Wage Cyclicality Revisited: The Role of Hiring Standards *

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Abstract

In this paper we study the cyclicality of wages, using online job board information representative of the Chilean economy. While previous studies pay careful attention to job upgrading biases and worker behavior, here we focus on the demand side: we find evidence of firms cyclically altering requirements (at narrow job title categories) in order to upgrade/downgrade their pool of applicants. When we use this information in a standard estimation of semi-elasticities of wage to unemployment rates, we find high levels of wage (pro)cyclicality. Thus, ignoring job requirements leads to the underestimation of the cyclicality of offered wages, a result which survives a number of robustness checks. To rationalize the facts, we pose a standard model with labor market frictions and idiosyncratic match productivity.

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

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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, 2005b; 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 wage cyclicality is partly due to a composition bias. A number of papers 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, conclude, after accounting for composition in their datasets, that wages of newly hired workers are highly procyclical.

In this paper we use ten years of data from `www.trabajando.com`, an internet job board operating in the Chilean economy. We have access to information on job ads and offered wages, which are point estimates of what employers expect to pay to a prospective match. In the website, employers must enter a wage when posting the advert, but are allowed to hide this information from job seekers. While only a small fraction posts wages publicly, we observe offered wages for around 85% of the ads (both hidden and public), a unique feature to the best of our knowledge. 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.

Thanks to the richness of our dataset, our first contribution is to estimate the cyclical sensitivity of wages, controlling not only for the composition of employers and job titles, as done by previous research, but also for a rich set of contract terms and hiring standards. Using the later variables

such as requirements of education, major (for jobs requiring a university degree), experience, etc., we can reliably control for job quality. This is a measurement advantage with respect to other data in which requirements are obtained through text mining algorithms, with some misclassification error. With our data, we are close to run an ideal thought experiment: consider a firm offering a wage for a job, with specific requirements and contract terms in a recessive labor market. Keeping all of these constant, let the firm post again a wage for the same job ad in a booming market, so we can compare and assess the cyclicality of the offered wage.

A second 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 *realized 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.[1]

Due to the features of our data, we are able to directly address the concerns of cyclical job quality and mismatch, only partially responded in the literature by firm- and worker-fixed effects models. The paper closest to ours is Hazell and Taska (2019), who study posted wages from the U.S. economy collected by Burning-Glass Technologies (BGT). However, in their data only 10% of ads post wages, which likely entails an overrepresentation of unskilled jobs as shown by Brenčič (2012); Banfi and Villena-Roldán (2019). Also, nearly half of their wage data comes in the form of wage brackets, which probably overstates their cyclical rigidity.

From our preferred specification, when we control for requirements, job titles and firm fixed effects, we find significant procyclical offered wages. Our estimated semi-elasticity of wages with

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

respect to unemployment falls in the upper range of (absolute value) estimates previously found in the literature: -1.576, which is close to Albagli et al. (2017) who estimate a range between -1.7 and -2.0 for the Chilean economy. These numbers are not far from estimates for other countries. On the lower spectrum of estimates, Gertler and Trigari (2009) find a semi-elasticity of -0.33, while Hazell and Taska (2019) report a comparable estimate of -0.95.

Furthermore, using the Gelbach (2016) decomposition, we show that requirements related to high wages are countercyclical. This finding connects our paper to the literature on the cyclicality of job requirements.[2] Data from online job ads has allowed researchers to study the cyclicality of requirements to explain the well-known outward shift of the Beveridge curve in the aftermath of the Great Recession. In line with our own findings, using BGT job ads Modestino et al. (2016, 2020) report that educational and experience requirements move countercyclically, even for job titles within the same firm, which helps explain the Beveridge curve shift. Following a macro approach, Sedláček (2014) can partially explain the same fact by introducing job requirement as an employer choice.

Using the Gelbach (2016) decomposition, we measure how much the cyclicality of wages is underestimated if the countercyclical behavior of job requirements is not considered, as is the case of previous studies. Although in this paper we primarily concern about the cyclicality of wages, a rigourous analysis necessarily requires an assessment of the cyclical interdependent movements of wages and requirements within an occupation, and even at the job title and firm level. So far, the wage and requirement cyclicality literatures have evolved without realizing their close relationship. The key intuition is simple: an increased hiring standard in a recession masks the reduction of offered wages, leading to an underestimation of the procyclical behavior of wages.

Taken at face value, our estimated semi-elasticity of wages with respect to unemployment implies that the assumption of wage rigidity, needed to explain unemployment fluctuations in sequential search and matching models along the lines of Shimer (2005b), is not warranted by the data. However, our results reveal a more complex picture. Employers are more demanding on qualifications when the labor market is weak, and viceversa. The business cycle affects labor quality, wages, and match probability margins, even within the same firm and job. In light of this evidence, joint cyclicality of wages and requirements should be studied together empirically and theoretically. Baydur (2017); Carrillo-Tudela et al. (2018) take a first step in later direction.

[2] For old discussions on this topic, see Reder (1964); McGregor (1978).

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 employers 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 as suggested by Swanson (2007).[4]

Table 1: Characteristics of Job Postings

	Ads	Vacancies
Observations	1,166,362	6,442,817
Wages (thousand CLP)	656.36	428.72
Experience (years)	1.26	0.80
High School	0.25	0.54
College	0.30	0.11
Full time contract	0.67	0.54
General knowledge	0.66	0.55
Specific knowledge	0.13	0.15
Computer knowledge	0.23	0.2
Big Firm (> 51)	0.60	0.60

Information from job advertisements in www.trabajando.com, for the period March 1st 2010 to March 31st 2020.

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

[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.

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 a higher number of positions. According to the Chilean National Statistics Institute,[6] the median 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.

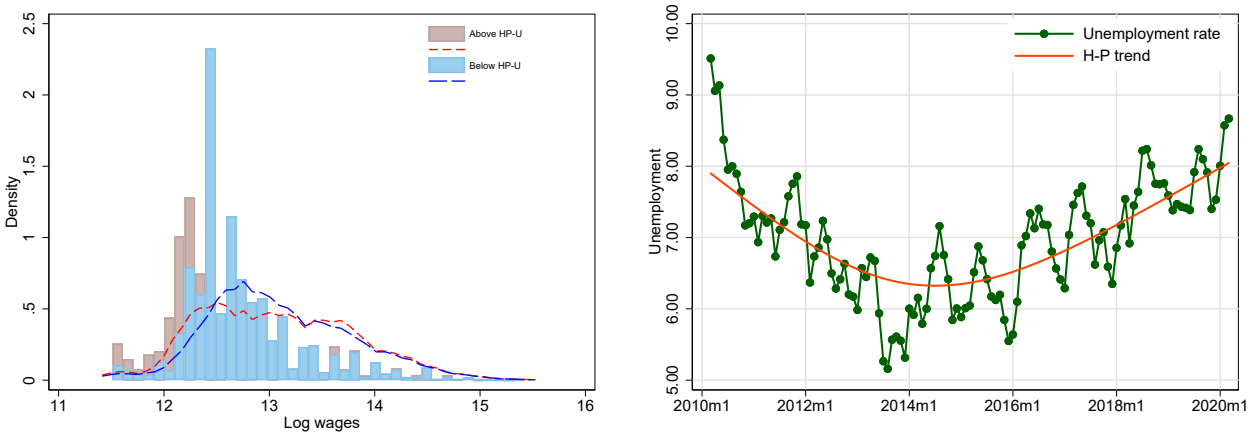

Figure 1: Histogram of log wages, according to the aggregate unemployment rate at the time of posting (left) and time series of unemployment rate and its Hodrick-Prescott smoothed trend (right).

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 higher wages during periods of low unemployment.

[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

[7] For reference, the Chilean unemployment rate during the time period considered was on average 6.8%, fluctuating between 5.7% and 11.6%.

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.

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 the 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 Outgoing Rotation Group of the Current Population Survey (CPS-ORG) in the US, but each household stays in the sample for six consecutive quarters.[8]

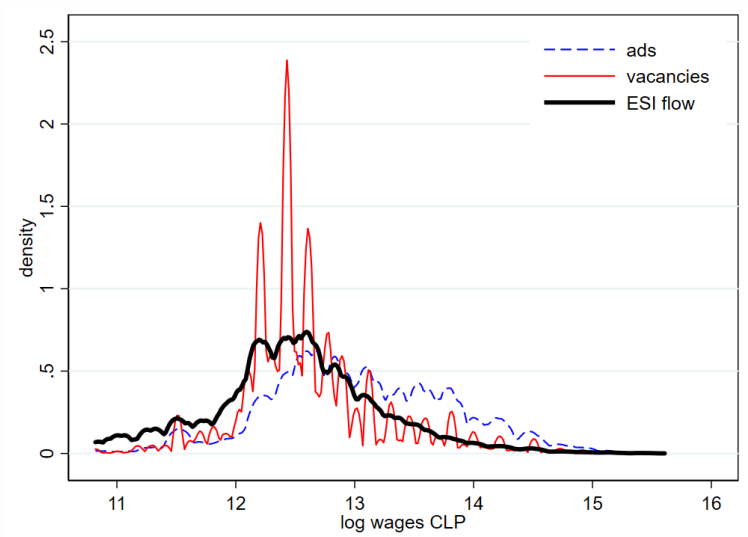

Figure 2: Epanechnikov Kernel density estimates of log wages, comparing website posted ad wages, website posted vacancy wages, and job creation wages in ESI.

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

[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.

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. 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, despite some bunching near "round" wage numbers (e.g., 250, 500, etc. thousand CLP). Figure 2 depicts density estimators of log-wage distributions.

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.

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 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 7 shows these results in the appendix.

In terms of industry, we show in table 8 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.

[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. (2018a) and Banfi et al. (2018b).

3 The Facts

3.1 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).

The above specification identifies a causal effect of unemployment on wages mimicking as close as possible the baseline strategy of papers in the matched employer-employee studies (Carneiro et al., 2012; Stüber, 2017) considering that we need not to deal with worker's heterogeneity when studying offered wages. Job title and firm fixed effects take care of confounding compositional changes, adjusting for the cyclical behavior of hiring standards, as do Modestino et al. (2020). Hence, our specification implements our thought experiment of comparing the posted wage for the same firm, job title, requirements, and contract terms, under weak and strong labor markets.

3.2 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 specifications: the first one is a simple regression between log wages and the unemployment rate, which confirms

[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.

the correlation shown in figure (1). The semi-elasticity in this specification is -5.257. Next, we consider a specification with time controls, as well as firm and job title fixed effects only. In this case, we find a semi-elasticity of -0.398. This estimate is similar to the estimate in Gertler and Trigari (2009) of -0.33. Using our preferred specification, which controls for hiring standards in X_a (last column in table 2), we obtain an estimate of -1.576.

Table 2: Estimation results

	Dependent variable: log ad wage		
	(1)	(2)	(3)
Unemployment rate	5.608***	-1.442***	-2.237***
	(0.043)	(0.039)	(0.037)
Job ad characteristics	N	N	Y
Firm and Job title fixed effects	N	Y	Y
Adjusted R2	0.003	0.636	0.679
Adjusted within R2	0.003	0.065	0.175
Sample size (vacancies)	6,395,040	6,395,040	6,395,040

Estimation results of equation (1), between log posted wages and the aggregate unemployment rate. Sample period is March 1st 2010 to March 31st, 2020. 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 3, 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 2. 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 an offered wage 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 an 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

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

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 90% 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. This also aligns with the literature surveyed by Pissarides (2009) showing that job movers drive a great deal of wage growth.

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 3 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 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 asymmetry is also found 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.

A caveat on our results: it is a widely extended practice to post net monthly wages in job ads in Chile, as is to write work contracts in that fashion. As hours worked are somewhat procyclical, monthly wages might be affected by longer hours in expansive times. During 2010-18, ESI data shows that 44% of newly hired formal employees usually work the maximum of 45 weekly hours (with no overtime compensation) determined by law.

In table 4 we present estimates when restricting the sample by industry of posting firms. From

Table 3: Estimation results: Robustness

	estimate	std. err.	Sample Size
Baseline	-2.237***	(0.037)	6,395,040
Explicit ads	-2.776***	(0.075)	1,508,593
No Firm FE	-2.718***	(0.034)	6,395,040
No Job Title FE	-0.556***	(0.038)	6,395,040
No weights	-0.664***	(0.080)	1,137,684
Regional U.	-1.104***	(0.024)	5,214,389

Estimation results for alternative specifications. Sample period is March 1st 2010 to March 31st 2020. All regressions control for time effects by way of a monthly trend and month-of-year dummies to control for seasonality.

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.

Table 4: Estimation results by Industry groups

	estimate	std. err.	adj. R2	within R2	Sample Size
BASELINE	-2.237***	(0.037)	0.679	0.175	6,395,040
Services	-2.337***	(0.067)	0.766	0.180	1,732,466
Transport	-0.268**	(0.109)	0.745	0.172	1,285,806
Finance	-1.145***	(0.140)	0.698	0.159	601,083
Manufacture	-2.677***	(0.148)	0.811	0.189	503,415
Elect. and utilities	-3.563***	(0.132)	0.749	0.184	485,953
Agriculture	0.071	(0.124)	0.769	0.186	448,818

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.

3.3 Hiring standards and wage cyclicality

Our main result from table 2 is that our estimates *without* job characteristic controls, such as requirements and contract terms (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, we show that the lower cyclicality found in the second specification of table 2 (third column of the table), where we ignore information on job characteristics, is due to the comovement 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 2. 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 2). 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 terms in the right-hand side in equation 2). Since we are interested in the decomposition for the point estimate of the semi-elasticity of 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.

Table 5: Decomposition: cyclical variation of hiring standards

Job ad characteristic	β_{X_a}	$\partial X_a / \partial U$	Fraction of $\hat{\beta} - \beta$
Two years experience	0.189	0.757	0.143
Full time contract	0.151	0.377	0.057
Computer: User level	-0.087	-3.347	0.290
No General knowledge	-0.042	-3.487	0.147
No Specific knowledge	-0.042	-3.024	0.127

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 $(\hat{\beta}^{\text{base}} - \hat{\beta}^{\text{full}})$.

In table 5, we present a summary of the results for the decomposition exercise. As 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 $\hat{\beta}^{\text{base}} - \hat{\beta}^{\text{full}}$.[13]

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. These findings are very similar to those by Modestino et al. (2016, 2020).

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, em-

[13] In table 12 in the appendix we present the full results.

ployers 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.

4 The Model

In this section we describe the quantitative model we use to rationalize the facts with respect to wage and hiring standard cyclicality. The model is an extension of the standard frictional labor market setup with non-competitive wage setting in Mortensen and Pissarides (1994) and similar to Sedláček (2014).

Time is discrete and goes on forever. All agents are risk neutral and discount the future at rate β. There is a single good in the economy which is produced when one firm and one worker meet. Production in these matches depends multiplicatively on aggregate (z) and idiosyncratic (x) productivity shocks, the latter being match specific.[14] Aggregate shocks follow a standard autorregressive process

$$\log(z_t) = \rho \log(z_{t-1}) + \epsilon_t \tag{3}$$

where $\epsilon \sim N(0, \sigma_\epsilon^2)$. Idiosyncratic match shocks are iid across matches and time periods and are distributed according to $F(x)$.

Firms and workers meet in a frictional market, mediated through a matching function. When not matched, workers are deemed unemployed (u) and firms are vacant and post vacancies (v). We use the standard Cobb-Douglas functional form to model new hires, m:

$$m(u, v) = \phi_0 u^{\phi_1} v^{1-\phi_1}$$

with $\phi_1 \in (0, 1)$. Let market tightness be defined as $\theta = v/u$. Given the matching function above, one can define the job finding probability as $f(\theta) = m(u, v)/u$ and the job filling probability as $q(\theta) = m(u, v)/v$. Matches can be destroyed at exogenous rate s or due to endogenous separations (see details below).

[14] As noted by Sedláček (2014), the mechanisms in the model are identical whether one assumes that x is match or worker specific.

The value of being matched with a worker for a firm is given by the dynamic Bellman equation

$$J(z,x) = zx - w(z,x) + (1-s)\beta\mathbb{E}_z \int \max\{J(z',x'), V(z')\}dF(x') \tag{4}$$

where zx is the productivity of the match, $w(z,x)$ is the wage paid to the worker, $\mathbb{E}_z$ is the expected value with respect to aggregate conditions z and V represents the value of having an unmatched vacancy in the labor market, which can be posted at flow cost c_v. The value of holding such vacancy is defined by

$$V(z) = -c_v + \beta\mathbb{E}_z \left[(1-q(\theta_z))V(z') + q(\theta_z)\int \max\{J(z',x'), V(z')\}dF(x')\right] \tag{5}$$

where notation θ_z implies that labor market tightness depends on aggregate conditions (z). Note that the last term in the Bellman equation makes it explicit that the match may be terminated endogenously given bad draws of the idiosyncratic shock x.

When in a match, workers receive the wage (that depends on aggregate conditions and idiosyncratic productivity of the match). When unemployed, they receive value b, which can be thought of as extra leisure or home production (not a government transfer). The value function for unemployment and employment are (respectively)

$$U(z) = b + \beta\mathbb{E}_z \left[f(\theta_z)\int \max\{W(z',x') - U(z'), 0\}dF(x') + U(z')\right] \tag{6}$$

$$W(z,x) = w(z,x) + \beta\mathbb{E}_z \left[(1-s)\int \max\{W(z',x') - U(z'), 0\}dF(x') + U(z')\right] \tag{7}$$

As is standard with this type of models, a key object is the match surplus:

$$S(z,x) \equiv W(z,x) - U(z) + J(z,x) - V(z) \tag{8}$$

Assuming free entry, $V(z) = 0$ throughout. We follow the literature and assume that workers and firms share the surplus from productive matches using Nash bargaining, with parameter η representing the bargaining power of workers. This implies that

$$W(z,x) - U(z) = \eta S(z,x) \tag{9}$$

$$J(z,x) = (1-\eta) S(z,x) \tag{10}$$

Given that idiosyncratic shocks are iid across matches and time periods, it's straightforward to show that there is a threshold value x (generically depending on z) that determines the profitability of any given match. We label this threshold as $\underline{x}(z)$ in what follows. Then, we can define the surplus equation as

$$S(z,x) = zx - b + \beta\left(1 - s - f(\theta)\eta\right)\mathbb{E}_z \int_{\underline{x}(z')}^{\infty} S(z',x')dF(x') \tag{11}$$

where we realize that some matches may be broken because of a low enough idiosyncratic productivity shock in x: surplus is only defined by shocks above threshold $\underline{x}$.

Finally, the wage equation is derived using the definition of the Bellman equations and of the surplus (8). After some standard algebra, the individual wage is given by:

$$w(z,x) = \eta\left(zx + c_v \frac{v}{u}\right) + (1-\eta)b \tag{12}$$

4.1 Parameterization

We set the time period in the model to be a month. Accordingly, we set $\beta = 0.996$ so that the interest rate is 4 per cent per year.

We approximate the aggregate shock using a numerical approximation to the continous process in (3): we use the method in Galindev and Lkhagvasuren (2010) due to it being appropriate for highly persistent processes.[15] As for the idiosyncratic shock x, we use a log-normal distribution with standard deviation σ_x and a normalized mean equal to $-(1/2)\sigma_x^2$ so that the unconditional mean of x is equal to one.[16]

There are 9 parameters to determine: the parameters of the matching function (ϕ_0, ϕ_1), the exogenous separation rate (s), the standard deviation of the distribution of idiosyncratic shocks (σ_x), the flow cost of vacancy costs (c_v), worker's bargaining weight (η) and non-working value for individuals (b) and the two parameters of the AR(1) process for z (ρ, σ_ϵ).

[15] We use a grid with 51 points to approximate the process.

[16] We approximate this log-normal distribution using a log-linear grid of 501 points, centered at 1.

To obtain parameter values, we compare predictions from our model to the empirical results in the previous section and to empirical moments from the Chilean economy, computed from the *Encuesta Nacional de Empleo* (national employment survey, ENE hearafter) between 2010 and 2020, a representative survey of the Chilean workforce. Whenever we compare our model predictions to quarterly frequency indicators, we aggregate our monthly simulations by simple averaging.[17]

While the parameters above determine jointly the numerical equilibrium and simulations from of our model economy, below we provide a simplified discussion linking model parameters and some moments closely linked to them which we use for calibration.

For the matching function parameters, we target the quarterly job finding probability according to ENE (0.457) which informs parameter ϕ_0. For the elasticity of m with respect to vacancies, we take the value estimated by Kirchner and Tranamil (2016). On the other hand, the quarterly job separation rate (0.029) informs parameter s.

As in Sedláček (2014), we parameterize σ_x to match the relative volatility of the job separation rate to that of the aggregate unemployment rate (1.686). For both Chilean and model simulated data, we take quarterly time series which we log and then apply the Hodrick-Prescott filter. We then compute the ratio of standard deviations as the moment to match.

For the flow vacancy cost c_v, we follow Andolfatto (1996) and target an aggregate expenditure in vacancies over GDP of one percent while b is informed by a standard normalization of the average tightness to be equal to one, as suggested by Shimer (2005a).

Finally, we choose ρ and σ_ϵ to match the estimates for the autocorrelation and standard deviation of aggregate productivity in the Chilean economy as estimated by Kirchner and Tranamil (2016). These are estimated at quarterly frequency, which we match by time aggregating our simulated data.

Calibrate parameter values are in table 4.1. Although the model is matching moments from the Chilean economy, the parameterization is similar to Hagedorn and Manovskii (2008) and Sedláček (2014), in that the value of unemployment for individuals b is high (relative to average productivity WHICH IS... (CHECK CODE, IT IS NOT ONE BUT ONE TIMES TRUNCATED EXP X.)).

[17] The ENE is the official employment survey in Chile, conducted by the *Instituto Nacional de Estadísticas* (INE) to produce official labor force statistics. It is a quarterly rotating panel survey in which urban households remain up to 6 quarters in sample and rural ones, up to 12 quarters.

Table 6: Parameter Values

parameter	description	value
ϕ_0	constant, matching function	0.457
ϕ_1	elasticity matching fcn wrt vacancies	0.629
s	exogenous separation rate	0.028
σ_x	std. dev. Idiosyncratic shock	0.245
c_v	flow cost vacancy	0.170
η	worker's bargaining weight	0.305
b	flow value of unemployment	0.915
ρ	autocorrelation AR(1)	0.935
σ_ϵ	std. dev. AR(1)	0.006

4.2 Model results

4.3 Discussion

In terms of aggregates, the average wage in our model economy is the integral of wage equation (12) across all producing firms. These are the worker-firm matches, either recently formed or surviving the exogenous destruction shock s, which receive a contemporaneous productivity shock greater than $\underline{x}(z)$.

Note that this theory gives a theoretical interpretation to the the semi-elasticity of wages to the aggregate unemployment rate, since the wage function depends on the term $c_v(v/u)$. Thus, the semi-elasticity in the model is

$$\frac{\partial \log w}{\partial u} = \frac{1}{w}\left(\frac{-\eta c_v v}{u^2}\right) \tag{13}$$

which given the setup of the model, is unambiguosly negative. Note that this semi-elasticity is wage-level specific, so to obtain a model counterpart to the estimates of the previous section, we need to aggregate all individual wages. Given equation (12), we know that individual wages depend on x, while aggregate ones depend on $\mathbb{E}\left[x|x > \underline{x}(z)\right]$, which explicitly depends on aggregate conditions through hiring standard cyclicality. What would happen if we apply equation (1) to model simulated data?

5 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 applicant, firm or job composition changes, avoiding problems due to the cyclical upgrade, as remarked by Gertler and Trigari (2009). Second, the fact that we observed offered instead of realized wages allows us to minimize concerns about cyclical mismatch. Third, we show that job requirements associated with higher wages move countercyclically, as do Modestino et al. (2020). The latter is relevant since omitting fluctuating hiring standards affects the estimation of wage cyclicality, 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. Our treatment of the evidence shows the inevitable interlink between offered wages and job ad requirements. Although some models try to explain these facts (Baydur, 2017; Carrillo-Tudela et al., 2018), 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.

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Appendix: Additional tables and figures

Table 7: 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).

Table 8: 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 9: Estimation results: Regional Unemployment

	Dependent variable: log ad wage		
	(1)	(2)	(3)
Unemployment rate	2.539***	-0.861***	-1.104***
	(0.029)	(0.026)	(0.024)
Job ad characteristics	N	N	Y
Firm and Job title fixed effects	N	Y	Y
Adjusted R2	0.002	0.634	0.680
Adjusted within R2	0.002	0.073	0.190
Sample size (vacancies)	5,214,389	5,214,389	5,214,389

Estimation results of equation (1), between log posted wages and the aggregate unemployment rate. Sample period is March 1st 2010 to March 31st, 2020. 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.

Table 10: Estimation results: Robustness with Regional Unemployment Rates

	estimate	std. err.	Sample Size
Baseline	-1.104***	(0.024)	5,214,389
Explicit ads	-1.248***	(0.053)	1,225,866
No Firm FE	-0.687***	(0.023)	5,214,389
No Job Title FE	-1.034***	(0.021)	5,214,389
No weights	-0.416***	(0.055)	969,828

Estimation results for alternative specifications. Sample period is March 1st 2010 to March 31st 2020. All regressions control for time effects by way of a monthly trend and month-of-year dummies to control for seasonality.

Table 11: Estimation results by Industry groups (regional unemployment)

	estimate	std. err.	adj. R2	within R2	Sample Size
BASELINE	-1.104***	(0.024)	0.680	0.190	5,214,389
Services	-1.375***	(0.044)	0.771	0.194	1,434,848
Transport	1.094***	(0.067)	0.735	0.191	1,075,366
Finance	-1.072***	(0.088)	0.688	0.170	463,099
Manufacture	-1.669***	(0.101)	0.821	0.224	421,384
Elect. and utilities	-1.714***	(0.077)	0.750	0.195	410,434
Agriculture	0.410***	(0.084)	0.768	0.211	379,471

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.

Table 12: 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	0.0011	−0.5860	−0.0006
required experience (years): 1	0.0510	−0.3940	−0.0201
required experience (years): 2	0.1892	0.7571	0.1433
required experience (years): 3	0.2937	−0.0026	−0.0008
required experience (years): 4	0.4101	0.0585	0.0240
required experience (years): 5	0.3969	0.1878	0.0745
required experience (years): 6	0.2103	−0.0512	−0.0108
required experience (years): 7	0.5709	0.0109	0.0062
required experience (years): 8	0.6197	0.0055	0.0034
required experience (years): 9	0.6541	0.0008	0.0005
required experience (years): 10	0.5131	0.0026	0.0013
required experience (years): 11	0.2163	−0.0024	−0.0005
required experience (years): 12	0.5158	−0.0016	−0.0008
required experience (years): 13	0.8944	0.0017	0.0015
required experience (years): 14	0.4061	0.0002	0.0001
required experience (years): 15	0.5264	−0.0005	−0.0003
required experience (years): 16	0.3718	0.0001	0.0000
required experience (years): 17	0.1458	−0.0063	−0.0009
required experience (years): 18	-0.1159	0.0139	−0.0016
required experience (years): 19	0.1779	0.0004	0.0001
required experience (years): 20	(omitted)		
type of contract: full time	0.1512	0.3769	0.0570
type of contract: part time	(omitted)		
education: less than high school	-0.3357	−0.6026	0.2023
education: high school	-0.3119	0.6074	−0.189
education: technical (tertiary)	-0.2374	−1.0826	0.2570
education: university	(omitted)		
Computer: User level	-0.0867	−3.3473	0.2900
Computer: Advanced user	(omitted)		
general knowledge: no	-0.0421	−3.4870	0.1468
general knowledge: yes	(omitted)		
specific knowledge: no	-0.0420	−3.0236	0.1270
specific knowledge: yes	(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 13: Decomposition: cyclical variation of hiring standards (full table, Regional Unemployment)

Job ad characteristic:	β_{X_a}	$\partial X_a/\partial U$	% of $\hat{\beta}^{\text{base}} - \hat{\beta}^{\text{full}}$
required experience (years): 0	-0.1155	0.8907	−0.1029
required experience (years): 1	-0.0643	−1.1060	0.0711
required experience (years): 2	0.0710	0.1289	0.0092
required experience (years): 3	0.1714	−0.0089	−0.0015
required experience (years): 4	0.2965	0.0001	0.0000
required experience (years): 5	0.2579	0.0597	0.0154
required experience (years): 6	0.1018	0.0355	0.0036
required experience (years): 7	0.4718	0.0019	0.0009
required experience (years): 8	0.5066	−0.0115	−0.0058
required experience (years): 9	0.5138	−0.0004	−0.0002
required experience (years): 10	0.4063	0.0256	0.0104
required experience (years): 11	0.0284	−0.0009	0.0000
required experience (years): 12	0.3105	−0.0002	−0.0001
required experience (years): 13	0.9894	−0.0001	−0.0001
required experience (years): 14	0.4037	−0.0001	−0.0001
required experience (years): 15	0.4154	−0.0007	−0.0003
required experience (years): 16	0.2470	0.0001	0.0000
required experience (years): 17	0.1444	−0.0052	−0.0008
required experience (years): 18	-0.3212	−0.0115	0.0037
required experience (years): 19	-0.0444	0.0002	−0.0083
required experience (years): 20	(omitted)		
type of contract: full time	0.1642	−0.2920	−0.0479
type of contract: part time	(omitted)		
education: less than high school	-0.3443	0.4482	−0.1543
education: high school	-0.3240	−0.2875	0.0932
education: technical (tertiary)	-0.2484	−0.6448	0.1601
education: university	(omitted)		
Computer: User level	-0.0974	−1.2779	0.1245
Computer: Advanced user	(omitted)		
general knowledge: no	-0.0488	−0.8525	0.0416
general knowledge: yes	(omitted)		
specific knowledge: no	-0.0515	−1.9757	0.1018
specific knowledge: yes	(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 Unemploytment rate on the particular job ad characteristic (controlling for all other variables); the last column represents the fraction explained of the difference.