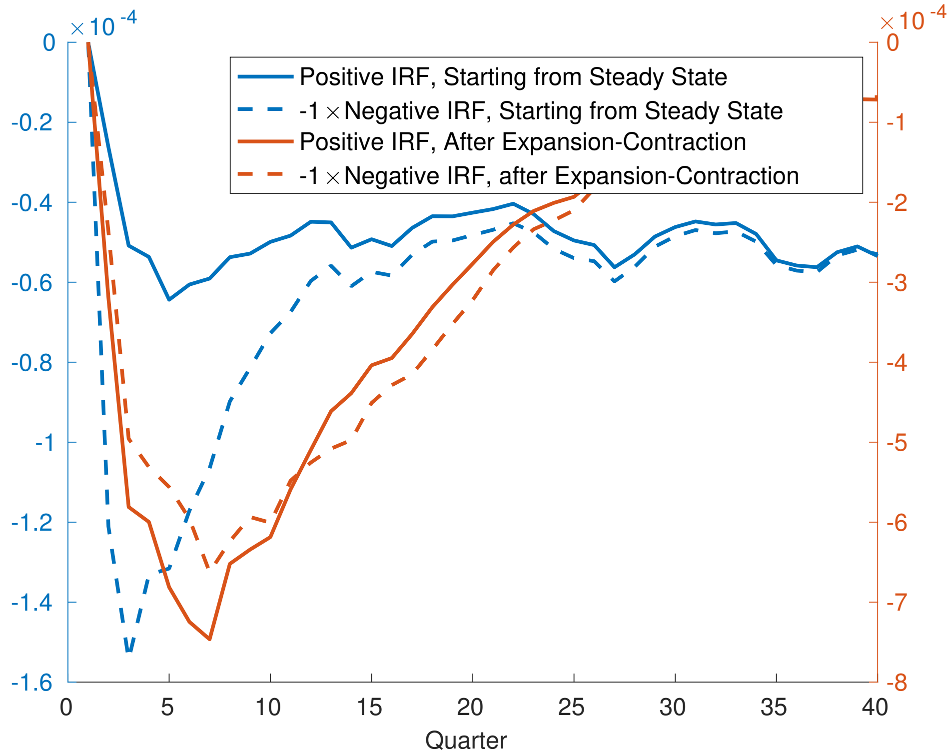
Free Entry and Equilibrium. There is free entry in vacancy posting. Vacancy posting continues until the labor market becomes tight. Then vacancies are hard to fill, driving the ex ante value of vacancies to zero. Free entry implies

$$K_{it} \geq 0 \quad v_{it} \geq 0 \tag{52}$$

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 $i \in [0,1]$, that satisfy the law of motion for unemployment (48), the definition of labor market tightness (49), wage setting equation (47), the Bellman equations for the value of an unfilled vacancy (50) and the value of a filled vacancy (51), and the free entry condition (52). The equilibrium is conditional on initial employment $l_{i,-1}$ for each job type and the AR(1) process (46) for y_{it}.

Figure 8: 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.1.2 Calibration

We set Π_t to a constant value, equivalent to 2% net inflation at annual frequency. We choose ρ_z and σ_z according to the estimates of Schaal (2017), Table 1. We choose b to target mean unemployment and ϕ to minimize the distance between regression coefficients in the model and the data. We choose ϕ_z to target the probability of wage increase, estimated in section 3. We set the number of jobs equal to 1000. All other calibrated parameters are the same as the model in the main text, and our estimation strategy is otherwise the same as in the main text.

F.1.3 Model Results

We simply conduct the same exercise as in Figure 10 of the main text, which reports the degree state dependence in the asymmetry of unemployment impulse responses. Figure 8 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.

F.2 Model with Nominal Wage Rigidity and Phillips Curve in Goods Markets

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

F.2.1 Model Setup

We augment the model with sticky prices, similarly to Gertler, Sala, and Trigari (2008), Blanchard and Gali (2010) and Christiano, Eichenbaum, and Trabandt (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_t^h/P_t. P_t is the price level of final goods. P_t^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

$$P_t w_t = \max[\overbrace{P_t w_t^*}^{\substack{\text{frictionless}\\ \text{nominal}\\ \text{wage}}}, (1-\xi)\underbrace{P_{t-1} w_{t-1}}_{\substack{\text{prior nominal}\\ \text{wage}}}]$$

where w_t is the current real wage, and P_t is the current price level. The frictionless real wage is

$$w_t^* = b + \phi\left(\frac{AP_t^h}{P_t}\right).$$

Thus ϕ parameterizes the pass through of real value added per worker into the wage for new hires. This wage setting rule is simpler than the bargaining game in the main text.

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

$$\pi_t = \tilde{\beta}\mathbb{E}_t\pi_{t+1} + \kappa\left(\hat{p}_t^h - \hat{p}_t\right),$$

where π_t is inflation, $\tilde{\beta}$ is the discount factor of price setting firms, and κ is the sensitivity of inflation to log real marginal costs. $\left(\hat{p}_t^h - \hat{p}_t\right)$ is the deviation of price setting firms' log real marginal costs from the steady state value.

For labor demand, we assume that changes in real value added per worker follows an AR(1) process, that is

$$D_t = \rho D_{t-1} + \left(1-\rho\right)\bar{D} + \varepsilon_t \quad \varepsilon_t \sim N(0, \sigma_\varepsilon^2)$$

where $D_t \equiv AP_t^h/P_t$ and $\bar{D}$ is the mean value. Thus in this model, ε_t captures shocks to labor demand, such as monetary or fiscal shocks.

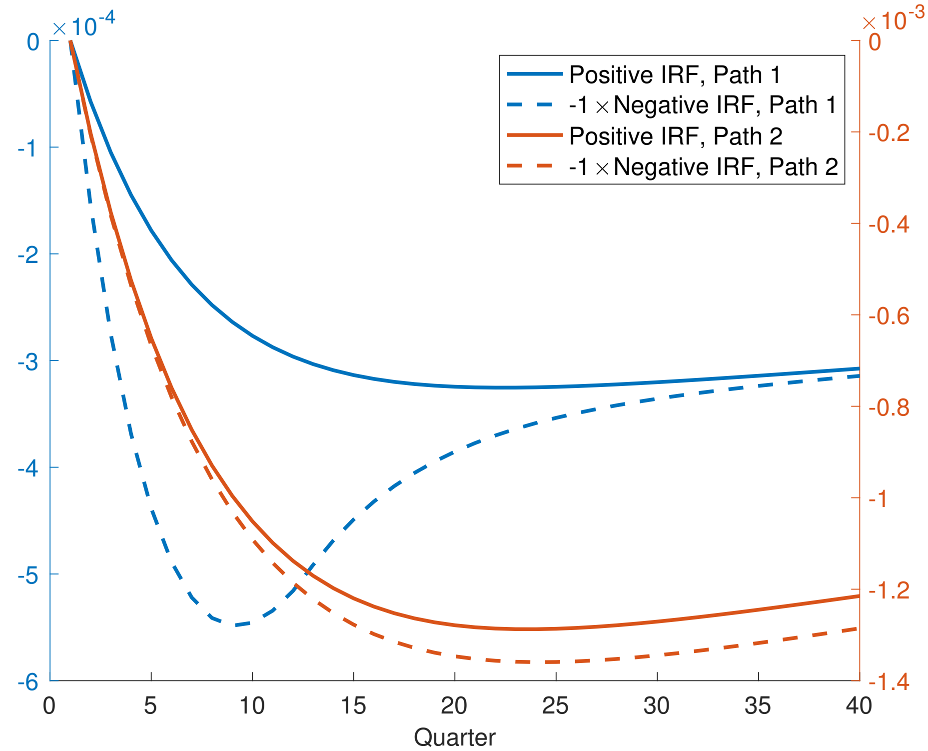
The equilibrium is a sequence$\left\{v_t, u_t, w_t, P_t^h, \pi_t\right\}_{t=0}^\infty$ given nominal demand shocks $\{\varepsilon_t\}_{t=0}^\infty$, such that hiring firms maximize profits, there is free entry in vacancy creation, there is downward nominal wage rigidity, and price setting firms maximize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

F.2.2 Calibration

We calibrate κ and $\tilde{\beta}$ using the median specifications in Table 5 of Mavroeidis, Plagborg-Møller, and Stock (2014), for the labor share specifications. We choose b to target mean unemployment and ϕ to minimize the distance between regression coefficients in the model and the data. All other calibrated parameters are the same as the model in the main text, and our estimation strategy is otherwise the same as in the main text.

Figure 9: 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.2.3 Model Results

We simply conduct the same exercise as in Figure 10 of the main text, which reports the degree state dependence in the asymmetry of unemployment impulse responses. Figure 9 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.

F.3 Model with Wage Posting and Directed Search

In this subsection we develop a model with wage posting and directed search in the spirit of Moen (1997). We derive an equivalence result between the model in this subsection and the model in the main text. So, our conclusions about the effect of downward rigidity on unemployment fluctuations, from the main text, apply equally to a model with wage posting and directed search.

F.3.1 Environment and Equilibrium

We modify the model from the main text to allow for directed search and wage posting. There are M distinct employment submarkets, denoted $i = 1, ..., M$. Every submarket has the same output per worker y_t, the same matching technology, and the same exogenous rate of job separation s. Output per worker y_t follows an exogenous AR(1) process with mean value 1, that is

$$y_t = (1-\rho) + \rho y_{t-1} + \varepsilon_t \quad \varepsilon_t \sim N(0, \sigma^2). \tag{53}$$

There is a unit measure of homogeneous workers, who are either employed and producing output y_t, 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 have flow utility z from unemployment.

F.3.2 Wage Setting

Workers search for employment in each submarket. In each submarket, risk neutral firms post vacancies to match with workers. When a worker and firm match at time t, wages are set. w_{it}^{posted} is the real wage for a worker newly matched in submarket $i$and wages are fixed for the duration of the match. We assume that firms post wages according to the function

$$w_{it}^{\text{posted}} = w(y_t, \theta_{it}, w_{i,t-1}^{\text{posted}}). \tag{54}$$

We do not take a stand on the precise mechanism that governs firms' wage posting decision—it will not matter for our equivalence result. However, equation (54) nests a wide range of plausible mechanisms. In particular, we allow for downward rigidity in posted wages. Equation (54) accommodates the possibility that posted wages can rise with labor demand y_t, but cannot fall below their wage in the previous period $w_{i,t-1}^{\text{posted}}$.

F.3.3 Frictional Labor Market

Each submarket involves a frictional matching technology. In each submarket there is a pair $\left\{w_{it}^{\text{posted}}, \theta_{it}\right\}$, which is the posted wage and the vacancy-unemployment ratio in the submarket. There is a large measure of firms in each submarket, who post vacancies and wages. There is a cost c per vacancy posted, and free entry in vacancy posting. The probability that a vacancy in submarket i is filled is $q(\theta_{it}) \leq 1$, which is decreasing in θ_{it}.

Workers are either employed in a submarket or unemployed and searching for work. Unemployed workers direct their search. They observe $\left\{w_{it}^{\text{posted}}, \theta_{it}\right\}_{i=1,\ldots,M}$ in each submarket, and then search in the submarket that yields the highest expected value. The total number of unemployed workers searching for work in each period is u_t.

F.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 $y_{i,t+j}$, and pays submarket-specific wage w_{it}^{posted} to the worker. The firm receives flow profit $y_{i,t+j} - w_{it}^{\text{posted}}$.

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

$$K_{it} = -c + q(\theta_{it}) J_{it,t} + \beta \left(1 - q(\theta_{it})\right) \mathbb{E}_t K_{i,t+1}. \tag{55}$$

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

$$J_{i,t,t+j} = y_{t+j} - w_{it}^{\text{posted}} + \beta \left[(1-s)(1-\omega) \mathbb{E}_{t+j} J_{i,t,t+j+1} + [1 - (1-s)(1-\omega)] \mathbb{E}_{t+j} K_{i,t+j+1} \right] \tag{56}$$

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

F.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

$$K_{it} \geq 0 \quad v_{it} \geq 0 \tag{57}$$

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

A symmetric equilibrium is a collection of stochastic processes $\left\{\theta_{it}, w_{it}^{\text{posted}}\right\}_{t=0}^{\infty}$ for $i = \{1, ..., M\}$, that satisfy the wage posting function (54), the Bellman equations for the value of an unfilled vacancy (55) and the value of a filled vacancy (56), and the free entry condition (57). Workers direct their search by applying to the submarket that yields the highest expected value. The equilibrium is conditional on initial wages $w_{i,-1}^{\text{posted}}$ for each submarket and the AR(1) process (53) for y_{it}. In the symmetric equilibrium, θ_{it} and w_{it}^{posted} are the same for all i.

F.3.6 Equilibrium Characterization and Equivalence Result

We now characterize the equilibrium of the economy with wage posting and directed search, and show its equivalence to the economy in the main text.

By substituting and rearranging equations (56), (55) and (57), we arrive at the expression in the symmetric equilibrium of

$$\frac{y_t - \bar{y}}{1 - \rho\tilde{\beta}} + \frac{\bar{y} - w^{\text{posted}}(y_t, \theta_t, w_{t-1}^{\text{posted}})}{1 - \tilde{\beta}} = \frac{c}{q(\theta_t)} \tag{58}$$

where we drop the subscript i given symmetry. Equation (33) characterizes the equilibrium of the model in the main text. For convenience, we repeat that equation below, it is

$$\frac{y_t - \bar{y}}{1 - \rho\tilde{\beta}} + \frac{\bar{y} - w(y_t, w_{t-1})}{1 - \tilde{\beta}} = \frac{c}{q(\theta_t)}. \tag{59}$$

Using equations (58) and (59), we can state our equivalence result.

Proposition *(Equivalence). The allocations in the model in the main text coincide with the allocations in the model with wage posting and directed search if for all y_t and w_{t-1}, we have in equilibrium $w_t^{posted}(y_t, \theta_t, w_{t-1}) = w(y_t, w_{t-1})$.*

Equations (58) and (59) show that if the wage is the same in the model in the main text, and the model with wage posting, then market tightness will also be the same. Then, all allocations will be the same in both economies. So, for a given sequence of wages, that is the same in both economies, unemployment will be the same in both economies as well. So, our conclusions about the effect of downward wage rigidity on unemployment fluctuations, using the model of the main text, will apply equally to a model with wage posting and directed search. If the economy with posting and directed search generates similar wage behavior to the economy with bargained wages, unemployment will be similar in both economies.

G Time Series Evidence on State Dependent Asymmetry

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

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

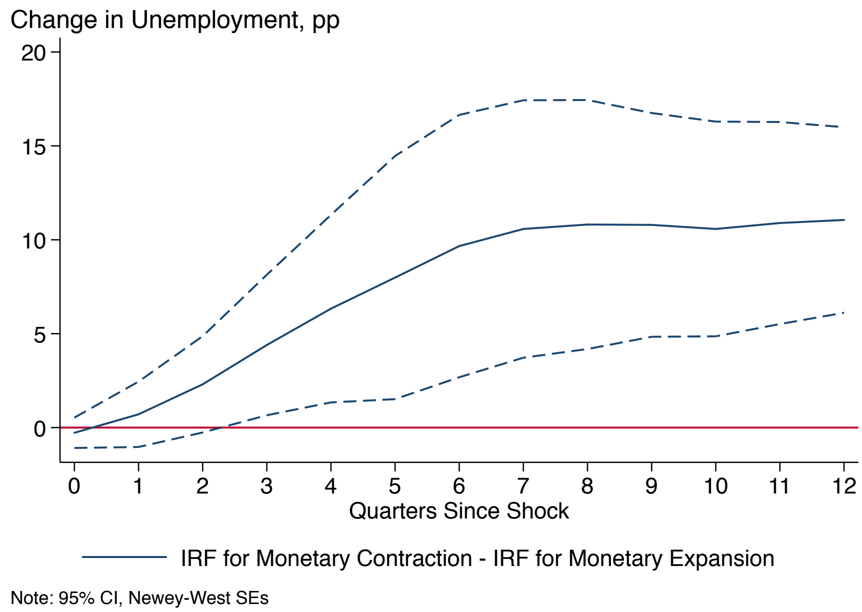
where U_t is quarterly national unemployment for 969-2007; and ε_t is a monetary shock as in Romer and Romer (2004), extended to 2007 by Wieland and Yang (2016).

Then β_h is the IRF of unemployment to MP shock γ_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 $\text{employment}_t < \max\left\{\text{employment}_j\right\}_{j=1969,Q1}^{t}$, 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 10: Estimated Impulse Responses

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



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