Wage Cyclicality Revisited: The Role of Hiring Standards

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Wage Cyclicality Revisited: The Role of Hiring Standards *

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Abstract

We use a decade of online job ads to get robust estimates for real wage cyclicality, controlling for job title and firm fixed effects as well as *hiring standards*, i.e. posted requirements for applicants. Our estimates lie in the high range of semi-elasticities of real wages to unemployment rate found in the literature. Controlling for hiring standards is conceptually important to appropriately compare wages of the same position aiming at hiring the same kind of worker in different phases of the business cycle. Moreover, as hiring standards are countercyclical, omitting them leads to the underestimation of real wage procyclicality. To rationalize the facts, we calibrate a search and matching model with aggregate and idiosyncratic match productivity shocks in which employers set hiring standards. Simulations from the model and analytical results show both highly procyclical wages and countercyclical hiring standards under typical parameterizations.

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

JEL Codes: E24, J64

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1 Introduction

The debate surrounding the "unemployment volatility puzzle" has resurfaced interest in documenting the sensitivity of wages to aggregate fluctuations.[1] As the Diamond-Mortensen-Pissarides model is unable to explain large fluctuations of unemployment under standard calibrations, some authors such as Hall (2005) and Shimer (2010), among others, emphasize that wage rigidity could help reconcile evidence and theory: if wages are rigid, aggregate shocks affect profits more than wages, triggering a larger response of job creation by firms. However, empirical studies have not provided a definite answer on the level of wage cyclicality. One important issue is job *upgrading*, highlighted by Gertler and Trigari (2009) and Gertler et al. (2020): in an upturn, workers can take jobs from a pool with better composition rather than job positions increasing their offered compensations (and viceversa in a downturn). In general, researchers may face measurement problems if match quality moves cyclically or if the data is not representative of all formed matches.

We use a decade of data from www.trabajando.com, an internet job board operating in the Chilean economy, which provide us with detailed information on both job posters and job seekers' characteristics as well as high quality wage information, in the form of offered salaries for each advertised position.[2] We study posted wages as the key labor price for hiring decisions, as forcefully argued by Pissarides (2009).[3] Using posted wages is important for two reasons. First, they are an ex ante intention to offer a base pay[4] of employers that drive applications, as shown in previous research (Dal Bó et al., 2013; Banfi and Villena-Roldán, 2019). Second, there is substantial evidence of cyclical mismatch in the labor market, as noted by Şahin et al. (2014), likely affecting realized wages: for a *given composition* of jobs and workers, poor matches are more frequent, resulting in underpaid workers and shorter tenures in a recession.[5] Due to the ex ante nature of posted wages, we can minimize concerns about cyclical quality of the match while also controlling for the ex ante quality of the job itself.

As our main result, we find significant procyclical offered salaries for full-time jobs, controlling not only for the composition of employers and job titles but also for contract terms and hiring

[1] See Shimer (2005), Hall (2005), Hagedorn and Manovskii (2008), and Costain and Reiter (2008)

[2] See Banfi and Villena-Roldán (2019) for a detailed description of these posted salaries and their reliability, even if they are provided to the website but concealed to applicants.

[3] Studies using similar data to ours are Hazell and Taska (2020) and Faryna et al. (2022). Nevertheless, it is not straightforward to compare our results to these papers since they rely on variation across regional or sector markets to identify the impact of unemployment on wages.

[4] According to Swanson (2007), a fraction of cyclicality of wages is accounted for variable labor income such as bonuses, overtime, and commissions, something we want to exclude from our analysis.

[5] See Bowlus (1995), Oreopoulos et al. (2012), Baydur and Mukoyama (2020), and Bellou and Kaymak (2021)

standards. Our estimated semi-elasticity of wages with respect to unemployment rate falls in the upper range of (absolute value) estimates previously found in the literature: -1.725. This estimate is similar to the findings in Albagli et al. (2017) who estimate a range between -1.7 and -2.0 for the Chilean economy using administrative tax records.

As a second result, we also show that hiring standards and the pool composition of ads *and* jobseekers have important effects on this estimation. We show that ignoring either (i) job requirement information or (ii) compositional changes in labour markets leads to wage procyclicality underestimation. The first bias is due to firms changing hiring standards countercyclically: in a downturn employers offer lower wages but also rise the hiring standard. A likely explanation is that employers do not reduce wages very much to attract more qualified applicants. Thus, wages may look less rigid if hiring standards remain fixed. The second bias occurs because both firms and job seekers may decide to participate in the labor market or not, depending on aggregate market conditions, leading to cyclical changes in the pool of potential matches. This is related to results in Bils (1985) and Solon et al. (1994), highlighted more recently by Gertler et al. (2020) and Grigsby et al. (2021). To avoid this issue, we use the reweighing technique of DiNardo et al. (1996), where we assign scores to job postings according to how likely they are to belong to a baseline period, considering ad characteristics and average traits of workers who apply to them.

Using the empirical framework just described, we find that hiring standards leniency significantly increases in upturns, in line with results in Modestino et al. (2016, 2020).[6] Using the decomposition exercise of Gelbach (2016), we show that employers changing education and knowledge requirements at the job level account mostly for the underestimation of wage procyclicality.

A third result relates to the *representativeness* of wage posting data and calls for caution with its use. The website www.trabajando.com explicitly asks posters about the actual number of vacancies each job ad represents. Our results show that ignoring this information biases the estimates significantly downwards, since ads which post more vacancies per ad post more procyclical wages. In the same vein, most online job boards have only 15%-25% of ads with posted wages[7] which tend to require unskilled workers, as shown in Brenčič (2012) and Banfi and Villena-Roldán (2019). Moreover, some posted wages are mid points of brackets, which likely leads to estimates overstating wage rigidity. Fortunately, www.trabajando.com requires employers to enter a point offer, allowing them to conceal it from applicants later. This policy allows us to reliably observe

[6] A similar idea and some evidence of countercyclical hirings standards is already present in Reder (1964) and McGregor (1978).

[7] See for instance, Kuhn and Shen (2013), Marinescu and Wolthoff (2020), and Hazell and Taska (2020)

wages of approximately 75% of postings.[8]

Overall, the results of our empirical exercise give context to the wide array of estimates found in the literature, which vary in terms of the type of data source used and level of controls. Papers such as Carneiro et al. (2012), Martins et al. (2012), Haefke et al. (2013), Stüber (2017), Schaefer and Singleton (2019), Dapi (2020), and Hahn et al. (2021) find high levels of wage procyclicality, in contrast to results in Gertler and Trigari (2009), Grigsby et al. (2021), and Hazell and Taska (2020). We argue that this diversity may be reconciled if one acknowledges the effect of sample composition, cyclical hiring standards, and representativeness of job board ad data.

To rationalize our facts, we extend a Diamond-Mortensen-Pissarides (DMP) search & matching model of the labor market to include both idiosyncratic and aggregate shocks that affect productivity of the match, along the lines of Sedláček (2014). In our setting, employers may find it optimal to set a *hiring standard*, i.e. a minimum required level of match quality to hire or keep a match. Employers might accept any match, even if it yields zero production in the present if aggregate productivity is high and persistent enough for the future. However, in a recessive scenario, employers may set a binding (not zero) hiring standard to ensure a sufficiently high (expected) match productivity. We show analytically (in line with this intuition) that for hiring standards to vary countercyclically, we need a small *fundamental surplus* calibration, i.e. a small difference between average productivity and the outside option value for the unemployed. As Hagedorn and Manovskii (2008) and Ljungqvist and Sargent (2017) show, this can explain strong procyclicality of labor market tightness. We show that there are two opposite forces whenever employers reduce hiring standards after a positive aggregate shock: on one hand, firms want to ease hiring because they find more matches profitable now, something we label as the *participation effect*; on the other hand, there is a negative *average productivity* effect, as the mean quality of accepted matches decays after lower hiring standards. As long as employers affect a sizeable share of matches by varying their standards, the model generates both procyclical wages and countercyclical hiring standards. Under the prevalence of the participation effect, a small fundamental surplus rationalizes high absolute magnitudes for both market-tightness and hiring standards elasticities with respect to the cycle.

We calibrate the model to the Chilean labor market. We then use it to simulate micro data of wages and hiring standards to run regressions mimicking the ones we perform with real data. Al-

[8] Banfi and Villena-Roldán (2019) perform an exercise to show the reliability of this wages even in the case employers decide to conceal them.

though the simulated data generates more procyclical wages than the empirical ones, the model does qualitatively account for the cyclical patterns of both variables. The introduction of hiring standards is a way to discipline the relevant mechanisms at work when building models to explain the cyclical behaviour of the labor market. Our mechanism is based on a directly empirical counterpart of the notion of hiring standards, simultaneously observed with ex ante posted wages. Comparable wages over the business cycle must ideally be taken by workers of the same qualifications.

In sum, we empirically and theoretically show that not accounting for the change in hiring standards leads to an underestimation of the procyclicality of wages, and misconstrues the role of real wage stickiness as a source for high unemployment cyclical volatility. Although our paper uses Chilean data, results in Modestino et al. (2016, 2020) using US (Burning Glass) data, strongly suggest that the main point we make here applies to the US economy, too.

2 Data

We use information from the private job board www.trabajando.com. We use data on job advertisements posted online between March 1st 2010 and March 31st 2020 and the job seekers who applied to those positions using the website. Job seekers can use the website for free, while firms pay to display ads for 30 to 60 days.

There are two main advantages of the information from this job board: First, employers are required to provide an estimated net monthly salary to be paid at the position: a monthly figure, net of taxes, social security, and health contributions. Note that by definition, this offered wage data is not influenced by characteristics of any individual worker. Additionally, the wage information we analyze does not consider bonuses nor other payments workers may receive which may be subject to aggregate conditions as suggested by Swanson (2007).[9] Second, each job advertisement contains information on the number of actual vacancies the posting firm is wishing to fill, hence our dataset is a close representation of the real labor demand in the Chilean economy.

For the current exercise, we consider only job postings with valid wage information and that were applied to by at least one job seeker.[10] Also, we focus exclusively on job postings related to full-time jobs. In table 1 we show some summary statistics with respect to both individual job ads

[9] 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.

[10] See Banfi and Villena-Roldán (2019) for a detailed description of the cleaning of the dataset. Roughly 20% of posted job ads have posted wages that we deem to be invalid, such as 0, 111, 123, etc. This leaves a potential pool of $2,139,079$ job ads. From these we remove job ads with outliers in terms of requested experience (demanding above 20 years) and number of vacancies (more than 200 vacancies) or that offer salaries below minimum wage (e.g. internships).

Table 1: Characteristics of Job Postings

	Ads	Vacancies
Observations	1,194,445	4,745,918
Wages (thousand CLP)	726	497
Exp. requirement: 0 yrs	0.16	0.30
Exp. requirement: 1 yrs	0.36	0.49
Exp. requirement: 2 yrs	0.23	0.12
Exp. requirement: ≥ 3 yrs	0.25	0.10
Ed. requirement: $\geq$University	0.37	0.16
Foreign language	0.09	0.04
General knowledge	0.69	0.59
Specific knowledge	0.20	0.20
No or basic computer knowledge	0.31	0.48
Long-term contract	0.68	0.54
Big Firm ($>$ 51 employees)	0.44	0.47
Explicit wage	0.16	0.23

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

(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. In Appendix A.1 we present statistics for all ads.

The table shows the importance of weighing by the number of vacancies when computing averages. While average wages amount to roughly 726 thousand pesos (monthly, after tax)[11] when considering job adverts alone, this figure decreases to around 497 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,[12] the median after tax wage in Chile during 2015 (mid point of our sample) was 350 thousand pesos.

In the rest of the table, we also display required experience (in years), as well as the fraction of job positions with particular requirements (e.g., university degree or higher) or offering certain characteristics (e.g., long-term contracts). From the raw text of job ads, we categorize jobs in terms

[11] 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.

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

of whether they require any form of knowledge (general or specific),[13] and foreign language[14]. In a similar way, we look for keywords linked with computer knowledge in the ad text, from where we can produce a categorization of job positions that require either no or basic computer knowledge (compared to *advanced* knowledge).

The main takeaway from the information in the table, is that weighting information in job ads by number of vacancies has a first order effect in final computed statistics. All results in what follows are weighted by the number of vacancies to appropriately represent the actual job creation flow generated by the website.

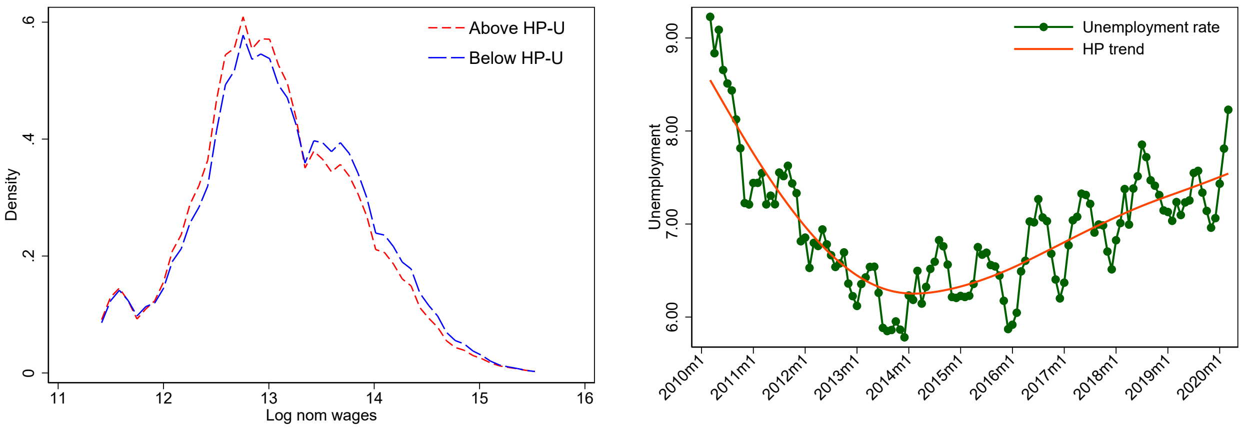

Figure 1: Histogram of log nominal wages, according to the aggregate unemployment rate trend deviation at the time of posting (left) and time series of unemployment rate and its Hodrick-Prescott smoothed trend with parameter $\lambda = 14,400$ (right).

In the left panel of figure 1 we plot kernel density estimates for (vacancy weighted) log wages 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,[15] separating by whether unemployment was above or below the Hodrick-Prescott filtered trend.[16] As seen from the figure, there is a shift towards higher wages during periods of low unemployment, especially for wages over $e^{13.5} \approx 730,000$ CLP. The right panel in the same figure shows the aggregate unemployment rate in the Chilean economy during our sample period, along

[13]We produce this categorization by simply looking for certain word stems in Spanish (e.g., "conocim" and "especiali" for "knowledge" and "speciality") that are related to firms requiring particular knowledge from the applicant at the position.

[14]We look for stems of terms referring to foreign language in both Spanish and English, as well as mentions of other less frequently required languages.

[15]We use unemployment statistics reported by the *OECD*: `https://data.oecd.org/unemp/unemployment-rate.htm`, based in turn in the Chilean National Statistics Institute (INE)

[16]For reference, the Chilean unemployment rate during the time period considered was on average 6.9%, fluctuating between 5.8% and 9.2%.

a Hodrick-Prescott trend. From the figure we can see a decline in unemployment due to recovery of the economy following the global financial crisis of 2008-2009. After the mid part of 2015, the figure shows an increase in the unemployment rate.

Since ad wages in www.trabajando.com are associated with job creation in the short term, in order to assess representativeness of our data set with respect to the entire labor market, we need to compare them to the wages of jobs actually created in the economy around the publication dates of the ads. To do this, we use a nationally representative survey: the *Encuesta Suplementaria de Ingresos* (ESI henceforth), a supplement of the *Encuesta Nacional de Empleo* (ENE henceforth) which measures salaries and characteristics of workers in the Chilean economy. This survey has questions about wages during the fourth quarter of each year and 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.[17]

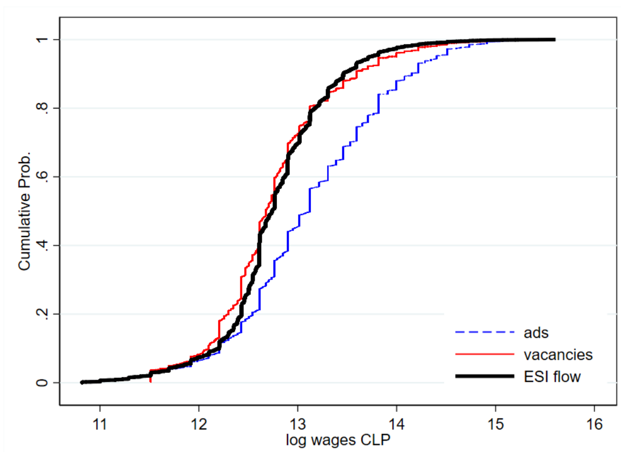

Figure 2: Cumulative Probability function of log wages in Chilean Pesos (CLP), for trabajando.com data and information from newly hired workers from the ESI supplement of the *Encuesta Nacional de Empleo* (ENE) dataset. For ESI data, we use the 2017 Census correction of weights, as recommended by INE.

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 hired within the last 12 months in the ESI for 2010-2019, [18] only considering full-time jobs. Note that this comparison relies on 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. Figure 2 depicts cumulative

[17]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.

[18]We did not consider 2020 data for the comparison because of COVID-19 pandemic effects largely affected the last quarter of that year.

probability function estimators of log-wage distributions, which shows that the website information lines up very accurately when compared to actual wages of newly hired workers in the Chilean economy. On the other hand, the cumulative distribution of wages from the website *without* vacancy weights is significantly shifted to higher wages, which shows that what we observe in table 1 for the average applies for the entire distribution of salaries.

To compare job composition in terms of educational requirements, we assume that employers requiring a specific educational level in their ads end up hiring workers matching those requirements.[19] 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.

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. Leaving aside primary school requirements, a 68.5% of vacancies targets high-school level workers, compared to the 71.2% of the ESI flow and a 55.2% of job seekers in general (i.e. unemployed and employed workers who search for a job in ESI data). For college-level workers the figures are 14.2% of vacancies, compared to 15.3% of ESI flow, and 24.7% of jobseekers. Table 9 shows these results in the appendix.

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 regression we estimate is

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

[19] 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, Choi, and Villena-Roldán (Banfi et al.) and Banfi et al. (2019).

where $t(a)$ is the month in which the job ad is posted, X_a is a set of characteristics of the job and $\varphi_{f(a)}$, $\lambda_{j(a)}$, and $\zeta_{m(a)}$ represent firm, job title, and required major fixed effects, respectively. The empirical setup can also be thought of as a monthly panel where we aggregate wage information at the job title / major and firm levels. From this equation, the main object of interest is the estimate of the semi-elasticity between wages and aggregate unemployment, $\partial \log w_a / \partial U_{t(a)}$.

The use of job titles and majors in the vein of Marinescu and Wolthoff (2020) and Banfi and Villena-Roldán (2019), follows from the idea that they describe jobs more precisely than occupations or other coarser categorizations. Following standard treatment pre-processing of texts, we detect the first four meaningful words of the job title and the first three of the major description.[20] Then, we construct a set of binary variables for the first job title word with a share greater than 0.1% of the whole sample, assigning those that do not reach the threshold as "non frequent word". We do the same procedure to create binary variables for the second, third, and fourth word in the job title, as well as for the first three words in the major description.

In X_a we include posted requirements or features of the job, in the form of dummies for educational level (less than high school, high school diploma, tertiary technical education, and university), experience in years (we define categories of 0, 1, 2, and 3+ years of requested experience), general/specific knowledge, foreign language, and computation knowledge requirements, as described in the previous section. We also include a dummy for long term offered contract, monthly dummies, and a linear trend.[21]

The above specification identifies a causal effect of unemployment on wages mimicking as close as possible the 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.

Our novel setup considers the effect behavior of hiring standards, as in Modestino et al. (2020) in the estimation of the cyclicality of wages. Moreover, while job title, major, and firm fixed effects can control partially for confounding compositional changes in the labor market, our particular dataset allows us to consider an even cleaner exercise, since we observe job applicants (and their application choices) at any point in time: we use the reweighing technique of DiNardo et al. (1996) (DFL henceforth). We implement the method by first choosing the composition of jobs and workers in 2017, the year with an unemployment rate (6.93%) closest to the sample average (6.92%). We

[20] We use the SnowballStemmer code in Python and its standard list of stop words in Spanish.

[21] We do not control for region, industry, and firm size as these variables are absrbed into firm fixed effects.

run a logit model[22] estimating the probability of being part of the 2017 sample as a function of observables on the average characteristics of applicants for a job[23] and on the job ad side.[24] We then compute a predicted probability of a job ad being present in the taget year, 2017. In what follows, we weight each job ad using the product of the latter predicted probability odds and the number of vacancies in the job ad, to appropriately represent the job creation with a composition of job ads at the reference year.

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, ceteris paribus.

3.2 Results

We estimate equation (1) using simple linear regressions and consider two mains sets of regressors: First, we consider a specification with firm and job title fixed effects only. In this case, we find a semi-elasticity of -1.345. Our preferred specification which controls for job characteristics and requirements (hiring standards) in X_a also, produces an estimate of -1.725. This is one of the main results of our empirical exercise: measured wage cyclicality is higher when we *include* controls for hiring standards.

In table 3, we present estimates for different specifications. The first row labelled *Full*, represents estimates from the last column of table 2. In the rest of the table, we use this exact same specification, but altering one thing at a time. Thus, all results in the table are based on the same sample of $1,031,199$ job ads and $3,950,909$ vacancies.

The three rows below the *Full* results show estimates when using different sets of sample weights: when using only the number of vacancies, only DFL weights or no weights at all. These results show the importance of weighting the data appropriately and how the estimated procyclicality of wages decreases significantly when we ignore either the actual labor demand (from vacancy information) and the composition of the market, represented by DFL weights. As mentioned in the introduction, this downward bias in the estimation of wage cyclicality is our main empirical results.

The *No Firm FE*, and *No Job Title FE* rows represent the estimation of equation (1) when we

[22] Due to our very large set of covariates, we follow Haggstrom (1983) to estimate a linear probability model whose coefficients are adjusted to obtain the logit estimates.

[23] average applicant expected wage, share of applicants making their wage expectation visible, and the share of applicants to a job belonging to groups by gender, age, experience, education, region, and labor status.

[24] Required experience categories; dummy for explicit wage posted; area; industry; major description words; computer, general, specific, and language knowledge; job title words; graduation status categories, long term contract, and educational level requirement categories.

Table 2: Estimation results

	Dependent variable: log ad wage	
	Base	*Full*
Unemployment rate	-1.345	-1.725
	(0.091)	(0.091)
Job ad characteristics	N	Y
Adjusted R2	0.587	0.627
R2	0.602	0.640
Sample size (ads)	1,031,199	1,031,199
Sample size (vacancies)	3,950,909	3,950,909

Estimation results of equation (1), between log of real posted wages and the aggregate unemployment rate. 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 and both firm and job title fixed effects. Observations are weighted using number of posted vacancies and the DFL methodology (see text). Standard errors in parenthesis.

remove either firm or job title fixed effects from our main specification. From the table we observe that removing firm fixed effects has some downward effect in the estimation of the semi-elasticity. However, there is a significant effect when we omit job titles fixed effects, since the estimate becomes positive (0.408). Both estimates suggest that firms and job titles typically paying lower wages tend to be more abundant in upturns, as emphasized by Gertler and Trigari (2009) and Gertler et al. (2020). This shows the importance of properly controlling for job characteristics and upgrading when studying business cycles and labor markets.

The next two rows of the table show results for a specification where we include an interaction between the aggregate unemployment rate and an indicator for the case that the job ad exhibits an explicit wage for job seekers to observe. This matters since ads showing their wages explicitly tend to target low-skill workers (Brenčič, 2012; 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[25], we have an opportunity to check how different these job ads behave in the cycle: results of the table show that these ads are more cyclical than the average (coefficient of -0.538 on the interaction of unemployment and the indicator of the job ad having an explicit wage).

In the last two rows, we study heterogeneity of job ads in terms of vacancies. For this case, we separate job ads in terms of the number of vacancies posted, creating a dummy indicator for

[25]See for instance Kuhn and Shen (2013); Marinescu and Wolthoff (2020); Hazell and Taska (2020)

ads with a number of vacancies above the sample median (20 vacancies). The results show that wage cyclicality for jobs that require higher than median vacancy requirements display significantly more cyclical wages (in response to unemployment), as observed in the coefficients: -1.583 for the interaction and -1.187 for the base semi-elasticity. While we are not aware of any similar result in the literature, the result seems intuitive as multiple vacancy ads typically post jobs aiming for unskilled workers, whose labor demand is likely to be more elastic.

Table 3: Semi-elasticity estimation results: different specifications

	Semi-elasticity	std. error
Full	-1.725	(0.091)
Vacancy weights	-1.309	(0.062)
DFL weights	-0.400	(0.031)
No weights	-0.551	(0.023)
No Firm FE	-1.360	(0.089)
No Job Title FE	0.408	(0.097)
Explicit ads: coeff. on U	-1.524	(0.108)
Explicit ads: coeff. on U x Explicit	-0.538	(0.160)
Vacancy heterogeneity: coeff. on U	-1.187	(0.066)
Vacancy heterogeneity: coeff. on U x Above median vac.	-1.583	(0.185)

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 and have a sample size of 1,031,199 ads and 3,950,909 vacancies.

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 pro-cyclical, monthly wages might be affected by longer hours in expansive times. During 2010-20, 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. Therefore, we restrict our analysis to full-time jobs to minimize this issue as much as possible.

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, 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 wages with respect to unemployment 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. 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 a two step estimation: 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, something akin to $\partial X_a/\partial U$. Second, we multiply the latter by the associated coefficient β_{X_a}, which reflects the impact of job ad characteristics on offered wages.

In table 4 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 knowledge requirements) and characteristics (type of contract offered), which we list in the first column of the table. When estimating the full regression, we omit a base category for each categorical variable which is absorbed in the constant of regression 1, which explains the presence of zeros in column β_{X_a}. Estimates in this second column follow intuitive patterns: jobs requiring higher experience, education, some form of general/specific/computer knowledge or that offer long-term contracts, pay more than their counterparts.

Table 4: Decomposition: cyclical variation of hiring standards

Job ad characteristic	β_{X_a}	$\partial X_a/\partial U$	pct. of $\hat{\beta}^{\text{base}} - \hat{\beta}^{\text{full}}$
Required experience (years):			
0	-0.325	0.024	−0.008
1	-0.260	−0.365	0.095
2	-0.143	0.410	−0.059
>= 3	0.000	−0.069	0.000
Required education:			
Less than High School	-0.414	−2.074	0.858
SH Secondary	-0.393	1.419	−0.558
TP Secondary	-0.361	0.667	−0.241
Technical/Some College	-0.256	−0.995	0.254
College and above	0.000	0.983	0.000
Job requirements:			
Language	0.153	0.326	0.050
General knowledge	0.035	2.076	0.072
Specific knowledge	0.040	4.230	0.169
No PC knowledge	-0.031	8.126	−0.253
Long-term job	0.082	0.000	0.000

Decomposition exercise for the semi-elasticity of wages to the aggregate unemployment rate. Column β_{X_a} shows 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 $(\hat{\beta}^{\text{base}} - \hat{\beta}^{\text{full}})$.

The third column in table 4, labelled $\partial X_a/\partial U$, shows how job characteristics change when aggregate unemployment changes. For *Language*, *General* and *Specific* knowledge requirements, the result is clear in that when unemployment increases, job ads are more likely to include these requirements (estimates of $\partial X_a/\partial U$ are large and positive). The opposite occurs with *No PC knowledge*. As for education categories, higher aggregate unemployment affects the likelihood of job ads requiring either *less than high school* or *Technical/Some College* education, in detriment of requirements of both types of Secondary education and *College and above* requirements. Taken as a whole, this is evidence that in times of high unemployment, job positions upgrade educational requirements: from no high school diploma to some secondary education degree and from technical education to a college degree. Finally, we observe a mixed result in terms of required experience: when unemployment increases, job ads tend to diverge asking either zero or two years of experience. However, taken as a whole, the evidence indicates that job positions upgrade requirements in a counter-cyclical manner.

The last column in table 4 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 columns, divided by $\hat{\beta}^{\text{base}} - \hat{\beta}^{\text{full}}$ (which given our previous results, equals $-1.345 - (-1.725) = 0.380$). From the table we observe that, taken jointly, counter-cyclical educational and knowledge requirements are the most important to explain this difference, while experience requirements play a smaller (albeit significant) role also.

The intuition of our results is clear: 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 (on the firm's side) leads to underestimating the true cyclicality of wages.

4 A quantitative model

In this section we describe a quantitative model we use to rationalize the cyclicality of wages and hiring standards. This section accomplishes two goals: first, it shows that a simple extension of one of the workhorse models in modern macro can explain the facts; second, our quantitative exercise sheds light on a novel mechanism through which firm's profit levels interact with amplification mechanisms in the model.

The model is an extension of the standard frictional labor market setup with non-competitive wage setting and endogenous separations 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 $\delta \in (0, 1)$. There is a single good in the economy which is produced when one firm and one worker mutually agree to form a match. Production in these matches depends multiplicatively on aggregate (z) and idiosyncratic (x) productivity shocks, the latter being match specific.[26] 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 i.i.d. across matches and time periods and are distributed according to cdf $F(x)$. Although this is a strong assumption, its relaxation (e.g.,

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

x being persistent for the worker) creates quantitative complications without adding much to the intuition and analysis.

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 $p(\theta) = m(u, v)/u$ and the job filling probability as $q(\theta) = m(u, v)/v$. Matches can be destroyed both at exogenous rate s, or due to endogenous separations if their surplus becomes negative.

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

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

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

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

where notation $\theta_z \equiv \theta(z)$ stresses that labor market tightness depends on aggregate conditions (z). Note that the last term in the previous Bellman equations makes it explicit that the match may be terminated endogenously given low draws of the idiosyncratic shock x.

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

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

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

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

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

We assume there is free entry of firms, $V(z) = 0$ 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 i.i.d. across matches and time periods, it's straightforward to show that there is a threshold value of 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

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

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 the threshold or hiring standard $\underline{x}$. The latter is defined, in turn, as

$$S(z, \underline{x}(z)) = 0.$$

Hence, the hiring standard $\underline{x}$ is a function on the aggregate productivity shock, z.

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:

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

4.1 Parameterization

We set the time period in the model to be a month. Accordingly, we set $\delta = 0.996$ so that the interest rate is 4 per cent per year.[27] We approximate the aggregate shock using a numerical approximation to the continuous process in (3): we use the method in Galindev and Lkhagvasuren (2010) due to it being appropriate for highly persistent processes.[28] 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. We approximate this log-normal distribution using a log-linear grid of 501 points, centered at one and width of two standard deviations.

There are nine parameters to determine jointly: 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/leisure value (b) and the two parameters of the AR(1) process for aggregate shocks (ρ, σ_ϵ).

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* (ENE) between 2010 and 2020, a representative survey of the Chilean workforce.[29] From this survey, we take aggregate time series of unemployment, job finding and separation rates. Whenever we compare our model predictions to quarterly frequency indicators, we aggregate our monthly simulations by simple averaging.

While the parameters above determine jointly the numerical equilibrium and simulations from of our model economy, below we provide a simplified discussion of 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 (0.457) which informs parameter ϕ_0. For the elasticity of m with respect to vacancies, we take the value estimated by Guerra-Salas et al. (2021) of 0.629 which lays in the range of values estimated in previous literature (Petrongolo and Pissarides, 2001). On the other hand, the quarterly job separation

[27] This is close to the annual average yield of 10-year government bonds in Chile (4.69%) for the period. See series IRLTLT01CLA156N from FRED (St. Louis Fed).

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

[29] The ENE is the official employment survey in Chile, conducted by the *Instituto Nacional de Estadísticas* (National Statistics Institute) 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. Micro level data is available here: https://www.ine.cl/estadisticas/sociales/mercado-laboral/ocupacion-y-desocupacion.

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 (2005).

We choose ρ and σ_ϵ to match the estimates for the autocorrelation (0.872) and standard deviation (0.008) of aggregate productivity in the Chilean economy as estimated by Guerra-Salas et al. (2021). These are estimated at quarterly frequency, which we match by time aggregating our simulated data.

Finally, we calibrate the bargaining weight η by making the model match the estimate in table 2 for the specification without job ad characteristics (*base* semi-elasticity of -1.345). We do this by simulating a panel of worker-firm matches in the model and estimating a pooled linear regression between log wages, a constant, a linear trend and the simulated unemployment rate. There are two main reasons for this choice: First, it is a calibration strategy which is similar to that in Hagedorn and Manovskii (2008) and Sedláček (2014). Second, we want to quantify how much of the difference in estimates found in the data (*base* versus *full* estimations) can be captured by the simple mechanisms in the model. Thus, we treat the *full* estimate from model simulated data as a non-targeted moment below.

Table 5: Parameter Values

parameter	description	value
ϕ_0	constant, matching function	0.469
ϕ_1	elasticity matching fcn wrt vacancies	0.629
s	exogenous separation rate	0.027
σ_x	std. dev. Idiosyncratic shock	0.346
c_v	flow cost vacancy	0.251
η	worker's bargaining weight	0.335
b	flow value of unemployment	0.820
ρ	autocorrelation AR(1)	0.982
σ_ϵ	std. dev. AR(1)	0.011

Calibrated parameter values are in table 4.1. Although the model is matching moments from the Chilean economy, the parameterization is similar to the one found in exercises related to the

Table 6: Business cycle statistics

	Data			Model		
x	σ_x	σ_x/σ_y	$\rho_{x,y}$	σ_x	σ_x/σ_y	$\rho_{x,y}$
Output (y)	0.02	1.00	1.00	0.05	1.00	1.00
Unemployment	0.10	6.61	-0.76	0.24	5.24	-0.91
Vacancies	0.21	13.67	0.72	0.17	3.70	0.13
Job Finding	0.04	2.82	0.17	0.10	2.10	0.93
Job Separation	0.09	6.12	-0.67	0.23	4.85	-0.71

US economy. Note that we find a high value for the outside option for the workers and a low value for their bargaining weight, as in Hagedorn and Manovskii (2008) and Sedláček (2014).

4.2 Model results

In table 6, we show standard business cycle statistics for both the model and the Chilean economy. Both in actual and model simulated data we aggregate monthly to quarterly frequency (when applicable) by way of simple averaging and take natural logs and detrend each series using a Hodrick-Prescott filter.[30] As mentioned above, the main source of data for the Chilean economy is the ENE, while a monthly series of total job vacancies is provided by the Central Bank of Chile.[31]

As with the US economy (see for example Shimer, 2005; Hagedorn and Manovskii, 2008) the Chilean labor market exhibits significant levels of cyclicality of unemployment rates and aggregate vacancy postings, as seen from the third column in the table: unemployment and vacancies are an order of magnitude more volatile than total output. We also find that job finding and job separations are pro-cyclical and counter-cyclical, respectively. Table 6 also shows that our model economy can replicate well these business cycle statistics, with significant amplification from productivity to unemployment, vacancies and job separations.

In terms of measured wage cyclicality, we perform the same estimation as with the website data. We create a panel of wages, unemployment and *requirements* from the quantitative model. The requirements variable is constructed as a dummy which takes the value of one if the minimum required level of the idiosyncratic productivity $\underline{x}(z)$ at the vacancy/job is greater than the boundary of the numerical grid of x in the quantitative model. The rationale for this interpretation of hiring standards in our setup follows from the fact that for sufficiently high levels of the aggre-

[30] Following Shimer (2005), we use as smoothing parameter of 10^5.

[31] See https://si3.bcentral.cl/Siete/ES/Siete/Cuadro/CAP_EMP_REM_DEM/MN_EMP_REM_DEM13/ED_IND_VACM/a211.

gate productivity z, firms in the model do not require any minimum level of x. Thus, $\underline{x}(z)$ takes the minimum value in the predetermined grid of x. This shows that for sufficiently high levels of aggregate productivity, the main part of the match surplus $zx - b$ is not significantly affected in order to trigger separation decisions. Note that, although technically firm decisions are idiosyncratic, minimum productivity requirements are the same for all firms and are affected by aggregate productivity z.

As mentioned in the previous section, to estimate the *base* specification, we run a regression with simulated data, between log wages as a dependent variable, on a constant, a time trend and aggregate unemployment. While we target this *base* semi-elasticity of wages with respect to unemployment in the calibration stage, we put no restrictions on the *full* estimates, i.e., the estimates that arise when we control both for hiring standards and unemployment rates. In table 7 below, we show the results from this exercise, where we estimate both $\hat{\beta}^{base}$ and $\hat{\beta}^{full}$ from model simulated data.

Table 7: Model Experiments

	Data	Model
$\hat{\beta}^{\text{base}}$	-1.345	-1.344
$\hat{\beta}^{\text{full}}$	-1.725	-2.181

As seen from the table, the model is able to replicate the findings in the empirical section, in that ignoring a measure of requirements leads to lower values (in absolute term) of the semi-elasticity of wages to unemployment.The result for the *full* estimation using model simulated data is qualitatively the same as in the results section, but with a significantly higher semi-elasticity, which can be attributed to the fact that in the model, aggregate productivity, unemployment and hiring standards are highly collinear: this makes the latter two variables significantly correlated, which reinforces the mechanisms described in the previous section.

4.3 Discussion: unemployment amplification and wage rigidity?

By now it is well understood that replicating the high volatility of unemployment relative to productivity may be a difficult task for the textbook Diamond-Mortensen-Pissarides search and matching model. This observation has lead some researchers (see for example, Shimer, 2005; Hall, 2005) to suggest that rigid wages are needed for the model to perform as in the data: (temporary) rigid wages create short term profits for firms on the onset of a positive productivity shock, giving incentives for them to create more vacancies and affect unemployment.

However, Hagedorn and Manovskii (2008) claim that a different calibration of the model is sufficient to create amplification as observed in the data without assuming real wage rigidity. Since in the model, amplification from productivity to unemployment goes through labor market tightness (through vacancy creation), it is key to understand what influences the elasticity of this variable with respect to productivity. Ljungqvist and Sargent (2017) (as well as some others [WHO?]) summarize well the issue, showing that the size of this elasticity has a negative relationship with the size of the *fundamental surplus*, which in most models, equals the productivity minus the outside option of workers.

Our model is quite similar to the standard one, but exhibits an adjusted *fundamental surplus*, given the presence of idiosyncratic productivity shocks. As employers can adjust the hiring standard, the empirical evidence on joint countercyclical requirements in job ads and procyclical wage offers provides a novel way to discipline the model calibration and rule out some potential explanations for the cyclical behavior of unemployment. Through the lens of our model, a small surplus calibration, as in Hagedorn and Manovskii (2008) and Sedláček (2014) is a natural way to simultaneously explain both facts.

In appendix A.3 we elaborate the formal arguments, but the main intuition is as follows: in a model calibrated with a high fundamental surplus a continuously differentiable distribution of types F, employers hire eventually anyone they contact since the future value of profits is high enough to compensate very low or no production in the present. Thus, a high fundamental surplus delivers two counterfactual predictions: to the well-known limitation of this calibration to replicate the cyclical response of market-tightness and unemployment, we add acyclical (rather than countercyclical) hiring standards. In contrast, a small surplus makes hiring standards relevant. Employers change hiring standards because it is consequential for their profits. This can only occur if the surplus is small in our model.

To provide further support to our argument, in figure 3 we show how the minimum level of idiosyncratic productivity x accepted by firms behaves vis-a-vis the aggregate productivity z and also the average of x across active jobs. The figure shows that if aggregate productivity is higher than a critical level ($z \approx 0.95$ given our baseline parameterization) the conditional expectation of x in the model becomes fixed (at its unconditional mean of one). This implies that there are no minimum idiosyncratic productivity requirements for vacancies/jobs when productivity is high, and taken as a whole, hiring standards are counter-cyclical in the model (they occur more frequently

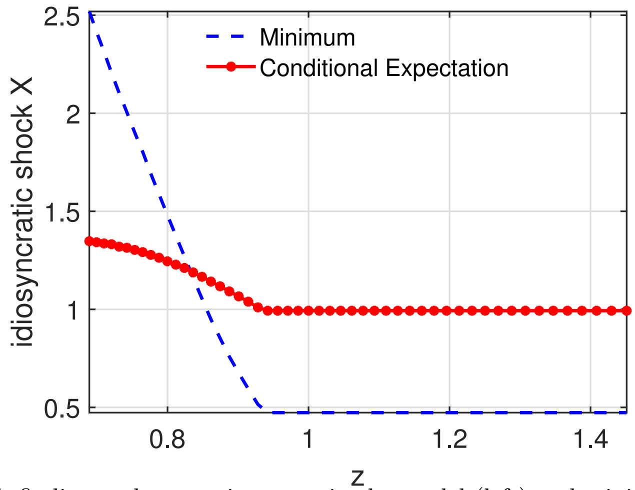

Figure 3: Endogenous job finding and separation rates in the model (left) and minimum productivity thresholds along with the conditional expectation of shocks (right).

with low levels of z). Note that this fact depends on the size of the *fundamental surplus*: if on average the latter is large, as occurs to the right of the threshold in the figure, firms do not require higher idiosyncratic productivity from workers to initiate/continue matches.

On the other hand, how market tightness and productivity are linked in our model with cyclical hiring standards has a similar, but not the exact same implications as in previous literature (Ljungqvist and Sargent, 2017). To be more precise, consider the surplus equation from section 4 but in steady state (we make z constant and omit it as a state variable) to ease intuition:

$$S(x) = zx - b + \delta\left(1 - s - p(\theta)\eta\right)\int_{\underline{x}}^{\infty} S(x)dF(x) \tag{13}$$

From here, we can compute

$$\int_{\underline{x}}^{\infty} S(x)dF(x) = \frac{zy - b}{(1/F_{+}) - \delta\left(1 - s - p(\theta)\eta\right)} \tag{14}$$

where we define the censored idiosyncratic productivity average $y = E[x|x > \underline{x}]$ and the probability of drawing a value above the minimum threshold $F_{+} = 1 - F(\underline{x})$, which is the share of workers who actually participate in the market. The free entry condition in steady state then boils down to

$$(zy - b)\left(\frac{1-\eta}{c_v}\right) = \frac{1/\delta F_{+} - 1 + s}{q(\theta)} + \eta\theta \tag{15}$$

which resembles textbook formula found in, e.g., Pissarides (2000), with a discount rate $1/\delta F_{+} - 1$ adjusted by the chance of obtaining a idiosyncratic productivity draw above the hiring standard $\underline{x}$.

Implicit differentiation under the assumption of no cyclical movements of hiring standards (the derivative $\underline{x}'$ is assumed to be zero) we obtain:[32]

$$\epsilon_{\theta,z}\Big|_{\underline{x}'=0} = \left(\frac{zy}{zy-b}\right)\underbrace{\left(\frac{\eta p + \frac{1}{\delta F_+} - 1 + s}{\eta p + (1-\phi_1)\left(\frac{1}{\delta F_+} - 1 + s\right)}\right)}_{\Upsilon} \tag{16}$$

where we have removed dependency on θ to ease exposition, $1-\phi_1$ is the match-vacancy elasticity and note that Υ cannot be a factor much larger than 1 given a reasonable calibration in which the job finding rate p is an order of magnitude larger than the sum of the adjusted discount rate $\frac{1}{\delta F_+} - 1$ and the separation probability s.

The equation above shows that the elasticity in our model depends on the relative size of the expected *fundamental surplus* in the case the hiring standard is endogenously zero, i.e. $\underline{x} = 0$. Under the assumption of no cyclical hiring standards, equation (16) would essentially yield the same results as in the standard model. On the other hand, when hiring standards are actually active and vary over the cycle, the market-tightness cyclicality is typically magnified. If the calibration of parameters allows the model to have a realistic job finding and separation probabilities, in appendix A.3 we show that

1. The model predicts procyclical market-tightness and countercyclical hiring-standards.

2. The procyclicality of market-tightness is greater than the one generated in a model without endogenous hiring standards or with a non-binding one (i.e. whenever $\underline{x} = 0$).

3. The model market-tightness becomes more procyclical in general if there is a large mass of matches in the neighborhood of a binding hiring standard, that is, when the density $f(\underline{x})$ is high.

4. The model hiring-standard elasticity typically becomes more countercyclical when there is a small fundamental surplus.

To understand these results, we highlight that the model has two opposing forces affecting hiring standards when the aggregate productivity increases. The usual search & matching model mechanism works here: all ongoing and potential jobs become more productive, so that employers post more vacancies to recruit workers who have become more valuable. Since idiosyncratic and

[32] For details, see section A.3.

aggregate shocks are complementary in production, employers become interested in matches that were not profitable enough under lower aggregate productivity. Hence, if the employer lowers the bar, a larger mass of matches are created, and the participation (F_+) increases. However, there is also a second force at play: as employers lower the bar to hire, the average productivity of new hires decreases, offsetting, to some extent, the initial aggregate productivity shock and the larger mass of acceptable matches. The first *participation effect* prevails when there is a relatively large mass of workers around the binding hiring standard, i.e. moving the bar will sizeably affect the mass of available workers because the density $f(\underline{x})$ is high. If this is the case, market-tightness and hiring-standard cyclical responses will have opposite signs. On the contrary, if the aggregate productivity increases when the hiring standard is set where the density $f(\underline{x})$ is low, the *average productivity effect* prevails, and the procyclicality of the market tightness decreases (even could turn negative in rare cases).

5 Conclusions

In this paper we use a decade of internet data on posted wages to study cyclicality of wages at new positions. The richness of the dataset allows us to make several contributions: First, our estimates minimize concerns about cyclical mismatch because the nature of our wage data (job postings instead of realized wages) and because we use the weighting method in DiNardo et al. (1996); Second, we document that hiring standards are counter-cyclical (as in Modestino et al., 2020) and that ignoring them biases estimates downwards. Third, we show that ignoring how many actual job positions a job ad represents also biases results towards finding more rigid cyclical wages. Our empirical results show that different estimates in the literature may be rationalized if one takes these issues into account.

We then build a search and matching model introducing aggregate and idiosyncratic shocks. In the model, employers and potential workers can reject forming a match if the idiosyncratic shock they draw is so low that they prefer to search for another match, which can be taken as a hiring standard. Both analytical results and model simulations show that pro-cyclical wages, counter-cyclical hiring standards and significant movements in equilibrium vacancies and unemployment can arise jointly if the *fundamental surplus* of matches is small, as noted by Hornstein et al. (2005), Hagedorn and Manovskii (2008), and Ljungqvist and Sargent (2017), among others. Thus, our exercise provides a novel way of disciplining these type of models.

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A Appendix: Additional tables and figures

A.1 Decriptive statistics for ALL jobs

Table 8: Characteristics of Job Postings

	Ads	Vacancies
Observations	1,515,013	7,565,102
Wages (thousand CLP)	655	428
Exp. requirement: 0 yrs	0.21	0.37
Exp. requirement: 1 yrs	0.36	0.46
Exp. requirement: 2 yrs	0.20	0.09
Exp. requirement: ≥ 3 yrs	0.34	0.13
Ed. requirement: $\geq$University	0.37	0.16
Foreign language	0.08	0.03
General knowledge	0.65	0.54
Specific knowledge	0.19	0.19
No or basic computer knowledge	0.34	0.51
Full-time job	0.79	0.63
Long-term contract	0.64	0.53
Big Firm ($>$ 51 employees)	0.44	0.46
Explicit wage	0.17	0.24

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

A.2 Results on data representativeness

Table 9: Educational requirements (website) vs. attainment (survey)

website data			survey data			
Requirement	Ads	Vacancies	Achieved educ	Flow	Stock	Seekers(1)
SH high school	23.3	56.2	SH high school	37.7	32.6	27.9
TP high school	13.5	12.3	TP high school	19.4	17.2	15.7
			incomplete TP tertiary	6.8	4.9	5.5
			incomplete college	7.2	5.3	6.1
high school req		68.5	high school req	71.1	60.1	55.2
TP tertiary	28.3	17.1	TP tertiary	12.5	16.4	16.4
college	34.2	14.2	college	15.3	21.2	24.7
			incomplete graduate	0.2	0.3	0.5
tertiary req		31.3	tertiary req	27.8	37.6	41.1

Information from job advertisements in www.trabajando.com, for the period March 1st 2010 and March 31st 2020, and ESI flow from the last quarter of the year, from 2010 to 2019. Ads and realized jobs in ESI are full time only. Under the "website data" title we show the fraction of total ads and vacancies by the educational required level. Under the "survey data" we show the fraction of workers by their educational attainment. We portray these shares by flow (i.e. hired a year ago or less), seekers (those actually searching for a job regardless employment status), and stock (those currently hired). The acronym SH denotes Scientific-Humanities (SH) while TP refers to Technical-Professional (see the main text for more details). For ESI data, we use the 2017 Census correction of weights, as recommended by the Chilean National Statistical Institute (INE).

A.3 Detailed model derivations

Below we drop the dependence of functions on θ for ease of exposition. Differentiating the free-entry condition with hiring standards in (15), we obtain

$$(zy'\underline{x}'+y)\left(\frac{1-\eta}{c_v}\right)=\eta\theta'+\frac{(1-s)q'\theta'}{q^2}-\frac{1}{\delta}\left(\frac{q'\theta'}{q^2F_+}+\frac{F'_+\underline{x}'}{qF_+^2}\right)$$

where primes denote differentiation with respect to their argument.

In particular, $\underline{x}'\equiv\frac{d\underline{x}}{dz}$, $\theta'\equiv\frac{d\theta}{dz}$, $q'\equiv\frac{dq}{d\theta}$, $y'\equiv\frac{dy}{d\underline{x}}=\frac{dE[x|x\geq\underline{x}]}{d\underline{x}}=\frac{f(\underline{x})}{F_+}(y-\underline{x})$ and $F'_+\equiv\frac{dF_+}{d\underline{x}}=\frac{d(1-F(\underline{x}))}{d\underline{x}}=-f(\underline{x})$

After some algebra and using Leibniz rule for differentiation, the equation becomes

$$\left(zy\left(\frac{y'\underline{x}}{y}\right)\left(\frac{z\underline{x}'}{\underline{x}}\right)+zy\right)\left(\frac{1-\eta}{c_v}\right)=\eta\theta\left(\frac{z\theta'}{\theta}\right)+\frac{1-s}{q}\left(\frac{\theta q'}{q}\right)\left(\frac{z\theta'}{\theta}\right)-\frac{1}{\delta qF_+}\left(\frac{\theta q'}{q}\right)\left(\frac{z\theta'}{\theta}\right)+\frac{\underline{x}f(\underline{x})}{\delta qF_+^2}\left(\frac{z\underline{x}'}{\underline{x}}\right)$$

Considering that $(1-\phi_1)\equiv-\theta q'/q$ is the vacancy-elasticity in the matching function and replacing the free-entry equation (15) into the last result and reorganizing generates

$$\left(\frac{zy}{zy-b}\right)(1+\epsilon_{y,\underline{x}}\epsilon_{\underline{x},z})=\epsilon_{\theta,z}\Upsilon^{-1}-\epsilon_{F_+,\underline{x}}\epsilon_{\underline{x},z}\Lambda \tag{17}$$

where

$$\Upsilon=\frac{\eta p+\frac{1}{\delta F_+}-1+s}{\eta p+(1-\phi_1)\left(\frac{1}{\delta F_+}-1+s\right)}$$

$$\Lambda=\frac{\frac{1}{\delta F_+}}{\eta p+\frac{1}{\delta F_+}-1+s}$$

Moreover, elasticities are defined as

$$\text{Market-tightness cyclical elasticity: }\epsilon_{\theta,z}\equiv\frac{d\log\theta}{d\log z}=\frac{z\theta'}{\theta}$$

$$\text{Hiring-standard cyclical elasticity: }\epsilon_{\underline{x},z}\equiv\frac{d\log\underline{x}}{d\log z}=\frac{z\underline{x}'}{\underline{x}}$$

$$\text{Average type to hiring-standard elasticity: }\epsilon_{y,\underline{x}}\equiv\frac{d\log y}{d\log\underline{x}}=\frac{\underline{x}y'}{y}=\frac{\underline{x}f(\underline{x})}{yF_+}(y-\underline{x})>0$$

$$\text{Type participation to hiring-standard elasticity: }\epsilon_{F_+,\underline{x}}\equiv\frac{d\log F_+}{d\log\underline{x}}=-\frac{f(\underline{x})\underline{x}}{F_+}<0$$

From equation (17) it is clear that if hiring standards did not vary over the cycle, i.e. $\epsilon_{\underline{x},z}=0$, we would obtain the well-known link between the fundamental surplus and the cyclical elasticity of market-tightness, as shown by Ljungqvist and Sargent (2017).

$$\epsilon_{\theta,z}\Big|_{\underline{x}'=0} = \left(\frac{zy}{zy-b}\right)\Upsilon \tag{18}$$

For reasonable calibrations, Υ, the term accompanying $\frac{zy}{zy-b}$ is positive and not much larger than 1 because the empirical magnitude of the job finding probability p is generally an order of magnitude larger than the sum of the adjusted discount rate $\frac{1}{\delta F_+}-1$ and the separation probability s. Therefore, the sensitivity of market tightness to z is mainly driven by the size of the expected fundamental surplus $zy-b$. Reorganizing (17) we present below the elasticity of tightness to aggregate conditions z when hiring standards are not constant.

$$\epsilon_{\theta,z} = \epsilon_{\theta,z}\Big|_{\underline{x}'=0}\left(1+\epsilon_{y,\underline{x}}\epsilon_{\underline{x},z}\right) + \Lambda\Upsilon\epsilon_{F_+,\underline{x}}\epsilon_{\underline{x},z} \tag{19}$$

On the hiring standard determination: Given the multiplicative form of output inside a match (zx), we assume that the distribution of types has support on $[0,\infty)$, as the lognormal distribution we use in the calibrated model.

We can define the hiring standard as the productivity type $\underline{x}$ that makes a match surplus exactly zero

$$S(\underline{x},z) = 0 = z\underline{x} - b + \delta(1-s-p\eta)F_+\int_{\underline{x}}^{\infty} S(x)dF(x)$$

If there is a solution for this equation, and we replace the free-entry condition (15), we obtain

$$\left(\frac{1-\eta}{c_v}\right)(b - z\underline{x}) = F_+\left(\frac{1-s}{q} - \eta\theta\right) \tag{20}$$

which implies that the productivity of the lowest match productivity $z\underline{x}$ is lower than the unemployment income b because the employer can afford to accept a bad draw of x today if the expected value is high enough next period. Nevertheless, (20) may not have a solution, just because the expected payoff in the future of hiring someone today is just too high. In the extreme, the employer can afford zero productivity today if the expected return is high enough *given a high enough value of* z. In that case, $\underline{x}=0$ if

$$S(x,z) > 0 \quad \forall x \geq 0$$

and therefore

$$\underline{x} = 0 \quad \Leftrightarrow \left(\frac{1-s}{q} - \eta\theta\right) > b\frac{1-\eta}{c_v}$$

This is exactly the situation that occurs when b is low and/or c_v is high. If b is high, the outside option of workers is low and employers can afford to hire anyone today since the expected profits in the future are sizable to offset the initial loss. The same occur if c_v is high: in equilibrium free-entry ensures sufficiently high profits, making any hire today bearable. Thus, the evidence showing cyclical movements of hiring standards is at odds with a low value of b.

If for a set of cyclical values z, there is no active hiring standard, i.e. $\underline{x} = 0$ holds, then the model behaves a standard search and matching model, with no hiring standards. In the more interesting case in which the hiring standard matters, i.e. $\underline{x} > 0$, we can derive the cyclical properties of this variable by studuying comparative statics in steady state. To achieve that goal, we differentiate equation (20) with respect to z, to obtain

$$\left(\frac{1-\eta}{c_v}\right)\left(z\underline{x}' + \underline{x}\right) = f(\underline{x})\underline{x}'\left(\frac{1-s}{q} - \eta\theta\right) + F_+\left(\eta\theta' + \frac{1-s}{q^2}q'\theta'\right)$$

Doing some algebra, we get

$$\left(\frac{1-\eta}{c_v}\right)\underline{x}\left(\left(\frac{z\underline{x}'}{\underline{x}}\right)+1\right) = \left(\frac{f(\underline{x})\underline{x}}{F_+}\right)\left(\frac{z\underline{x}'}{\underline{x}}\right)\left(\frac{F_+}{z}\right)\left(\frac{1-s}{q} - \eta\theta\right) + \frac{F_+}{z}\left(\eta\theta\left(\frac{z\theta'}{\theta}\right) + \frac{1-s}{q}\left(\frac{q'\theta}{q}\right)\left(\frac{z\theta'}{\theta}\right)\right)$$

Using previously defined elasticities and substituting $\frac{1-\eta}{c_v}$ by a term proportional to the fundamental surplus, according to the free-entry (15), yields

$$\frac{z\underline{x}}{zy-b}(1+\epsilon_{\underline{x},z}) = \frac{F_+q}{\eta p + \frac{1}{\delta F_+} - 1 + s}\left(\left(\eta\theta - \frac{1-s}{q}\right)\epsilon_{F_+,\underline{x}}\epsilon_{\underline{x},z} + \left(\eta\theta - \frac{(1-\phi_1)(1-s)}{q}\right)\epsilon_{\theta,z}\right)$$

Some terms accompanying can be expressed in terms of quantities already defined, as follows

$$\frac{z\underline{x}}{zy-b}(1+\epsilon_{\underline{x},z}) = F_+\left((1-\Lambda)\,\epsilon_{F_+,\underline{x}}\epsilon_{\underline{x},z} + \left(\Upsilon^{-1} - (1-\phi_1)\Lambda\right)\epsilon_{\theta,z}\right)$$

Rearranging terms, the hiring-standard cyclical elasticity can be expressed as

$$\epsilon_{\underline{x},z} = -\frac{\Delta - \Psi\epsilon_{\theta,z}}{\Delta - \Gamma} \tag{21}$$

where

$$\Delta \equiv \frac{z\underline{x}}{zy-b} > 0,$$

$$\Psi \equiv F_+\left(\Upsilon^{-1} - (1-\phi_1)\Lambda\right) = F_+\frac{\eta p - (1-\phi_1)(1-s)}{\eta p + \frac{1}{\delta F_+} - 1 + s} \in [0,1],$$

and

$$\Gamma \equiv F_{+}\epsilon_{F_{+},\underline{x}}(1-\Lambda) < 0.$$

Replacing (21) into expression (19), we can solve for the market-tightness elasticity as

$$\epsilon_{\theta,z} = \frac{(\Delta - \Gamma)\,\epsilon_{\theta,z}\Big|_{\underline{x}'=0} - \chi\Delta}{\Delta - \Gamma - \chi\Psi} \tag{22}$$

where

$$\chi = \epsilon_{y,\underline{x}} + \Lambda\Upsilon\epsilon_{F_{+},\underline{x}}$$

has an ambiguous sign. Two forces work against each other. On one side, the average productivity type increases due to a hiring standard increase, but on the other, there is a negative effect in participation when employers raise the bar, i.e. $\epsilon_{F_{+},\underline{x}} < 0$. As long as $\chi < 0$, i.e the participation effect is more important, the model delivers a procyclical market-tightness elasticity. This is likely to occur when the mass of workers at $\underline{x}$ is high, so that an increase of $\underline{x}$ excludes from the labor market a significant share of workers. On the contrary, if the aggregate productivity increases when the hiring standard does not react much, the average productivity effect will prevail and the procyclicality of the market tightness may decrease. This is the key intuition: as the participation effect matters more than the average productivity effect, when aggregate productivity increases, it becomes more profitable lowering the bar and hire more people rather than raising the bar and increase the average productivity even more.

Does the model with hiring standards deliver higher procyclicality of the market-tightness than the plain-vanilla model without endogenous hiring standards? If we realize that $\epsilon_{\theta,z}\Big|_{\underline{x}'=0} = \Upsilon\Delta\frac{y}{\underline{x}}$, we obtain

$$\epsilon_{\theta,z} = \epsilon_{\theta,z}\Big|_{\underline{x}'=0}\left(\frac{1 - \frac{\chi}{\Delta-\Gamma}\frac{\underline{x}}{y}\Upsilon^{-1}}{1 - \frac{\chi}{\Delta-\Gamma}\Psi}\right) \tag{23}$$

By inspection of the previous equation, the hiring-standard model may be more or less procyclical than the regular one provided $\frac{\underline{x}}{y}\Upsilon^{-1} > \Psi$. Replacing the definitions of these quantities, we obtain the following condition

$$\underline{x} > F_{+}y\left(\frac{\eta p - (1-\phi_1)(1-s)}{\eta p + (1-\phi_1)(1-s)}\right) \tag{24}$$

Thus, the hiring-standard model has a more procyclical market tightness if, in equilibrium, the hiring standard is not too low with respect to the unconditional expected type of a new hire, F_+y. The term accompanying F_+y lays between 0 and 1, thus making the condition more likely to be met, especially if $(1-\phi_1)$ is high.

The last result concerns with the importance of the size of the fundamental surplus $zy-b$. If condition (24) holds, making the model to deliver a more procyclical market-tightness than its plain vanilla version, a smaller fundamental surplus makes the market-tightness more procyclical. This occurs because a drop in the fundamental surplus affects more the numerator than the denominator in .

We can also study the cyclical behavior of the hiring standard, $\underline{x}$. To do so, we solve for $\epsilon_{\theta,z}$ by combining (21) and (22)

$$\epsilon_{\underline{x},z} = -\frac{\Delta}{\Delta-\Gamma}\left(\frac{\Delta-\Gamma-2\chi\Psi}{\Delta-\Gamma-\chi\Psi}\right) - \epsilon_{\theta,z}\Big|_{\underline{x}'=0}\left(\frac{\Psi}{\Delta-\Gamma-\chi\Psi}\right) \tag{25}$$

A simple inspection of the formula tells us that if the participation effect offsets the average productivity effects of raising hiring standards, i.e. $\chi < 0$, the hiring standards are always countercyclical. If that's not the case, the countercyclicality still holds unless the participation effect is much smaller that the average productivity increase after a raise in hiring standard. If the type distribution has thin tails, this may occur if the economy operates in a region in which almost all types are accepted, or nearly no type is. Another version of the same equation is

$$\epsilon_{\underline{x},z} = -\epsilon_{\theta,z}\Big|_{\underline{x}'=0}\left(\frac{\frac{\underline{x}}{y}\Upsilon^{-1}}{\Delta-\Gamma}\left(\frac{\Delta-\Gamma-2\chi\Psi}{\Delta-\Gamma-\chi\Psi}\right)+\left(\frac{\Psi}{\Delta-\Gamma-\chi\Psi}\right)\right) \tag{26}$$

A second conclusion is that an economy with a higher procyclicality of the market-tightness without hiring standards, i.e $\epsilon_{\theta,z}\Big|_{\underline{x}'=0}$ makes the hiring standard more countercyclical, specially if $\chi < 0$. Finally, as $\Delta \to \infty$, i.e. the fundamental surplus becomes nearly zero, $\epsilon_{\underline{x},z}$ approaches -1, no matter how procyclical the market-tightness in a plain-vanilla model is.