Posted Wage Rigidity

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Abstract

This paper documents three new facts about posted wage rigidity, using a comprehensive and newly available dataset from the United States. First, posted wages change infrequently. Wages for the typical job remain unchanged for 20 quarters. Second, posted wages are especially unlikely to fall for a given job, implying downwards rigidity in the posted wage. Third, posted wages are nearly acyclical for the typical job. We derive sufficient statistics in a class of labour search models, and calibrate them with our estimates. In the calibrated model, the estimated wage rigidity generates large fluctuations in unemployment over the business cycle. In future work, we plan to introduce similar datasets for the Euro Area, to apply our methods to Euro Area wage setting.

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1 Introduction

Why does unemployment rise during recessions? A leading hypothesis is wage rigidity. At the onset of the typical recession, in both the US and within the Euro Area, hiring falls sharply. Unemployment subsequently rises. A leading explanation (Hall, 2005; Hall and Milgrom, 2008; Hagedorn and Manovskii, 2008; Gertler and Trigari, 2009) for hiring fluctuations is rigidity in the wage for new hires, so that wages vary little with the business cycle. The cost of hiring then remains high during recessions, even as labour demand falls. Firms respond by hiring fewer workers, leading to a rise in unemployment. According to this theory, the relevant quantity is the wage for new hires, because it measures the marginal cost of adding a new worker. The wage for incumbent workers, who have already been hired, is less important. In New Keynesian models of the business cycle (Christiano et al., 2005; Smets and Wouters, 2003, 2007), wage rigidity also plays an important role in amplifying unemployment fluctuations.

Despite its importance in theory, we understand little about the *empirical* behaviour of the wage for new hires[1]. This paper takes up the challenge of measuring the wage for new hires, and traces out the implications for unemployment fluctuations. We present three new facts, which suggest substantial wage rigidity. We then map the estimated rigidity to a model, and show that it rationalises large fluctuations in unemployment over the business cycle.

We start by introducing a new and comprehensive dataset of posted wages. We use a proprietary dataset of online job vacancy postings, provided by Burning Glass Technologies, a labour market analytics firm. The dataset has numerous advantages compared with existing survey or administrative datasets. The data contains posted salaries, with both posted hours worked and bonus or over time pay where applicable. By contrast, administrative data often does not record hours worked, and survey data tends to have noisy measures of both pay and hours—hampering measurement of the cost of labour. The posted wage dataset is larger than existing surveys, covering roughly 10% of vacancies posted either online or offline in the United States since 2010. We observe the job title and establishment[2] of the job posting. We can then study multiple wage postings for the same job, allowing us to observe the rigidity of wages at the job level.

We present three new stylised facts. First, posted wages change infrequently. Wages for the typical job remain unchanged for 20 quarters. Second, posted wages are especially unlikely to fall within a given job, implying downwards rigidity in the posted wage. Third, posted wages are nearly acyclical for the typical job. Overall, these three new facts suggest substantial rigidity in the wage for new hires, at the job level. To our knowledge, the findings have never previously been documented for posted wages. Previous work on wage rigidity has been largely limited to incumbent workers, which is not helpful for testing the relevant theory. By contrast, our estimates of posted wage rigidity directly pertain to the relevant quantity, the wage for newly hired workers. We are able to uncover the new facts because of the unique feature of dataset—whereby we can observe multiple wage postings for the same job, and so understand the strength of rigidity at the job level. The previous literature tends to find that the wage for new hires is procyclical. We show that cyclical changes in job composition, and imprecise estimates, makes previous findings of procyclicality hard to interpret.

We then feed our estimates into a model, to understand the implications for unemployment fluctua-

[1]There is a large literature on wage rigidity for incumbent workers, including Card and Hyslop (1997) for the United States, Le Bihan et al. (2012) for France, Bauer et al. (2007) for Germany and Devicienti et al. (2007) for Italy. However wage rigidity for new hires—the relevant concept according to benchmark theories—is less studied.

[2]Each physical location at which a firm employs workers is a separate establishment.

tions. We show that in a large class of labour search models, the cyclicality of posted wages is a key force determining unemployment fluctuations. When we calibrate our model to the estimated posted wage rigidity, fluctuations in hiring are large, in line with the US time series data. Thus posted wage rigidity is an important contributor to the volatility of unemployment over the business cycle.

In the future, we plan to apply our methods to Euro Area wage setting. As previously discussed, our dataset of online vacancy postings has unique advantages for measuring posted wage rigidity. Moreover, we have developed a theoretical framework for relating estimated wage rigidity to unemployment fluctuations. Through Burning Glass Technologies, we will soon gain access to similar vacancy posting data for France, and potentially other Euro Area countries in the future. Hence we can use the methods developed in this paper to assess whether posted wage rigidity can rationalise large fluctuations in unemployment in the Euro Area.

Related literature. This paper relates to the literature on wage rigidity and unemployment fluctuations. An influential paper by Shimer (2005) argues that benchmark models of labour search cannot rationalise large unemployment fluctuations. Various papers—in particular by Hall (2005), Hall and Milgrom (2008), Hagedorn and Manovskii (2008) and Gertler and Trigari (2009)—argue that wage rigidity for new hires can rationalise large fluctuations in hiring and unemployment. These papers use variants of the canonical labour search model, the Diamond-Mortensen-Pissarides model, to study unemployment fluctuations. A parallel literature has studied the effect of wage rigidity on unemployment in New Keynesian models with both sticky prices and wages—key contributions include Smets and Wouters (2003), Christiano et al. (2005) and Smets and Wouters (2007). Christiano et al. (2016) unite the two modelling frameworks, and show that labour search with rigid wages, and sticky prices, can explain many key business cycle moments. Nevertheless, the importance of wage rigidity is contested. Pissarides (2009) argues that estimated wage rigidity is not large enough to rationalise large hiring fluctuations. Chodorow-Reich and Karabarbounis (2016) show that existing models imply a procyclical opportunity cost of employment, which nullifies endogenous wage rigidity.

This paper also speaks to the literature on *downwards* wage rigidity. Many papers argue that downwards wage rigidity implies asymmetric effects of labour demand on unemployment. Two leading examples are Chodorow-Reich and Wieland (2016) and Dupraz et al. (2016). In these papers, the relevant wage is the wage for new hires. However, outside our paper, there is minimal evidence of downwards rigidity for new hires. Our paper provides new evidence supporting the key assumption in this literature.

Finally, our work belongs to the literature estimating the cyclicality in the wage for new hires. Previous work tends to find strongly procyclical wages for new hires, both in the US and in the Euro Area. Examples in the US include Bils (1985), Shin (1994), Haefke et al. (2013) and Hagedorn and Manovskii (2013). Examples in the Euro Area include Peng and Siebert (2008), Martins et al. (2012) and Carneiro et al. (2012). Equally, when measuring the cyclical of the hiring wage for workers entering from unemployment, Gertler et al. (2016) estimate a nearly acyclical wage in US data. We argue that imprecision and cyclical change in job composition makes these estimates hard to interpret.

2 Dataset

Our main resource is a proprietary dataset of online vacancy postings, provided by Burning Glass Technologies (BGT). The coverage is 2010-2016. BGT uses machine learning algorithms to extract vacancy posting data from online job boards, and company websites. Independent work (Carnevale et al., 2014) finds that the BGT's algorithms correctly classify a high share of job postings. The job posting data contains posted salaries, which includes a measure of hours worked. Posted salaries are classified as hourly, weekly, monthly or annual. The salary includes bonus or overtime pay where applicable. These features of the wage data are an advantage compared with existing datasets. Administrative data often does not contain measures of hours worked, which is necessary for uncovering the marginal cost of labour. Survey data tends to have noisy measures of both hours worked and salary payments, especially when including bonus and overtime pay. The posting data reports both establishment and job title. Each physical location at which a firm employs workers is an establishment. An establishment is therefore a location identifier. Job titles are standardised using BGT's algorithm.

An example clarifies the granularity of the dataset. Consider a large firm, such as Costa Coffee, which has many physical locations across the United States, and hires for many positions, such as baristas or managers. For each vacancy posting by Costa, we can observe the establishment, i.e. the physical location; the job title, e.g. barista or manager; the salary, inclusive of bonus if applicable; and the pay frequency, e.g. hourly or annual.

The dataset of posted wages is also large, covering roughly 10% of vacancies posted either online or offline in the US (Carnevale et al., 2014). A key advantage of this dataset is that we see how posted wages for the *same job* vary over time. We can then study rigidity in job-level posted wages. The dataset also contains industry and occupation information about the vacancy posting. The industry information is at the 2- 4- and 6-digit NAICS code level. Occupation information is at the 2- 4- or 6-digit SOC code level.

2.1 Validating the Posted Wage Data

The posted wage data matches variation in actual US wages. We compare wages by occupation. We study occupation at the six-digit SOC level[3]. We take the median posted wage within each occupation for Burning Glass for 2010-2016; and the median hourly wage within occupation from the 2014-2016 Occupational Employment Statistics (OES), the establishment-level survey of occupational wages in the US. We regress OES wages on Burning Glass wages, by occupation. The results are in Appendix Table 4 and Appendix Figure 6. Wages by occupation in Burning Glass closely match the OES.

We also compare wages by region. We study regions at the core-based statistical area[4] (CBSA) level. We take the median posted wage within each CBSA for Burning Glass for 2010-2016; and compare to the 2010-2016 Quarterly Census of Employment and Wages (QCEW), the regional census of wages in the United States. We regress QCEW wages on Burning Glass wages, by CBSA. The results are in Appendix Table 5 and Appendix Figure 7. Wages by CBSA in Burning Glass closely match the QCEW.

2.2 Representativeness

Next, we study the representativeness of our dataset. Appendix Figure 8 plots the relative share of Burning Glass occupations, at the 2-digit SOC level, versus the 2014-2016 Occupational Employment Statistics.

Burning Glass overweights transportation, healthcare, computation, and finance; and underweights construction, education, and food preparation. Where important for robustness, we reweight to target the US occupation distribution, to deal with issues of data representation.

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

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

Table 1: Summary Statistics, Data Differenced by Job

	Min	Max	Average	
Total Number				1319756
Occupation Coverage				.97
Postings Per Job	2	25	2.76	
Jobs Per Occupation	1	192471	1144	
Jobs Per CBSA	1	24175	760	

Notes: Occupation is by 6-digit SOC code. Occupation share is the total share of 6 digit SOC occupations, by employment in the 2014-16 OES, which are represented in the Burning Glass data. Burning Glass data is 2010-2016. A job is an establishment by job title by pay frequency by salary type unit. Posted wages are averaged within each job-quarter.

2.3 Regional and occupational data

In many specifications, we will use regional business cycle variation. We will use regional unemployment from the Local Area Unemployment Statistics (LAUS), regional employment from the Quarterly Census of Employment and Wages (QCEW), regional industry-by-employment shares from the County Business Patterns (CBP), and national industry employment from the Current Employment Statistics (CES).

Finally, we use occupational data from the 2014-2016 Occupational Employment Statistics (OES).

3 Empirical Results

Fact 1: Posted Wages Change Infrequently

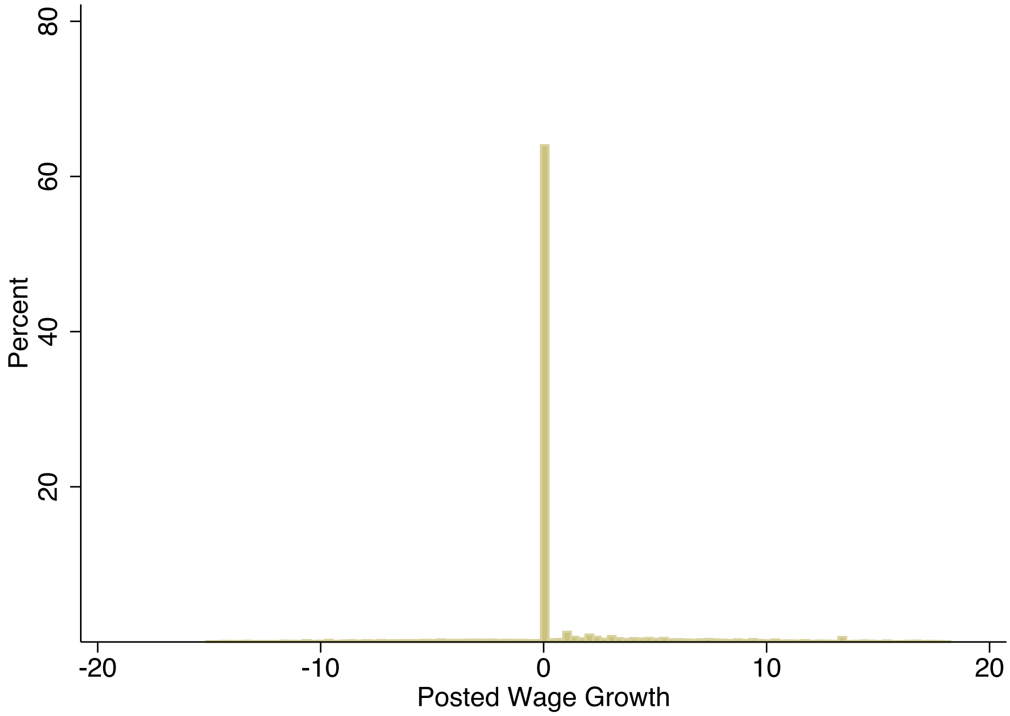
This section introduces the first new fact about posted wage rigidity. For a given job, posted wages change infrequently—rather, they remain constant over many vacancy postings, and for a long period of time. Though this fact has previously been documented for incumbent workers, this paper is the first to document infrequent wage changes in posted wages.

Firstly, we discuss measurement details. We define a job as a job-title by establishment by pay category unit. So, using the example of a Costa Coffee barista, a job is a barista at a given physical location of Costa, with an hourly wage. We aim to study multiple posted wages for the same job, and therefore restrict to jobs with multiple wage postings. We take the mean posted wage within each job-quarter. This step sweeps out high frequency variation in wages, due to, for example, multiple vacancy postings by the same firm within the same month. After these steps, there are roughly 1.4 million postings remaining. Table 1 details summary statistics for this restricted sample.

Figure 1 presents the first fact. Within a given job, posted wages change infrequently. In the figure, the x-axis is the growth in the posted wage between two consecutive job postings by the same job. The graph shows the entire distribution of posted wage growth in the sample. The y-axis is the frequency of observations. The posted wage growth distribution is truncated at the 5th and 95th percentile. The graph shows that for most jobs, the posted wage growth is at or near zero.

This fact is new. Infrequent wage changes have previously been documented for incumbent workers—but never for repeated wage postings for the same job. This fact is the first piece of evidence indicating substantial rigidity at the job level. We can document this new stylised fact because of the unique feature of our dataset, whereby we observe multiple vacancy postings for the same job.

Figure 1: Posted Wages Change Infrequently



Notes: this graph measures the distribution of the growth in posted wages between two consecutive postings by the the same job. As before, a job is an establishment by job-title by salary type by pay frequency unit. The salary growth distribution is truncated at the 10th and 90th percentiles.

An alternative way to see the first key fact is through calculating summary statistics, presented in Table 2 . The typical wage posting spell is long. Posted wages within a job remain unchanged for long periods of time, spanning multiple vacancies.

For each job, we calculate the probability that the posted wage changes, after a new vacancy. We then take the median across jobs, to arrive at the overall probability that the wage changes on a new vacancy. We then calculate the median number of vacancy postings for which the posted wage is unchanged. In particular, we calculate the median implied duration of a posted wage spell, in terms of the number of vacancies, by inverting the probability[5] of posted wage change on a new vacancy. Finally, we report the median duration of a posted wage spell in terms of the number of quarters.

The key takeaway is that posted wages change infrequently within a given job. The probability that a wage changes on a new vacancy is 0.7. Meanwhile, posted wages for the typical job are unchanged for 20 quarters. The result is robust to multiple ways of calculating the main summary statistics[6].

Fact 2: Downwards Rigidity in Posted Wages

We now establish a second fact about posted wage rigidity at the job level. This section documents substantial *downwards* posted wage rigidity at the job level. The job level rigidity in posted wages, documented in the previous section, has asymmetric effects—and prevents firms from cutting posted wages.

[5]We use the implied duration formula $d = -1/\log(1-f)$ where d is the duration, and f is the probability that a posted wage changes.

[6]E.g. by weighting the medians to target the US occupation distribution from the Occupational Employment Statistics.

Table 2: Posted Wage Setting Statistics

Duration of Median Posted Wage Spell, in Quarters	19.5
Number of Vacancies in Median Posted Wage Spell	13
Probability of Posted Wage Change for Median Job	.07
Number of observations	1319756

Notes: a posted wage spell is the number of vacancy postings for a which a posted wage remains unchanged. The median implied duration inverts the median probability of posted wage change, and is given by the formula $d = -\frac{1}{\log(1-f)}$ where f is the frequency of posted wage change. Posted wages are averaged within each job-quarter.

Within a given job, posted wages are especially unlikely to fall. Figure 2 presents the main fact. From the graph, for most jobs the posted wage is more likely to rise than to fall.

To construct the graph, we take the distribution of posted wages as in Figure 1. We then exclude posted wage changes of zero, to leave only non-zero posted wage changes. Finally, we truncate the posted wage growth distribution at $\pm 10\%$. In the graph, posted wages are more likely to increase than to decrease. Moreover, the probability of a small increase is discontinuously higher than the probability of a small decrease in posted wages.

Again, this fact is new. Downwards rigidity was previously shown for incumbent workers (e.g. Le Bihan et al., 2012) but never for new wages. This second fact also supports the overall narrative of the paper—that posted wage rigidity is large at the job level. Again, we can document this new stylised fact because of the unique feature of our dataset, where by we observe multiple vacancy postings for the same job.

We next devise a test to underscore the importance of downwards wage rigidity. If downwards rigidity is important, then the probability of lowering posted wages should be low, and insensitive to labour demand. Since firms are constrained, they should rarely lower wages, regardless of labour demand. Meanwhile, the probability of raising posted wages should be more sensitive to labour demand. Firms are unconstrained upwards, and can raise wages in response to positive labour demand shocks. We find support for both these predictions.

We start by constructing regional labour demand measures. We construct regional measures of labour demand following Bartik (1991). For each CBSA, we calculate the employment share by industry, at the 2-digit NAICS level for 2007. We then weight national 2-digit NAICS industry employment growth for 2010-2016 by the regional weights[7]. The result is a CBSA-specific measure of the cumulative increase in labour demand over 2010-2016. The measure captures labour demand, and not labour supply, provided that regional labour supply shocks over 2010-2016 are orthogonal to the 2007 industry shares.

The probability of a wage rise increases with labour demand, consistent with firms being less constrained when raising wages. Figure 3 presents this fact. On the x-axis is the regional labour demand shock, in percentiles. On the y-axis is the median probability of a posted wage rise, in each CBSA. The graph is a binned scatterplot, with 5% bins of the labour demand shock, and a non-parametric regression estimate. The probability of a wage rise is high in high labour demand regions—which holds if firms are unconstrained when trying to increase posted wages for a given job.

By contrast, the probability of a wage fall is low and does not change with labour demand, consistent

[7] The 2007 regional weights are from the County Business Patterns. The 2010-2016 industry employment growth is from the Current Employment Statistics.

Figure 2: Posted Wages Are Rigid Downwards

Notes: this graph measures the distribution of the growth in posted wages between two consecutive postings by the the same job, excluding zero growth observations. As before, a job is an establishment by job-title by salary type by pay frequency unit. The salary growth distribution is truncated at $\pm 10\%$. Kernel density estimation uses an Epanechnikov kernel with a bandwidth of 0.65.

with downwards rigidity. The median posted wage change is *zero* in all CBSAs, regardless of the labour demand in the CBSA. Thus the probability of a posted wage fall within the job, is low and insensitive to labour demand—confirming the importance of downwards wage rigidity.

Overall, there is substantial rigidity in posted wages. Not only do they change infrequently at the job level, but they are especially unlikely to fall.

Fact 3: Posted Wages are Nearly Acyclical

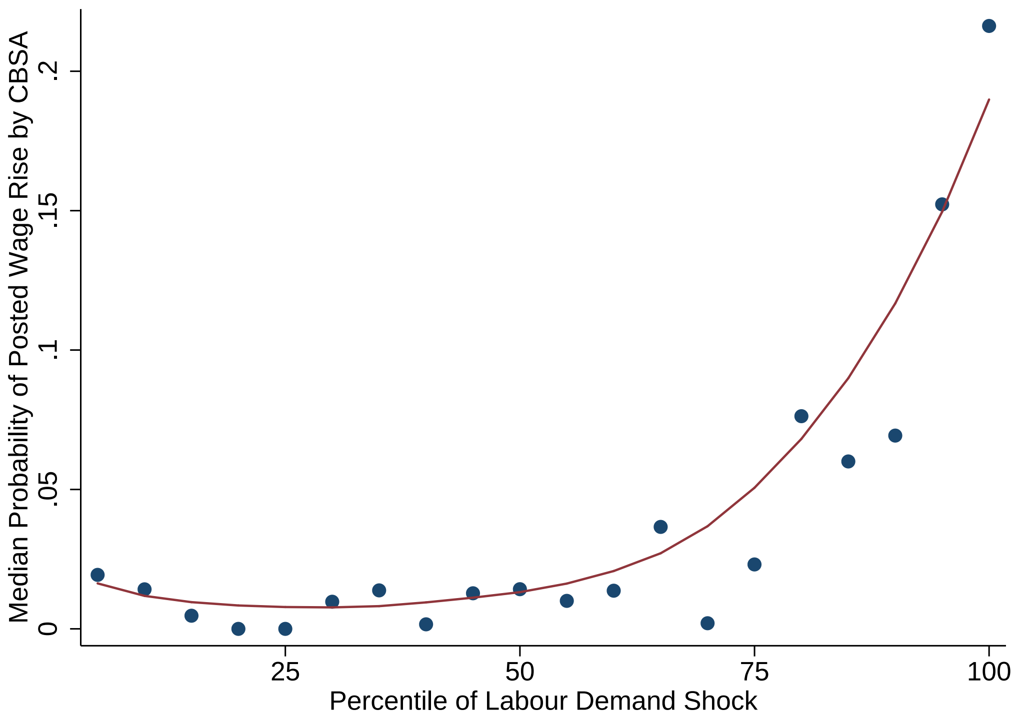
We already documented two new stylised facts: posted wages infrequently change for a given job, and are especially unlikely to fall. We now show that wages vary little within a given job over the business cycle. Cyclicality in posted wages captures firms' incentives to hire for the same job at different stages of the business cycle. Acyclical posted wages imply large fluctuations in hiring incentives. Therefore the rigidity previously documented at the job level has important business cycle implications[8].

To measure wage cyclicality, we build on the canonical regression of Bils (1985). Following this paper, the literature estimates the regression

$$\log w_{it} = \alpha + \beta U_t + \text{controls}_{it} + \varepsilon_{it},$$

[8]As suggested by Caplin and Spulber (1987) and Golosov and Lucas Jr (2007), infrequent posted wage changes at the job level may not have important cyclical implications, if firms optimally time when they change wages. By contrast, our estimates suggest that the job level rigidity has important cyclical implications.

Figure 3: Probability of Wage Rise Increases in Labour Demand



Notes: the probability of posted wage rise is the median by CBSA. Labour demand is a Bartik/shift-share measure, calculated with 2007 2-digit NAICS employment shares by CBSA, and 2010-2016 national 2-digit NAICS employment growth. Labour demand shocks are collected in 5% bins. The conditional mean probability of posted wage change is the mean probability within each bin, weighted by 2016 employment from the QCEW. The nonparametric regression line is estimated by lowess, with a bandwidth of 0.8.

where w_{it} is the cyclical component of the wage for new hires, and U_t is the cyclical component of national unemployment. β, the semi-elasticity of wages with respect to unemployment, then measures cyclicality in the wage for new hires.

We adapt the procedure to our setting in three ways. Firstly, we argued that wage variation within a given job is the relevant variation for studying change in incentives to hire for that job over the cycle. Wage variation between jobs may be less relevant. Therefore we only study within-job wage variation in our regressions—which is only possible because of the unique feature of our dataset, whereby we can observe multiple vacancy posts for the same job. Secondly, there are limited national business cycles in the United States over 2010-2016. We therefore harness extra variation from regional business cycles. Finally, regional unemployment is noisily measured in the United States. We therefore project unemployment onto a high quality administrative measure of employment.

Overall, our specification is a regional version of the canonical regression of Bils (1985), using only within-job variation. The regression is

$$\Delta \log w_{ijt} = \alpha + \text{controls}_{jt} + \beta \Delta U_{jt} + \varepsilon_{jt},$$

where w_{ijt} is the nominal posted wage in job i and CBSA j in quarter t. As before, a job is a job-title by

Table 3: Quarterly Posted Wage Cyclicality, Differenced By Job

	Dependent Variable: Posted Wage Growth, by Job				
	(1)	(2)	(3)	(4)	(5)
Independent Variable:					
Quarterly Unemployment Change	-0.0856	-0.122	-0.146	0.0314	-0.221
	(0.0917)	(0.0843)	(0.111)	(0.0739)	(0.166)
Seasonal Dummies	Y	Y	Y	Y	Y
Difference Length Dummies	Y	Y	Y	Y	Y
Time Effects	N	Y	N	N	N
OES Weights	N	N	Y	N	N
CBSA Fixed Effects	N	N	N	Y	N
Winsorized	N	N	N	N	Y
Number of Differenced Observations	1211948	1211948	1204026	1209224	1237127

Notes: the dependent variable is percentage posted wage growth $100 \times \Delta \log(w_{ijt})$, for job i in CBSA j at quarter t, from the 2010-2016 Burning Glass data. Posted wages are averaged within each job-quarter. The independent variable is the change in U_{jt}, the quarterly unemployment rate in CBSA j at time t, from the 2010-2016 LAUS. We project U_{jt} onto quarterly employment growth from the 2010-2016 QCEW. Posted wage growth is trimmed at the 1st and 99th percentile, except in column (5), in which they are Winsorized at the 1st and 99th percentiles. In column (3), the OES weights reweight the Burning Glass data to match the 2014-2016 OES at the 6-digit SOC level. A job is an establishment by job title by pay frequency by salary type unit. Standard errors are in parentheses, two-way clustered by CBSA and quarter. One, two and three asterisks denote significance at the 10, 5 and 1 percent levels, respectively.

establishment observation. U_{jt} is unemployment in CBSA j and quarter t. $\Delta \log w_{ijt}$ is differenced by job, and ΔU_{jt} is differenced by CBSA. We project ΔU_{jt} onto $\Delta \log\left(\text{Employment}_{jt}\right)$, which is CBSA employment growth from the QCEW. By design, this regression uses our dataset to only focus on within job variation. It uses regional business cycle variation. It deals with measurement error in unemployment, by projecting onto regional employment growth. Then β measures posted wage cyclicality. By running the regression in first differences, we also avoid issues with nonstationarity and a persistent error process.

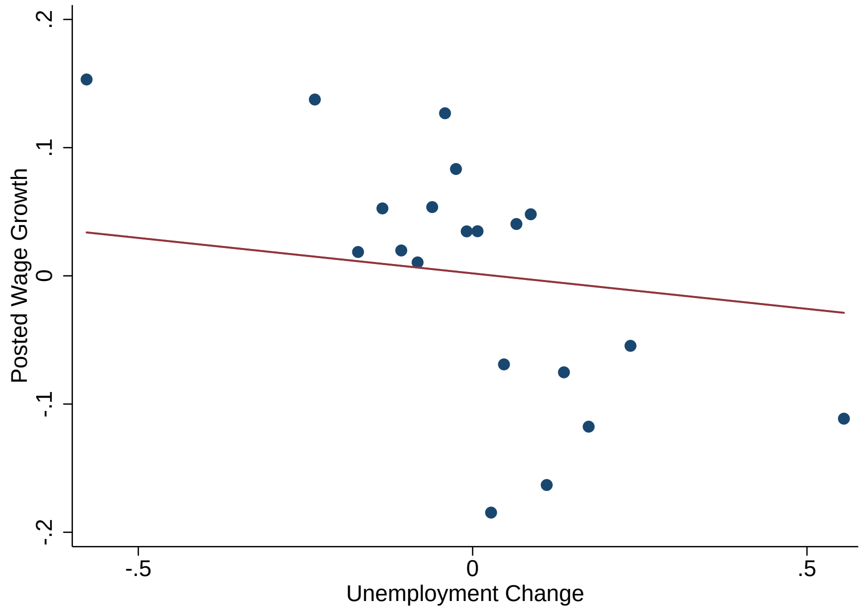
We estimate acyclical posted wages. Table 3 presents the results. In our benchmark specification, after a percentage point fall in quarterly regional unemployment, wages within the typical job growth by only 0.08%. Though posted wages are procyclical, the degree of procyclicality is small. This finding is robust to numerous specifications, including adding CBSA specific trends or time effects, reweighting to target the distribution of jobs in the US economy, different forms of dealing with outliers, using annual data, or using different measures of the local labour market other than CBSAs. These additional robustness tests are in Appendix Section B. Overall, the rigidity previously documented at the job level means that posted wages are nearly acyclical within the job. Figure 4 displays the results from our benchmark regression in a binned scatterplot.

Composition Bias, Precision and the Literature

We now relate our findings to the previous literature. The previous literature typically finds that wages for new hires are procyclical. We argue that these estimates are biased upwards by changes in the cyclical composition of jobs—and that we are able to overcome this bias due to the unique features of our dataset. Moreover, our relatively precise estimates are easier to interpret than those of the preceding literature.

In this paper we are interested in how incentives to hire for a a given job change over the cycle. The

Figure 4: Posted Wages are Nearly Acyclical



This graph is a binned scatterplot of the regression presented in Table 3, column (1).

incentives to hire for a job depend on how the labour cost of that job, i.e. the hiring wage, changes with the cycle. To calculate this cyclicality, we must focus only on within-job variation—or conversely, we must hold constant the cyclical composition in jobs.

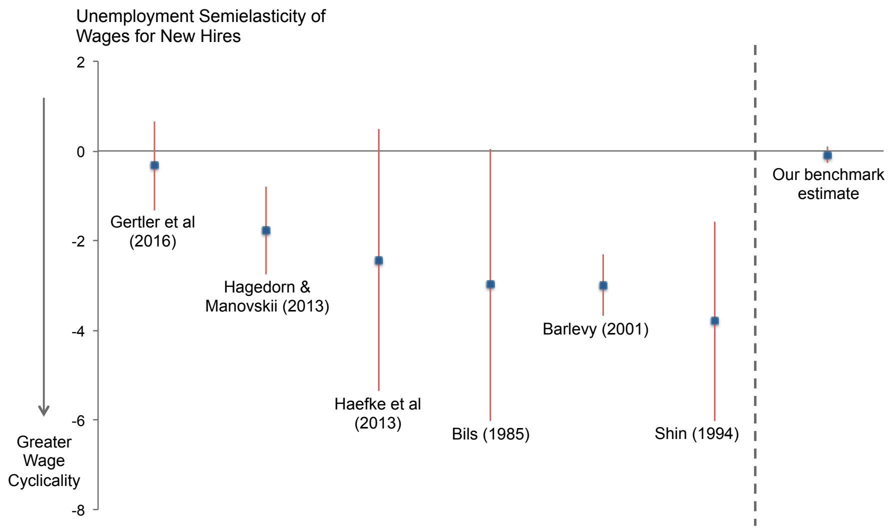
By contrast, cyclical changes in the composition of job quality give a procyclical bias to estimates of wage cyclicality. Suppose that higher wage jobs are created during booms than busts. This shift in job composition over the cycle will cause wages to be higher during a boom than a bust, and so will generate wage cyclicality. However, this wage variation will not capture changes in incentives to hire *within* a given job over the cycle—but rather incentives to shift *between* jobs. This variation is less helpful for studying hiring incentives at the job level.

Previous work attempts to deal with this issue by directly introducing compositional controls, using survey data. However, these controls are relatively coarse, and may be insufficient to control for cyclical variation. By contrast, a unique advantage of our dataset is that we observe repeat wage postings for the same job. We can study within-job variation directly, and therefore fully control for cyclical changes in job composition.

We find estimates of the new hire wage cyclicality that are much less cyclical than the preceding literature. Figure 5 compares our estimates with six leading papers that study the cyclicality of the new hire wage for the United States. Appendix Table 8 reports the values from the literature.

In the graph, the blue dots are point estimates and the red bands are 95% confidence interals. A more negative value indicates greater procyclicality. Our estimate is the least procyclical. Other papers control for cyclical changes in the composition of jobs to a varying extent, and with varying success, using survey data and coarse compositional controls. Thus a procyclical bias from job composition can explain the difference between our results and those of the preceding literature. Indeed, when we re-run our benchmark specification without conditioning on within-job variation, we uncover the procyclical estimates

Figure 5: Comparison of New Hire Wage Cyclicality with the Literature



from the preceding literature—confirming that composition bias generates the previous procyclical estimates. The special features of our dataset, with multiple wage postings for the same job, allow us to draw this comparison.

Our dataset offers a second benefit—substantially less noisy estimates. In figure 5, our estimates are much more precise than the previous literature. Moreover our standard errors are clustered to account for correlated residuals in the panel and cross-section. Therefore with our estimates, we can reject meaningful wage cyclicality. The greater precision comes from three sources. Firstly, we gain extra precision from regional business cycle variation. Secondly, by studying within-job variation, we eliminate residual noise on wages. Thirdly, we have many more observations than the preceding literature.

Overall, we find that posted wages within a given job are nearly acyclical. The preceding literature finds that the wage for new hires are procyclical. The discrepancy between our and the previous findings is explained by the failure of the previous literature to account for cyclical changes in job composition.

4 Posted Wage Rigidity in a Model

We showed that there was substantial rigidity in posted wages at the job level, and that this rigidity led to acyclical wages for a given job. We can now revisit the original motivation: can the posted wage rigidity estimated in the data rationalise large fluctuations in hiring? We derive a model which nests a wide class of labour search models. We show that in this class of models, the rigidity of the posted wage is a key force which amplifies hiring fluctuations. Finally, we show that in a plausible calibration, our estimated wage rigidity generates large hiring fluctuations. Thus rigid posted wages leads to large hiring fluctuations. This is the first paper, to our knowledge, that estimates rigidity in the new hire wage, and finds that it can rationalise large unemployment fluctuations.

4.1 Model Setup

The model is in discrete time, and nests a wide class of labour search models. Firms post vacancies, unemployed workers search for vacancies, and with some probability firms and workers match to form a job. The match lasts for an uncertain number of periods, and ends with fixed probability s in every period. The match produces output y_{t+j} in period $t+j$. Firms pay workers $w_{t,t+j}$, for a wage in period $t+j$ and a match starting in period t. At the beginning of the match, firms pay a fixed cost of matching H_t. In this model, y_t is the output per worker from the match—and so is a measure of labour demand.

Let V_t be the value of an unfilled vacancy, and J_t be the value of a filled vacancy. The value of an unfilled vacancy is given recursively by

$$V_t = -\gamma + q(\theta_t)J_t + (1 - q(\theta_t)\beta E_t V_{t+1}, \tag{1}$$

where $q(\cdot)$ is the probability that a vacancy is filled, and γ is a vacancy posting cost. θ_t is market tightness, defined by $\theta_t \equiv \frac{v_t}{u_t}$, where v_t is the total number of vacancies, and u_t is the total number of unemployed workers search for jobs. $q(\cdot)$ is decreasing in θ. When the labour market is tight, with many vacancies relative to unemployed workers, the probability of filling a given vacancy is low.

We assume a free entry condition, that the value of a vacancy is always zero in equilibrium, so that $V_{t+j} = 0$ for all j. Then equation 1 simplifies to

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

Under free entry, the value of a job is given by the cost of posting a vacancy for that job, γ, scaled by the probability of filling the vacancy.

The value of a job is also the present value of the output from that job. We have

$$J_t = \sum_{j=0}^{\infty} [\beta(1-s)]^j (y_{t+j} - w_{t,t+j}) - H_t.$$

The value of a job to a firm is the present value of the match output, after deducting wage payments, and the initial matching cost—and discounting to account for the probability that the match ends.

This framework nests a wide class of models. It captures the benchmark competitive search model (Moen, 1997). It also captures many common variants of the Diamond-Mortensen-Pissarides, including the models of Shimer (2005); Hall (2005); Hall and Milgrom (2008); Hagedorn and Manovskii (2008); Pissarides (2009); Christiano et al. (2016) and Chodorow-Reich and Karabarbounis (2016). The wage setting process is consistent with either wage posting or wage bargaining.

4.2 A Simple Formula

We now derive a simple formula to understand whether our estimated wage rigidity can rationalise large fluctuations in hiring, in response to changes in labour demand. Our formula maps from wage rigidity to fluctuations in tightness while nesting a wide class of models. It is therefore robust to the underlying details of the wage setting mechanism, and so allows us to map from wage rigidity to hiring while making relatively few assumptions.

Purely for ease of exposition, we make two assumptions:

1. The cyclical component of y_t is a random walk.

2. Wages are acyclical within the match.

Both assumptions are made purely to present a more simple formula. Equally, they both have support.Shimer (2005) and Ljungqvist and Sargent (2017) report that random walk assumption is a good approximation in this setting. Numerous papers have found that wages are sticky within a given match (e.g. Gertler and Trigari, 2009). Now, we derive a simple formula.

Proposition 1. *The elasticity of market tightness with respect to labour demand is*

$$\frac{d\log\theta_t}{d\log y_t} = \frac{1}{\alpha}\overbrace{\left(1-\frac{dw_t^p}{dy_t}\right)}^{\textit{Wage Rigidity Channel}}\underbrace{\frac{y_t}{y_t-K_t}}_{\textit{Profit Share Channel}}.$$

Here, w_t^p is the posted wage. α is the elasticity of the probability of vacancy-filling with respect to market tightness θ. $K_t \equiv w_t^p + (1-\beta(1-s))\,H_t$ is the average cost of labour of a match starting at t, inclusive of the initial fixed costs of matching.

This formula explains what determines the cyclicality of market tightness. Market tightness, in turn, governs hiring and unemployment—when tightness is high, hiring is large relative to unemployment, and unemployment falls rapidly. Therefore this formula explains what factors cause hiring and unemployment to be sensitive to labour demand, in a wide class of labour search models.

The first factor is wage rigidity. When wages for new hires are rigid, they remain high during a downturn, and low during a boom. Meanwhile, labour demand is low during a downturn and high during a boom. Hence the marginal incentive to hire is much larger in a boom than a downturn, leading to large fluctuations in hiring—and hence unemployment—over the business cycle. Many papers, including Hall (2005), Hall and Milgrom (2008) and Gertler and Trigari (2009), use this insight to rationalise large fluctuations in unemployment. Importantly, conditional on a given posted wage, wages for incumbent workers have *no further implications* for market tightness and hiring. As we previously argued, the relevant quantity is the wage for new hires, or the posted wage.

The second factor is a small profit share. When profits are small, a given change in output per worker has a larger *proportional* impact on profits. Thus profits respond more elastically, when they are small on average. When profits are sensitive to business cycle fluctuations, hiring is also sensitive—since high profits lead to increases in hiring, and low profits reduce hiring. Papers such as Hagedorn and Manovskii (2008) and Pissarides (2009) use this insight to rationalise hiring fluctuations.

Overall, in wide class of labour search models, we have characterised the sensitive of market tightness to labour demand, in terms of two sufficient statistics, $\frac{dw_t^p}{dy_t}$ and $\frac{y_t}{y_t-K_t}$.

4.3 Calibration

We now have, for a large class of models, a simple formula mapping from posted wage rigidity to fluctuations in market tightness—which captures movements in hiring. We now calibrate the model to our estimated posted wage rigidity, and ask if the resultant fluctuations in hiring are large. We find that they are. Therefore our estimated posted wage rigidity can rationalise large hiring fluctuations.

We calibrate with consensus values, where possible. We choose $\alpha = 0.5$, matching the values of Petrongolo and Pissarides (2001) and Şahin et al. (2014). We set $K_t = 0.7$, to match the average labour share in the US economy.

Finally, we calibrate a value of $\frac{dw_t^p}{dy_t}$ using our estimates. For simplicity, we set $\frac{dw_t^p}{dy_t} = 0$, to match our estimate of an acyclical posted wage. From our model, the implied elasticity of tightness with respect to labour demand is

$$\frac{d \log \theta_t}{d \log y_t} = 6.6.$$

Meanwhile, in the US time series data, the estimated value from Pissarides (2009) is

$$\frac{d \log \theta_t}{d \log y_t} = 7.56.$$

Thus our estimated wage rigidity generates large fluctuations in market tightness, in line with the time series data. Overall, estimated wage rigidity then generates substantial and quantitatively realistic fluctuations in hiring.

5 Conclusion

We introduced a new dataset of posted wages from online vacancies. This dataset has significant advantages, relative to existing survey datasets. We are able to study multiple wage postings for the same job, and control for the composition of jobs over the business cycle.

We use this dataset to answer a fundamental question in the macroeconomics of labour markets: can the rigidity of wages for new hires rationalise large unemployment fluctuations? We document three new stylised facts. Firstly, posted wages are rigid. For the typical job, the posted wage is unchanged for 20 quarter. Secondly, posted wages are especially rigid downwards. Thirdly, posted wages are acyclical for the typical job. We show that previous estimates of a procyclical wage for new hires are difficult to interpret, due to imprecision and a bias from cyclical changes in job composition.

We map our estimated wage rigidity into a model. The model transparently maps from rigidity in the wage of new hires, to hiring fluctuations, in a large class of models. The estimated wage rigidity rationalises large fluctuations in hiring and unemployment, in line with the data.

In future work, we hope to introduce a similar dataset of posted wages for the Euro Area. We will then use the methods developed in this paper to assess whether wage rigidity in the Euro Area contributes to large hiring fluctuations. A natural next step is to understand which policies can mitigate volatility in unemployment over the business cycle.

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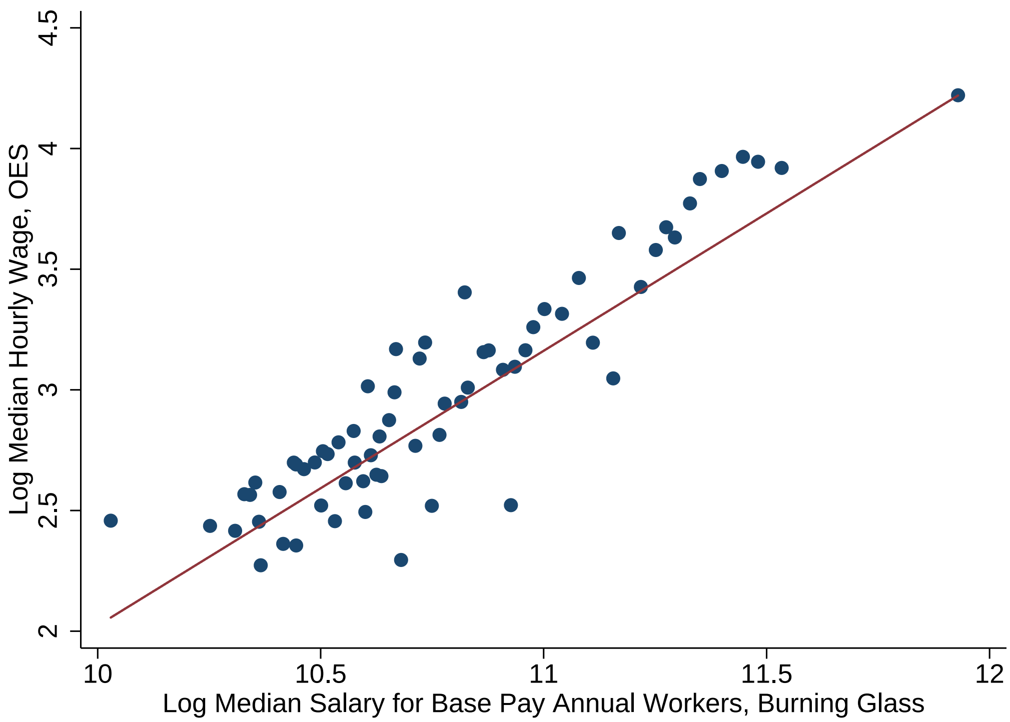
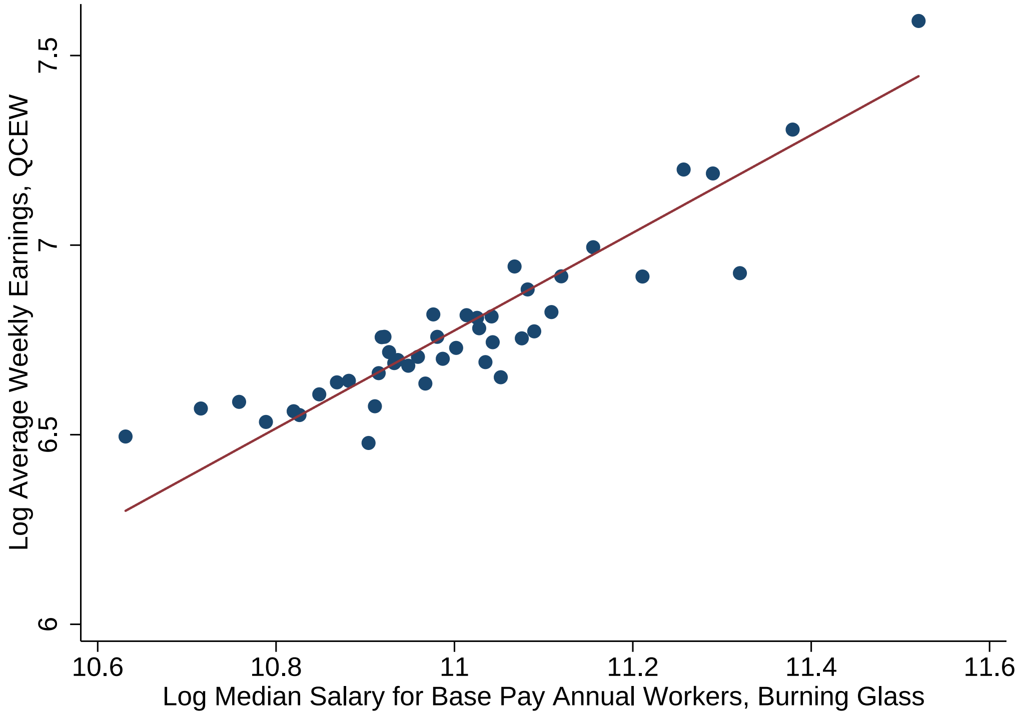
A Additional Figures

Figure 6: Burning Glass Salaries Match OES Hourly Wages



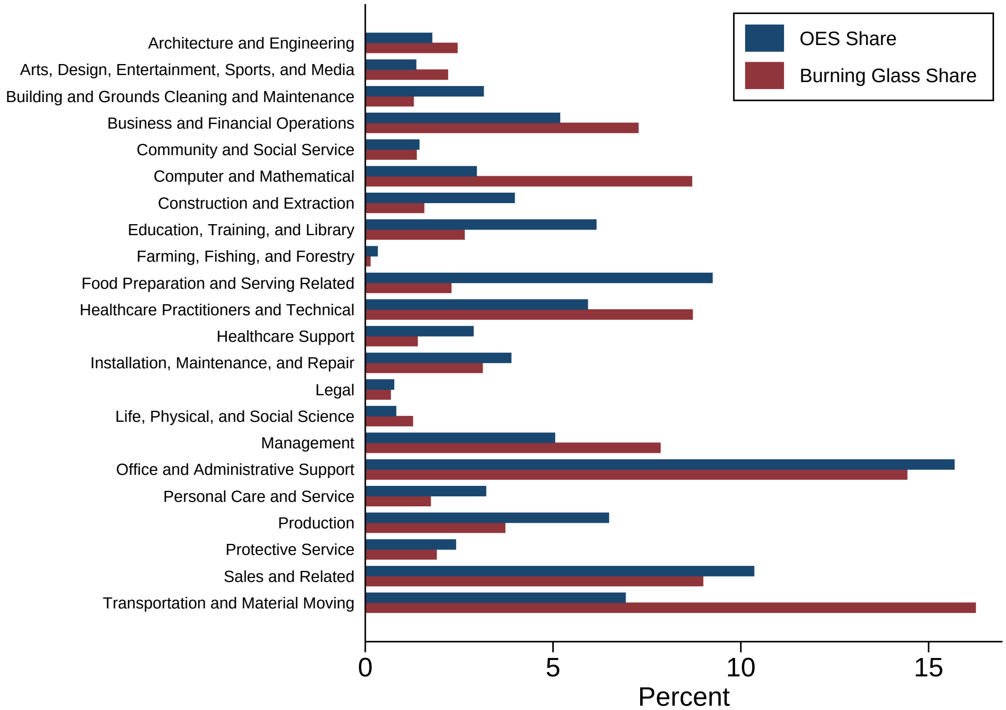
Notes: In both Burning Glass and the OES, the variable is the log of the median salary for hourly base pay workers, by 6-digit SOC cells. Burning Glass data is 2010-2016. The OES data is 2014-2016. The data are binned into percentiles of the regressor, and weighted by employment shares in the OES at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

Figure 7: Burning Glass Salaries Match QCEW Weekly Earnings



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

Figure 8: 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.

B Additional Tables

Table 4: Comparison of OES and Burning Glass Wages, by 6-digit SOC Occupation

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

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

Table 5: Comparison of QCEW and Burning Glass Wages, by CBSA

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

Notes: the dependent variable is average weekly earnings by CBSA, from the 2010-2016 QCEW. The independent variable is the median salary by CBSA, pay frequency and salary type, from the 2010-2016 Burning Glass data. The regression is weighted least squares, weighted by CBSA employment in the QCEW. Robust standard errors are in parentheses. One, two and three asterisks denote significance at the 10, 5 and 1 percent levels, respectively.

Table 6: Quarterly Posted Wage Cyclicality, Differenced by Job, Combined Statistical Area

	Dependent Variable: Posted Wage Growth, by Job, CSA Level				
	(1)	(2)	(3)	(4)	(5)
Independent Variable:					
Quarterly Unemployment Change, CSA	-0.151	-0.360**	-0.0558	0.151	-0.161
	(0.165)	(0.169)	(0.301)	(0.248)	(0.275)
Seasonal Dummies	Y	Y	Y	Y	Y
Difference Length Dummies	Y	Y	Y	Y	Y
Time Effects	N	Y	N	N	N
OES Weights	N	N	Y	N	N
CBSA Fixed Effects	N	N	N	Y	N
Winsorized	N	N	N	N	Y
Observations	920086	920086	914062	919702	939725

Notes: the dependent variable is the log posted wage $\log w_{ijt}$, for job i in CSA j at quarter t, from the 2010-2016 Burning Glass data. The independent variable is U_{jt}, the annual unemployment rate in CSA j at quarter t, from the 2010-2016 LAUS. We project U_{jt} onto $\log(\text{Employment}_{jt})$, log CSA employment from the 2010-2016 QCEW. Posted wages are trimmed at the 1st and 99th percentile, except in column (3), where they are Winsorized at the 1st and 99th percentile. The controls are dummies for 6-digit SOC code and 2-digit NAICS code. In column (4), the OES weights reweight the Burning Glass data to match the 2014-2016 OES at the 6-digit SOC level. Standard errors are in parentheses, two-way clustered by CSA and quarter. One, two and three asterisks denote significance at the 10, 5 and 1 percent levels, respectively.

Table 7: Annual Posted Wage Cyclicality, Differenced by Job

	Dependent Variable: Posted Wage Growth, by Job				
	(1)	(2)	(3)	(4)	(5)
Independent Variable:					
Annual Unemployment Change	-0.671	-0.700	-1.026	0.285	-0.516
	(0.431)	(0.451)	(0.586)	(0.581)	(0.575)
Difference Length Dummies	Y	Y	Y	Y	Y
Time Effect	N	Y	N	N	N
OES Weights	N	N	Y	N	N
CBSA Fixed Effects	N	N	N	Y	N
Winsorized	N	N	N	N	Y
Number of Differenced Observations	496199	496199	492463	495532	506351

Notes: the dependent variable is percentage posted wage growth $100 \times \Delta \log(w_{ijt})$, for job i in CBSA j at year t, from the 2010-2016 Burning Glass data. Posted wages are averaged within each job-year. The independent variable is the change in U_{jt}, the annual unemployment rate in CBSA j at time t, from the 2010-2016 LAUS. We project U_{jt} onto quarterly employment growth from the 2010-2016 QCEW. Posted wage growth is trimmed at the 1st and 99th percentile, except in column (5), in which they are Winsorized at the 1st and 99th percentiles. In column (3), the OES weights reweight the Burning Glass data to match the 2014-2016 OES at the 6-digit SOC level. A job is an establishment by job title by pay frequency by salary type unit. Standard errors are in parentheses, two-way clustered by CBSA and year. One, two and three asterisks denote significance at the 10, 5 and 1 percent levels, respectively.

Table 8: Our Estimates of the Cyclicality of the Wage for New Hires Compared With the Literature

	Unemployment Semi-elasticity of New Hire Wage	Standard Error	Data Source	Standard Error Type	Frequency
Gertler et al (2016)	-0.33	0.51	SIPP 1990-2012	Robust	Monthly
Hagedorn & Manovskii (2013)	-1.78	0.50	NLSY 1979-2004	Robust	Quarterly
Haefke et al (2013)	-2.44	1.50	CPS 1984-2007	Robust	Quarterly
Bils (1985)	-2.99	1.56	NLSY 1966-1981	Homoskedastic	Annual
Barlevy (2001)	-3.00	0.35	NLSY 1979-1993	Homoskedastic	Annual
Shin (1994)	-3.80	1.14	NLSY 1966-1982	Homoskedastic	Annual
Our Benchmark	-0.09	0.09	BG 2010-2016	Clustered	Quarterly

Notes: we adjust the estimates of Haefke, Sonntag & van Rens (2013) from the elasticity of wages with respect to real labour productivity, to the semi-elasticity of wages with respect to unemployment, using the estimate of the sensitivity of unemployment to real labour productivity estimated by Pissarides (2009). We take the median estimate from each paper, and use the more negative value where there is ambiguity. We use the wage for new hires, and only consider workers transitioning out of unemployment where these estimates are available. In Haefke et al (2013), the CPS data is from the Outgoing Rotation Group.