Wage Cyclicality Revisited:

The Role of Hiring Standards*

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Abstract

In this paper we analyze cyclicality of wages at the job level, using posted wage data from an online job board in an emerging economy. Our data contains a significant fraction of online job advertisements in the Chilean economy for the period 2009 to 2018 and is representative of the overall wage distribution of newly hired workers. One major advantage of our dataset is the availability of wage information along information on requirements for each job. We find significant levels of posted wage procyclicality, safely ignoring any cyclical mismatch. We show how omitted variable bias, by ignoring countercyclical changes in hiring standards, reduces the amount of cyclicality found in previous studies.

Keywords: Wage cyclicality, online job boards, composition bias, hiring standards.

JEL Codes: E24, J64

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1 Introduction

A large debate in macroeconomics concerns the sensitivity of wages to business cycle fluctuations. Recently, the "unemployment volatility puzzle" (Shimer, 2005; Hall, 2005; Hagedorn and Manovskii, 2008; Costain and Reiter, 2008) states that the widely used Nash bargaining wage-setting mechanism in the Diamond-Mortensen-Pissarides framework is unable to explain large fluctuations of unemployment in the data. As Hall (2005) and Shimer (2010) emphasize, wage rigidity would help reconcile evidence and theory: Intuitively, productivity shocks would affect profits much more than wages, triggering a larger response of vacancies and therefore, job creation.

Nevertheless, Pissarides (2009) shows that the relevant wage for job creation is the one paid to newly hired workers. Moreover, he summarizes existing results showing that wages for job movers are substantially procyclical, implying that the wage stickiness proposed by Hall and Shimer cannot be the reason behind high unemployment volatility. Gertler and Trigari (2009) provide an alternative interpretation of the evidence highlighted by Pissarides (2009): job composition quality is procyclical, so that high-quality jobs, paying higher wages appear much more frequently in booms than in recessions, so that the empirical high-wage cyclicality is partly due to a composition bias. A number of paper attempt to assess the relevance of this claim. Haefke et al. (2013), using CPS data, and Carneiro et al. (2012); Martins et al. (2012); Stüber (2017) and Dapi (2019) using matched employer-employee databases,[1] conclude that wages of newly hired workers are highly procyclical, trying to account for composition depending on the characteristics of their datasets.

Instead of focusing on realized wages, we study the cyclical behavior of *offered wages* in that the latter match more closely the corresponding theoretical concept present in search and matching models. We use ten years of data from `www.trabajando.com`, an internet job board operating in the Chilean economy, to make a number of contributions.

First, we present a consistent dataset for which a significant number of job ads contain information about offered wages, which are point estimates of what employers expect to

[1] The first two from Portugal, and the other two from Germany and Norway, respectively

pay to a prospective match. Employers in the website are required to enter a wage when posting the advert, but only a fraction of them chooses to display this information publicly. Independent of this choice by posters, we can observe offered wages for the majority of ads (around 85%). This feature is unique, to the best of our knowledge, and provides an excellent data source: Banfi and Villena-Roldán (2019) show that hidden wages are nearly as informative as the explicit ones. We provide additional evidence here on the representativeness of our dataset to the Chilean labor market on several dimensions.

Second, we carefully analyze the rich information on observables of positions advertised by employers, including job titles from individual job ads. Combined with information on requirements of education, major (for jobs requiring a university degree), experience, etc., we can control reliably for job quality in that employers directly provide requirement information in pre-specified categories. This is a measurement advantage with respect to other websites in which only the posted text is available, in which case requirement information is obtained through text mining algorithms with some misclassification error. In this paper, we are able to address directly the concern of cyclical job quality raised by Gertler and Trigari (2009) that is only partially responded by the literature through models with firm and worker fixed effects. The paper closest to ours is Hazell and Taska (2019), who use posted wages from the U.S. economy collected by Burning-Glass Technologies. However, they have only a small selection of job ads actually posting wages (10% of their sample) with likely overrepresentation of unskilled jobs as shown by Banfi and Villena-Roldán (2019); Brenčič (2012). In addition, nearly half of their wage data comes in the form of wage brackets, which may understate the cyclicality of wage offers as employers have lower incentives to update wage ranges.

Our third contribution is subtle but important. All previous papers in the literature (with the exception of Hazell and Taska (2019), to the best of our knowledge) draw their conclusions from *actual wages*, which may be affected by cyclical mismatch between workers and jobs (Şahin et al., 2014), leading to cleansing or sullying effects of recessions. Suppose that, in a recession, workers start applying for jobs they are unfit for due to the scarcity of

opportunities and larger unemployment durations. Realized matches of poor quality lead to lower wages and shorter expected tenures, as in Oreopoulos et al. (2012). Gertler et al. (2016) also make the case for countercyclical match quality. Most of the existing research control for worker fixed effects, but this is not enough since these measure the average wage an individual gets in a typical job. We address the lack of measurement of match quality since our data consists of *offered wages* before matches form. Thus, we can ignore concerns about cyclical quality of the match while also controlling for the ex ante quality of the job itself. Further, we do not have the problem of trying to disentangle cyclicality of wages from labor income, since we concentrate our analysis on base wages and can clearly identify full/part time jobs.[2]

Finally, we link our results to the existing literature. Here we argue that we can control better for characteristics of jobs, given explicit and measurable hiring standards available in our dataset. Furthermore, we show that these standards react to business cycle conditions, affecting estimates of the semi-elasticity of wages to aggregate unemployment rates. Our preferred estimates also control for firm and job title fixed effects, so we can measure how wages react to the unemployment rate for the same job title at the same firm, keeping hiring standards fixed as well. All previous studies do not consider measurement problems of cyclical hiring standards. By ignoring these, we show that estimated semi-elasticities can be biased. We find that hiring standards in our dataset are counter-cyclical and thus, estimates that ignore them are lower (in absolute value) than the ones that do consider them.

Our results show that offered wages (at the very disaggregated job level), are significantly pro-cyclical and fall in the upper range of (absolute value) estimates previously found in the literature: our baseline estimate for the semi-elasticity of log-wages with respect to the unemployment rate is -1.576 which is close to Albagli et al. (2017) who estimate a range between -1.7 and -2.0 for the Chilean economy. On the lower spectrum of estimates, Gertler and Trigari (2009) find a semi-elasticity of -0.33, while Hazell and Taska (2019)

[2] According to Swanson (2007), a great deal of cyclicality of wages accounts for variable labor income such as bonuses, overtime, and commissions.

report a comparable estimate of -0.95.

2 Data

We use information from the private job board www.trabajando.com. We have data on job advertisements posted online between March 1st 2009 and August 31st 2018. Job postings in the website represent a wide array of sectors, although it concentrates slightly on retail, services, and manufacturing sectors. Job seekers can use the website for free, while firms pay to display ads for 30 to 60 days.

The main advantage of the information from this job board is that job posters are required to provide an estimated net monthly salary to be paid at the position.[3] Thus, we have access to offered wage data which is not influenced by characteristics of any individual worker. The current setup has additionally a number of advantages: the wage information we analyze does not consider bonuses or other payments workers may receive which may be subject to aggregate conditions.[4]

For the current exercise, we consider only job postings with existing wage information and that were applied to by at least one job seeker. In table 1 we show some summary statistics with respect to both individual job ads (second column) and total number of vacancies (third column). The latter is simply the information contained in the ads, but weighted by the number of vacancies that each ad promotes in the text of the posting.

The table shows the importance of weighing by the number of vacancies when computing averages. While average wages amount to roughly 650 thousand pesos (monthly, after tax)[5] when considering job adverts alone, this figure decreases to around 398 thousand pesos when we take into account how many actual jobs the first figure represents. One direct implication from this, is that lower paying jobs in the website tend to advertise higher number of positions. According to the Chilean National Statistics Institute,[6] the median

[3] It is customary in the Chilean labor market to express wages in monthly terms, net of taxes, social security and health contributions.

[4] In terms of quality of wage data and representativeness, Banfi and Villena-Roldán (2019) analyze a subset of these data more in depth and provide statistics over several different dimensions.

[5] On October 31st 2018, one thousand pesos were equivalent to 1.44 US dollars. See https://www.xe.com/currencycharts/?from=CLP&to=USD&view=5Y.

[6] See https://www.ine.cl/estadisticas/ingresos-y-gastos/esi

Table 1: Characteristics of Job Postings

	ads	vacancies
Number	274,489	1,308,285
Mean (Std in parenthesis)		
Wage (thousand CLP)	650.22	398.91
	(562.16)	(390.44)
Required Experience (years)	2.03	1.12
	(1.80)	(1.40)
Percentage (%)		
Full time contracts	83.2	65.3
Part time contracts	5.8	11.4
High School	23.6	54.7
University	31.2	11.1
No computer knowledge	30.6	53.9
Expert computer knowledge	1.6	0.6
Explicit wage	16.2	23.3
Big firm (> 51)	45.3	54.0

Information from job advertisements in www.trabajando.com, for the period March 1st 2009 to August 31st 2018.

after tax wage in Chile during 2014 (mid point of our sample) was 305 thousand pesos.

In the rest of the table, we also display average required experience (in years), as well as the fraction of job positions with particular requirements (e.g., education) or offering certain characteristics (e.g., full/part time contracts). All results in what follows are weighted by the number of vacancies to better represent the actual job creation flow generated by the website.

In the left panel of figure 1 we plot histograms for log wages (unweighted) of job ads during our sample period. In the figure we split the sample according to the national unemployment rate in the Chilean economy during the month in which each particular ad was posted: in gray, we show log wages of vacancies posted when the unemployment rate was above its trend (computed using a standard Hodrick-Prescott filter), while in blue we show the case when it was below.[7] As seen from the figure, there is a clear shift towards

[7]For reference, the Chilean unemployment rate during the time period considered was on average 6.8%,

higher wages during periods of low unemployment. The right panel in the same figure shows the aggregate unemployment rate in the Chilean economy during our sample period, along a Hodrick-Prescott trend. From the figure we can see a decline in unemployment due to recovery of the economy following the global mortgage crisis of 2008-2009. After the mid part of 2015, the figure shows a small increase in the unemployment rate.

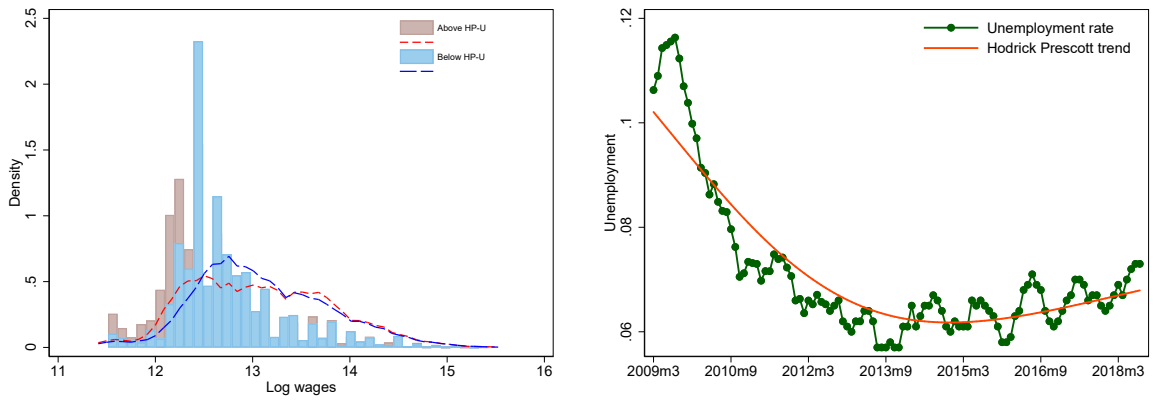

Figure 1: Histogram of log wages, according to the aggregate unemployment rate at the time of posting (left) and time series of unemployment rate and its Hodrick-Prescott smoothed trend (right).

The data of www.trabajando.com is quite representative of the Chilean labor market between 2010 and 2018. Since ad wages in this website are associated with job creation in the short term, we need to compare them to the wages of jobs actually created in the economy around the publication dates of the ads.

To show representativeness of the website, we compare it with the nationally representative survey *Encuesta Suplementaria de Ingresos* (ESI), which measures salaries and characteristics of recently hired workers in the Chilean economy. This survey has questions about wages for interviewees of the National Employment Survey of the *Instituto Nacional de Estadísticas* during October, November, and December of each year. The survey is similar to the Current Population Survey (CPS) in the US, but each household stays in the sample for six consecutive quarters.[8]

fluctuating between 5.7% and 11.6%.

[8]Data are available in https://www.ine.cl/estadisticas/sociales/ingresos-y-gastos/encuesta-suplementaria-de-ingresos. We report data on the declared monthly wage at the main job. The 2018 survey only has household heads information. Nevertheless, the results we report barely change if we exclude the 2018 data from the sample.

As noted above, to make the website and ESI flow data comparable, we weigh ad data in www.trabajando.com by the number of vacancies at each posting. We make a simple comparison between posted wages from our data with wages declared by those recently hired in the ESI. Note that this is a simplification, given that there is no guarantee that posted and realized wages are the same for a given match, because of wage bargaining or ex post compensations.

To compare job composition in terms of educational levels, we further assume that employers requiring a specific educational level in their ads end up hiring workers matching those requirements.[9] In terms of educational levels, there are two alternative high school tracks in Chile: the Scientific-Humanities (SH) track, aimed at students planning to attend university, and the Technical-Professional (TP) track, aimed at individuals targeting the labor market or wishing to pursue a technical degree. At the tertiary level, there is university education (4 to 6 year undergraduate degrees) as well as a Technical Professional tertiary (2 to 3 year degrees). Demand for graduate degrees is small partly due to the fact that many degrees such as lawyers, physicians, and engineers are granted as undergraduate university degrees. As for industry comparisons, we assume that firms in www.trabajando.com create jobs in the industry they belong to, which we characterize using a one-digit (aggregate) code.

Figure 2 depicts density estimators of log-wage distributions. As seen from the figure, the job ad wage distribution from our dataset has a greater average than the other two distributions, while the vacancy-adjusted and the ESI job flow distributions are very similar. The vacancy-weighted distribution exhibits spikes, because of bunching near "round" wage numbers (i.e. 250 and 500 thousand CLP). Results in table 2 show that the educational attainment of new hirings (ESI) roughly matches the distribution of educational requirements for workers (www.trabajando.com) with at least high school education: the website data apparently misses job creation for very low-educated workers, even though the

[9] Although we do not have hiring records, there is evidence showing that job seekers apply to jobs offering wages aligned to their own expectations, and tend to comply to requirements: see Banfi et al. (2018b) and Banfi et al. (2018a).

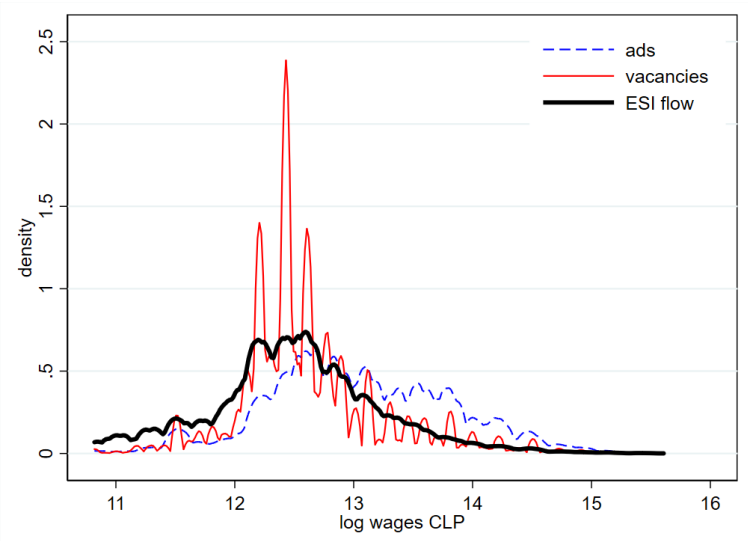

Figure 2: Epanechnikov Kernel density estimates of log wages, comparing website posted ad wages, website posted vacancy wages, and job creation wages in ESI.

educational level of the realized hiring is unobserved. The ESI flow contains 38% of workers with less than high school education, while only 11% of vacancy postings require primary or no specific educational level.

Table 2: Educational requirements (website) vs. attainment (survey)

Website data: required ed.			Survey data: attained ed.			
	Ads	Vacancies		Flow	Seekers	Stock
SH high school	22.70	57.63	SH high school	34.10	26.68	30.50
TP high school	14.47	13.87	TP high school	19.91	17.76	18.78
			incomplete TP tertiary	7.85	6.63	5.46
			incomplete university	11.10	9.61	7.92
high school req		71.50	high school req	72.96	60.68	62.66
TP tertiary	28.22	15.40	TP tertiary	10.55	13.12	13.42
university	34.05	12.92	university	14.89	23.17	21.00
			incomplete graduate	0.34	0.66	0.37
tertiary req		28.32	tertiary req	25.44	36.29	34.42
graduate	0.57	0.18	graduate	1.26	2.36	2.54

Information from job advertisements in www.trabajando.com, for the period March 1st 2009 to August 31st 2018 and ESI flow from the last quarter of the year, from 2010 to 2018. The table shows fraction of vacancies and workers, respectively. SH denotes Scientific-Humanities (SH) while TP refers to Technical-Professional (see the main text for more details).

In terms of industry, we show in table 7 in the appendix that the shares of industries (at the 1 digit level) align well across datasets. Again, in the website we measure the

fraction of job vacancies from firms in the different sectors, while in the ESI we compute the fraction of new hires in each of the same sectors. The caveat here is that agriculture, silviculture, construction and public administration jobs are excluded. The correlation of industry shares between website vacancies and survey data, once we omit these sectors, is as high as 0.74.

3 Methodology

Our analysis is based on estimating linear regressions relating the log offered wage w_a (for job a) with the aggregate unemployment rate at the time of its posting, $U_{t(a)}$ and a set of covariates describing the job, X_a. More specifically, the baseline regression we estimate is

$$\log w_a = \beta U_{t(a)} + X_a \alpha + \gamma t(a) + \varphi_{f(a)} + \lambda_{j(a)} + \epsilon_a \tag{1}$$

where $t(a)$ is the month in which the job ad is posted, X_a is a set of characteristics of the job and $\varphi_{f(a)}$ and $\lambda_{j(a)}$ represent firm and job title fixed effects, respectively. The use of job titles as in Marinescu and Wolthoff (2015) and Banfi and Villena-Roldán (2019), follows from the idea that they describe jobs more precisely than occupations or other coarser categorizations. The empirical setup can also be thought of as a monthly panel where we aggregate wage information at the job title and firm levels.[10]

We use the monthly unemployment rate reported by the *OECD*.[11] In X_a we include posted requirements or features of the job, in the form of dummies for educational level, experience (in years) and computation knowledge requirements, as well as dummies for the type of contract offered (full, part-time, and others).

4 Results

We estimate equation (1) using the multi-way fixed effects method described in Correia (2016), for models with high-dimensional fixed effects, as is our case. We run three different

[10] Below we use this interpretation to obtain alternative estimates based on first differences of the data.
[11] See https://data.oecd.org/unemp/unemployment-rate.htm.

specifications: the first specification is a simple regression between log wages and the unemployment rate, which confirms the correlation shown above in figure (1). The semi-elasticity in this specification is -5.257. On the other extreme, we have the full specification with time controls, as well as firm and job title fixed effects. We find significant and negative coefficients for the effect of the unemployment rate: the semi-elasticity is -0.398 when ignoring job characteristics X_a. This estimate is similar to the estimate in Gertler and Trigari (2009) of -0.33. Using our preferred specification on the other hand, (last column in table 3), we obtain an estimate of -1.576.

Table 3: Estimation results

	Dependent variable: log ad wage		
Unemployment rate	-5.257***	-0.398***	-1.576***
	(0.057)	(0.065)	(0.059)
Job ad charact.	N	N	Y
Firm and Job title FE	N	Y	Y
Sample	All	All	All
Adjusted R2	0.008	0.673	0.730
Adjusted within R2	0.008	0.265	0.199
Sample size (vacancies)	1,308,285	1,216,663	1,216,663

Estimation results of equation (1), between log posted wages and the aggregate unemployment rate. Sample period is March 1st 2009 to October 31st, 2018. Regressions in columns 2 and 3 control for time effects by way of a monthly trend and month-of-year dummies. Standard errors in parenthesis.

In table 4, we present estimates for different specifications, in order to provide a sense of how robust our results are. In the table, *Baseline* represents estimates from the last column of table 3. In the rest of the table, we use this exact same specification, but altering only one thing at a time.

The *Explicit wages* row, shows results for the *Baseline* specification, but restricting attention to job postings where wages are explicitly displayed in the text of the ad. This matters since ads showing their wages explicitly tend to target low-skill workers (Banfi and Villena-Roldán, 2019). Since employers have to enter a wage figure even if they choose not to post them in `www.trabajando.com`, we can assess whether showing wages makes a

difference in terms of cyclicality. Since 75-85% of job ads hide wages in most websites[12], we have a rare opportunity to check that wage explicitness does not matter much for ad wage cyclicality: the estimate for this case is very similar to our baseline.

The *No Firm FE* and *No Job Title FE* rows represent the estimation of equation (1) when we remove firm and job title fixed effects respectively. Since dropping firm fixed effects reduces procyclicality of wages, this suggests a cyclical change of firm composition. In contrast, the estimate without job title fixed effects is very similar to the baseline, suggesting that the job title cyclical variation is nearly captured as a compositional change in employers posting ads with particular job titles.

The results when we do not weight job advertisement by the number of vacancies in the ad are in row *No weights*. We notice the absence of weights reduces wage procyclicality because the number of vacancies per ad is procyclical as well. Hence, it is possible that estimates using other databases without vacancy information underestimate wage procyclicality.

The row *Likely UE* considers job postings where more than ninety percent of applicants are unemployed at the time of their application to the position. In line with Gertler et al. (2016), new jobs filled by unemployed workers are less procyclical than hirings originated in job-to-job transitions.

When we consider the interaction between job title and firm identifier as our definition of a job, as in Hazell and Taska (2019), we can estimate our baseline specification in differences (and thus, without time trends) which leads to results in row *Baseline (diffs)*. The main takeaway from all these different estimations is that the negative (and significant) semi-elasticity remains.

The last two rows of table 4 show results from performing a simple test of asymmetries in the effect of aggregate unemployment on log-wages. To obtain these numbers, we run our baseline equation but add an interaction term between the unemployment rate and a dummy variable for the case in which its value is above its long run trend, as computed using

[12]See for instance Kuhn and Shen (2013); Marinescu and Wolthoff (2015); Hazell and Taska (2019)

Table 4: Estimation results: Robustness

	estimate	std. err.	adj. R2	within R2	Sample Size
BASELINE	-1.576	(0.059)	0.730	0.199	1,216,663
Explicit ads	-1.694	(0.135)	0.732	0.200	291,900
No Firm FE	-0.793	(0.048)	0.634	0.282	1,221,212
No Job Title FE	-1.657	(0.061)	0.677	0.322	1,216,663
No weights	-0.565	(0.116)	0.721	0.222	251,882
Likely UE	-0.852	(0.089)	0.721	0.171	620,145
Baseline (diffs)	-2.835	(0.511)	0.088	–	91,069
U above trend	-1.136	(0.049)	0.731	0.199	1,216,663
U below trend	-4.696	(0.049)	0.731	0.199	1,216,663

Estimation results for alternative specifications. Sample period is March 1st 2009 to October 31st 2018. All regressions control for time effects by way of a monthly trend and month-of-year dummies to control for seasonality.

a standard Hodrick-Prescott (HP) filter. In the table we observe that when unemployment is above the HP trend, the estimated cyclicality of wages is below our baseline estimates (-1.136 vs -1.576) while when unemployment levels are low, the cyclicality is significantly higher (estimate of -4.696). These results show that when unemployment is high, wages are relatively more "sticky", in the sense that they do not react as strongly to unemployment as when unemployment is low. While this is consistent with a weak version of downward wage rigidity advocated by Hazell and Taska (2019), even in the *U above* trend scenario, the semi-elasticity estimate is still on the high side of the estimates in the literature.

In table 8 (in the appendix) we present estimates when restricting the sample by industry of posting firms. From the table, we can observe that the estimated semi-elasticities are heterogeneous across sectors, with *Services* displaying the highest cyclicality while the *Manufacture* sector displays almost acyclical wages. An interesting case is that of the *Finance* sector which displays highly counter-cyclical wages.

5 Hiring standards and wage cyclicality

Our main result from table 3 is that our estimates *without* job characteristic controls in X_a imply a lower cyclicality of wages than when we do include them. In what follows, we use a decomposition due to Gelbach (2016) to understand this result. In our exercise, Gelbach's results imply that the lower cyclicality found in the second specification of table

3 (third column of the table), where we ignore information on job characteristics, is due to the interaction of these with the unemployment rate.

Following the notation in Gelbach (2016), let $\hat{\beta}^{\text{full}}$ be a vector containing the set of estimators from the *full* regression in equation (1), with the exception of those related to X_a. One of these estimates corresponds to the particular coefficient for the semi-elasticity of -1.576 in the last column of table 3. On the other hand, let $\hat{\beta}^{\text{base}}$ be the vector containing the set of estimates from the specification with *no* job characteristic controls X_a (associated to the estimate of -0.398 in table 3). Using standard results on omitted variable bias in linear regressions, it can be shown that

$$\hat{\beta}^{\text{base}} - \hat{\beta}^{\text{full}} = (X_1' X_1)^{-1} X_1' X_a \hat{\beta}_{X_a} \tag{2}$$

where X_1 is a matrix containing all regressors in equation (1) with the *exception* of X_a. Hence, X_1 includes the unemployment rate plus all fixed effects from equation (1). On the other hand, $\hat{\beta}_{X_a}$ are the coefficients related to X_a in the *full* specification.

Thus, this result is useful for our analysis since it states that the difference in the point estimates related to the semi-elasticity of wages to the unemployment rate can be decomposed linearly in terms of both the effect of job characteristics on log wages (term $\hat{\beta}_{X_a}$ in the equation above) *and* how these characteristics interact with the unemployment rate, i.e., their cyclicality (the rest of the left hand side in equation 2). Since we are interested in the decomposition for the point estimate of the semi-elasticity of log-wages to the unemployment rate, the procedure suggested by Gelbach (2016) simplifies into two simple steps: First, we regress each column in X_a as a dependent variable on all X_1 variables and recover the estimate related to unemployment, which can be thought of as the correlation between that variable and unemployment conditional on firm and job title fixed effects, $\partial X_a / \partial U$. Second, we multiply the latter by the associated coefficient β_{X_a}, which reflect the impact of job ad characteristics on offered wages.

In table 5, we present a summary of the results for the decomposition exercise.[13] As

[13] In table 6 we present the full results.

Table 5: Decomposition: cyclical variation of hiring standards

	β_{X_a}	$\partial X_a/\partial U$	% of $\hat{\beta}^{\text{base}} - \hat{\beta}^{\text{full}}$
Job ad characteristic:			
No experience	-0.3347	−2.9388	83.53
One year experience	-0.2672	0.4509	−10.20
Full time contract	0.0820	1.7385	12.10
Part time contract	-0.2475	0.6961	−14.63
High school education	-0.4430	−1.3843	52.07
Technical tertiary schooling	-0.2822	0.4206	−10.08
No computer knowledge	-0.0816	−0.1993	1.38
Low computer knowledge	-0.0882	0.9680	−7.25

Decomposition exercise for the semi-elasticity of wage cyclicality: β_{X_a} refers to the effect of the variable on wages in the *full* specification (see main body of text); $\partial X_a/\partial U$ represents the regression coefficient of the unemployment rate on the particular job ad characteristic (controlling for all other variables); the last column represents the fraction explained of the difference: $\frac{\partial X_a}{\partial U}\beta_{X_a}$ divided by $(\hat{\beta}^{\text{base}} - \hat{\beta}^{\text{full}})$.

noted above, in X_a we include dummies for the categorical variables describing job post requirements (experience, education and computer knowledge) and characteristics (type of contract offered). When estimating these in the full regression, we omit a base category which is absorbed in the constant of regression 1. We do not show all elements in X_a, but those which have a stronger effect on the difference $\hat{\beta}^{\text{base}} - \hat{\beta}^{\text{full}}$.

The second column in the table (labelled β_{X_a}) shows the associated coefficient to each characteristic on the offered wage. For experience levels (in years), we see that, relative to the base category (dummy for the highest level of experience dummy, or 18 years in our sample), jobs requiring either no or only one year of experience pay less than jobs with higher requirements. In terms of offered contracts, full-time contracts pay more while part-time contracts pay less than the base category, which is "no contract information" in the ad. For education, the omitted category is "university education" and, as expected, jobs requiring both high school education or a technical tertiary diploma pay relatively less. Finally, for computer knowledge, we see from the table that jobs requiring low or no computer knowledge pay less than the omitted related category ("expert knowledge").

The third column in table 5, labelled $\partial X_a/\partial U$, shows how job characteristics change when aggregate unemployment changes. For each sub-group of characteristics (experience, education, contract type and computer knowledge) we see that increases in the unemployment rate lead to hiring standards to be risen and viceversa. This can be seen for example, in the two considered categories of required experience: the correlation between "no experience" jobs and unemployment is negative, while it is positive for "one year experience" jobs and unemployment. In other words, rising unemployment is associated to periods of time when jobs increase hiring standards for prospective applicants, and to times when employers reduce the quality of jobs offered in attributes other than wages.

The last column in table 5 shows the relative importance of each particular characteristic in the table to explain the difference in estimates (base minus full). Given the results in Gelbach (2016) and equation (2), the last column is simply the ratio between the product of the terms in the second and third column, divided by $\hat{\beta}^{\text{base}} - \hat{\beta}^{\text{full}}$. From the table we see that "no experience" and "high school" education requirements are the ones that explain the most of the difference.

These results are evidence of countercyclical hiring standards. In an economic downturn, employers adjust in two ways. First, for a given job position, they pay less for a given set of attributes embedded in a worker profile. Second, they raise the bar regarding the type of attribute requirements for prospective applicants. Hence, in downturns employers intend to hire workers of better qualifications for a lower wage to do the same job and this leads to our main conclusion: not accounting for countercyclical upgrade of requirements leads to underestimating the true cyclicality of wages.

6 Conclusions

In this paper we use internet data on posted wages to study cyclicality of wages at new positions. Our setup provides at least two advantages over previous literature: First, we can study how wage offers evolve over the cycle, without worrying about cyclical mismatch patterns that may occur when the unemployed pool composition changes or when job seekers

are attempting to do "job upgrade". Second, we construct job requirement measures and document how they move countercyclically. This is relevant since omitting fluctuating hiring standards can affect the estimation of wage cyclicality in previous literature, even if one focuses in a narrowly defined job title. Employers ask for more education or more experience to fill the vacancies in a downturn, effectively widening the gap between the offered wage and a counterfactual wage that a more educated or experienced worker would obtained in a neutral cyclical situation.

These results enrich the view of the hiring process beyond the role of wage stickiness as a major driver of the cyclical behavior of the labor market. More theoretical research needs to shade light on the facts we uncover here to gain understanding of the cyclical behavior of wages and worker flows, particularly in a context of online job search with heterogeneous and changing hiring standards.

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Appendix: Additional tables and figures

Table 6: Decomposition: cyclical variation of hiring standards (full table)

Job ad characteristic:	β_{X_a}	$\partial X_a/\partial U$	% of $\hat{\beta}^{\text{base}} - \hat{\beta}^{\text{full}}$
required experience (years): 0	-0.3347	−2.9388	83.53
required experience (years): 1	-0.2672	0.4509	−10.23
required experience (years): 2	-0.1162	1.1968	−11.81
required experience (years): 3	-0.0120	0.6967	−0.71
required experience (years): 4	0.0633	0.1182	0.63
required experience (years): 5	0.1242	0.3566	3.76
required experience (years): 6	-0.0424	0.0026	−0.01
required experience (years): 7	0.2252	0.0259	0.50
required experience (years): 8	0.2682	0.0106	0.24
required experience (years): 9	0.3881	−0.0017	−0.06
required experience (years): 10	0.2453	0.0186	0.39
required experience (years): 11	-0.4991	0.0018	−0.07
required experience (years): 12	0.2499	0.0053	0.11
required experience (years): 13	0.6644	−0.0002	−0.01
required experience (years): 14	0.8150	0.0001	0.00
required experience (years): 15	0.2788	0.0187	0.44
required experience (years): 16	-0.0792	−0.0001	0.00
required experience (years): 17	-0.2801	0.0375	−0.89
required experience (years): 18	(omitted)		
type of contract: comission	0.0987	−0.2978	−2.50
type of contract: full time	0.0820	1.7385	12.10
type of contract: half time	-0.1298	0.0942	−1.04
type of contract: part time	-0.2475	0.6961	−14.63
type of contract: shifts	0.0289	−2.3037	−5.65
type of contract: replacement	-0.6943	−0.0315	1.86
type of contract: NA	(omitted)		
education: less than high school	-0.4430	−1.3843	52.07
education: high school	-0.3883	−0.0045	0.15
education: technical (tertiary)	-0.2822	0.4206	−10.08
education: university	(omitted)		
Computer: No knowledge	-0.0817	−0.1993	1.38
Computer: Basic knowledge	-0.0882	0.9680	−7.25
Computer: Expert knowledge	0.1106	0.0236	0.22
Computer: Professional knowledge	0.0378	0.1940	0.62
Computer: Technical level	-0.1040	−0.0630	0.56
Computer: User level	-0.0570	−1.3143	6.36
Computer: Advanced user	(omitted)		

Decomposition exercise for the semi-elasticity of wage cyclicality: β_{X_a} refers to the effect of the variable on wages in the *full* specification (see main body of text); $\partial X_a/\partial U$ represents the regression coefficient of the Unemployment rate on the particular job ad characteristic (controlling for all other variables); the last column represents the fraction explained of the difference.

Table 7: Industry employment shares: website vs survey data

	website data		survey data	
Industry	Ads	Vacancies	Flow	Stock
Fishing	0.2	0.1	1.1	1.1
Mining	2.3	1.1	5.5	4.9
Manufacturing	11.7	7.8	12.6	12.8
Energy & water	2.7	1.4	1.1	1.0
Retail	20.9	26.7	25.1	24.3
Restaurants & Hotels	1.6	1.5	6.9	4.9
Transport & Communication	7.0	14.0	9.1	8.8
Financial Services	4.0	2.9	1.8	2.6
Real State	22.4	19.1	7.8	7.3
Education Services	5.8	2.7	7.9	10.4
Health & Social Services	5.6	3.5	4.5	6.0
Other Services	8.8	13.0	4.2	4.7
Other	6.9	6.2	12.4	11.2
Observations	299,430	1,559,962	80,142	258,709
Correlation matrix				
	Ads	Vacancies	Flow	Stock
Ads	1.00	0.93	0.46	0.62
Vacancies		1.00	**0.74**	0.72
Flow			1.00	0.98
Stock				1.00

Industry shares in the website denotes the fraction of job ads/vacancies posted by firms in each industry category; for the survey data, it's the fraction of new hires in each of those sectors. In the table we ignore agriculture, silviculture, construction and public administration jobs. The correlation matrix is computed using the columns in the first part of the table.

Table 8: Estimation results: INDUSTRY

	estimate	std. err.	adj. R2	within R2	Sample Size
BASELINE	-1.576	(0.059)	0.730	0.199	1,216,663
Services	-2.336	(0.121)	0.743	0.218	316,273
Finance	2.182	(0.183)	0.806	0.171	195,072
Manufacture	-0.070	(0.223)	0.814	0.222	85,613
Elect. and utilities	0.480	(0.635)	0.822	0.150	17,551
Agriculture	-0.037	(0.838)	0.896	0.254	8,417
Mining	8.325	(1.553)	0.828	0.253	7,687
Transport	-3.759	(1.139)	0.845	0.183	7,146

Estimation results of baseline specification, but conditioning on aggregate industry sector of posting firm. Sample period is March 1st 2009 to October 31st 2018. All regressions control for time effects by way of a monthly trend and month-of-year dummies to control for seasonality.