Wage Cyclicality Revisited: The Role of Hiring Standards *

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Abstract

We estimate a high cyclical sensitivity of real wages using a decade of online job ads in Chile, an accurate measure of labor's marginal cost for firms. Controlling for job title, firm fixed effects, and crucially, posted hiring standards, we make wage comparisons for equivalent positions at the same firm under identical hiring standards across different phases of the business cycle. As ad requirements are countercyclical, their omission leads to underestimating wage cyclicality. We also show that key strengths of our data –vacancy measurement, standardized hours worked, observable posted wages– play a key role in estimation and call for caution when using job posting datasets. Our findings support a search and matching model where a relatively small fundamental surplus and endogenous hiring standards generate realistic unemployment and wage volatility. The model suggests that countercyclical hiring standards offset cyclical shocks by allowing employers to reject poor matches in downturns.

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

JEL Codes: E24, J64

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1 Introduction

Although real wage cyclicality plays a pivotal role in disciplining macroeconomic models of the labor market, a wealth of empirical literature cannot reach a consensus. We study this issue drawing on over a decade's worth of data from `www.trabajando.com`, a Chilean job board. The website provides us detailed information on both job posters and job seekers and its most salient feature is the high quality information it contains on posted wages.[1] This allows us to provide novel evidence which closely mirrors the theoretical concept of a firm's *marginal cost of labor*, key for hiring decisions and the determination of labor market aggregates (Pissarides, 2009). Our setup answers the question of *how does the salary cost to a firm for the same job, performed by an employee with the same qualification, vary across different phases of the business cycle?*

Our main result reveals significant procyclicality in posted salaries for full-time jobs, even after controlling for the composition of the spot labor market. Our estimated semi-elasticity of real wages with respect to the unemployment rate lays in the upper range of estimates previously found in the literature.[2] By focusing on fine definitions of a job (using job titles and text information from job ads), our preferred estimates are not subject to the problem of cyclical job upgrading (Gertler and Trigari, 2009; Gertler et al., 2020) where observed changes in aggregate wages may reflect individuals changing the type of jobs they perform or the effect abundance/absence of high salary firms hiring on the market may have.[3]

We also show that ignoring cyclical changes in the composition of the labor market biases the estimates towards lower cyclicality. To counter this, 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. This approach takes into account both the characteristics of job advertisements and the average attributes of the workers applying to them. By doing so, we effectively control for composition effects on both the labor supply and demand sides, which is crucial for providing a more comprehensive understanding of the factors influencing equilibrium wages. Relying solely on survey data (supply) or job posting data (demand) offers an incomplete picture of these determinants.

Additionally, we find that overlooking hiring standards leads to underestimation of cyclicality: in a downturn, employers (may) lower offered wages but raise hiring standards simultaneously, likely to obtain a match of better quality from a larger pool of seekers. We find that hiring standards significantly increase in downturns, in line with results in Modestino et al. (2016, 2020).[4] Using a decomposition exercise due to Gelbach (2016), we show that employers changing education and knowledge requirements at the job level accounts for the underestimation. This underscores how important it is to keep jobs and skills constant in any empirical framework to understand cyclical movements in the cost of hiring.

[1] See Batra et al. (2023) on lack of wage information on job boards. Banfi and Villena-Roldán (2019) study wage information quality in the Chilean website.

[2] They also align with estimates in Albagli et al. (2022), who use rich administrative tax records for the Chilean economy.

[3] Papers who make this point are Bils (1985), Solon et al. (1994), Gertler et al. (2020) and Grigsby et al. (2021).

[4] The idea of countercyclical hiring standards is already present in Reder (1964) and McGregor (1978).

Methodologically, we show that ignoring vacancy information when using job posting data lowers estimated values of wage cyclicality. We are able to do this using the fact that www.trabajando.com explicitly asks posters about the number of vacancies each job ad represents. The under-estimation is mostly due to the fact that the actual number of jobs in the lower part of the wage distribution is more likely to be under-represented in online job boards.[5] This calls into question aggregate estimates of labor market variables using internet job boards information without correcting for actual numbers of jobs offered. Relatedly, we also discuss how the specifics of the Chilean labor market, with an extreme focal point in monthly salaries and 45 hour weeks (for full time jobs), minimizes measurement issues that may affect estimations focused on wage rates.

Our findings contribute to a vast literature studying the cyclicality of wages, which tends to find varied results. On the one hand, 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 significant levels of wage procyclicality. In contrast, Gertler et al. (2020) and Hazell and Taska (2024) find relatively less cyclical wages. Except for the latter, a common challenge across these studies is their reliance on realized wages at the individual worker level, derived from either survey or matched employer-employee datasets, as an approximation for the marginal cost of labor. This approach is problematic because realized wages are influenced by several factors, most importantly the cyclicality of match quality and the composition of jobs. While papers have dealt with these issues with different degrees of success (trying to fix the quality of a worker), a new literature attempts to find direct evidence on firms's behavior: Hazell and Taska (2024) and Faryna et al. (2022) use job posting data, while Grigsby et al. (2021) use firm payroll information. We contribute to this strand by focusing on a sample with both high-quality offered wage and job seeker information, which allows us to test different specifications and rationalize some of the heterogeneous results found in the literature. We additionally show an exercise trying to bridge our intrinsically demand-side estimations and those obtained in most of the literature based on survey data: We use job seeker's application data to show that median applied-for real wages are pro-cyclical. Given the richness of controls in the data, this suggests that job seekers target less attractive jobs in downturns.

Our estimates are also conceptually aligned with the literature showing the importance of controlling for match quality to disentangle the role of current versus initial market conditions on wages.[6] Our results offer an ex ante version of an estimation of the cyclicality of real wages controlling for match quality due to two reasons. First, employers post job ad wages before meeting applicants, making them free from idiosyncratic realized match quality. Secondly, we can control for expected match quality by including detailed job ad descriptors. Approaches like those in the referred papers are based on ex post proxies for the number of job offers received during the employment spell and the time that a match has survived, measured through the cumulative sum of market tightness. Despite the different approaches, Hagedorn and Manovskii (2013) and Bellou and Kaymak (2021) conclude that wages are

[5] Forsythe et al. (2020) also find over-representation of high-skilled jobs in online job boards in the US economy.

[6] See Devereux (2004),Hagedorn and Manovskii (2013), and Bellou and Kaymak (2021)

highly procyclical, especially if match quality is controlled for. Our results are quantitatively similar to these studies, even though they refer to different labor markets over a different time period.

To rationalize the facts, we extend a Diamond-Mortensen-Pissarides (DMP) model of the labor market to include both idiosyncratic and aggregate shocks that affect the productivity of a match, along the lines of Sedláček (2014). Employers may set a *hiring standard*, a minimum match quality level depending on business cycle conditions. We show analytically that for hiring standards to vary countercyclically, the model needs a relatively small *fundamental surplus* calibration. As Hagedorn and Manovskii (2008) and Ljungqvist and Sargent (2017) show, this can explain the strong procyclicality of the labor market tightness. We show that when employers reduce hiring standards after a positive aggregate shock, two opposing forces emerge: the *acceptability effect*, where firms find more matches profitable, and the *average productivity effect*, where the mean quality of accepted matches decreases (because of lower standards). If employers affect a sizeable share of matches by varying standards, the model generates procyclical wages and countercyclical hiring standards.

We calibrate the model to the Chilean labor market and contrast its predictions to our empirical results on wages and hiring standards. The model accounts for the cyclical patterns of both variables and we show that the introduction of hiring standards is a way to discipline the relevant mechanisms at work when building models to explain the cyclical behavior of unemployment.

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. Additionally, we use the information of individual *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 salary to be paid at the position: a monthly figure (not bracket), 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) and Grigsby et al. (2021).[7] 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.[8] 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

[7] 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.

[8] 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. From these, we remove job ads with outliers in terms of requested experience (demanding more than 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
Averages:		
Real wages (thousand CLP, 2018=100)	802	543
Years of experience	1.88	1.13
Share of jobs:		
Technical/tertiary education requirement	0.29	0.17
University education or above requirement	0.37	0.16
Foreign language	0.09	0.04
General knowledge	0.69	0.59
Specific knowledge	0.20	0.20
Big firm ($\geq$ 51 Employees)	0.44	0.47
Explicit wage on ad	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. Statistics for individual job ads ("Ads") and job ads weighted by number of positions ("Vacancies"). Definitions of foreign language , general knowledge, and specific knowledge are summarily described in the text and in further detailed in appendix A.4.

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. To convert nominal wages into real figures, we use the Chilean consumer price index, with base year 2018.[9]

The table shows the importance of weighing by the number of vacancies when computing averages. While average real wages amount to roughly 800 thousand pesos (monthly, after tax)[10] when considering job adverts alone, this figure decreases to around 540 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,[11] the median after tax wage in Chile during 2015 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., technical degree or higher)[12] or from firms with certain characteristics (e.g., firms with more than 51 employees). From the raw text of job ads, we categorize jobs in terms of whether they require any form of knowledge (general or specific), and foreign language[13].

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 on computed statistics. Otherwise, low wage jobs get

[9]See https://www.ine.gob.cl/estadisticas/economia/indices-de-precio-e-inflacion/indice-de-precios-al-consumidor

[10]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.

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

[12]This category boils down to any educational requirement beyond a High School diploma.

[13]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. See Appendix A.4 for details.

underrepresented. All results in what follows are weighted by the number of vacancies to appropriately represent the actual job creation flow generated by the website.

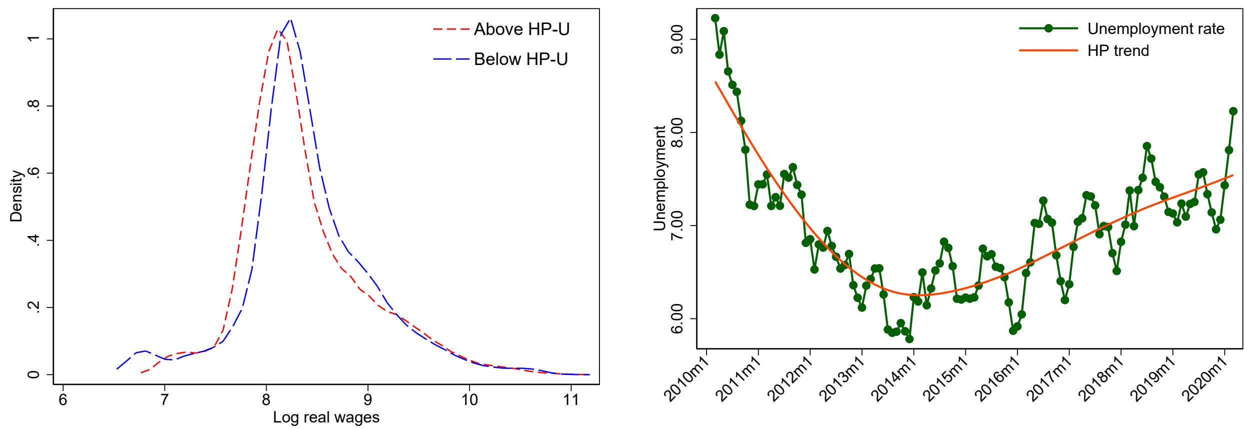

Figure 1: Histogram of log real wages (full time jobs), according to the aggregate unemployment rate trend deviation at the time of posting (left) and time series of unemployment rate. We also plot its Hodrick-Prescott smoothed trend with parameter $\lambda = 14,400$ as a reference (right).

In the left panel of figure 1 we plot kernel density estimates for (vacancy weighted) $\log$ real wages of ads for full time positions 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,[14] separating by whether unemployment was above or below its Hodrick-Prescott filtered trend. As seen from the figure, there is a shift towards higher wages during periods of low unemployment. The right panel in the same figure shows the aggregate unemployment rate in the Chilean economy during our sample period, along a Hodrick-Prescott trend shown for reference.[15] 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.

2.1 Wages and hours

We primarily focus on job ads qualified as full-time to sidestep discussions around wage rates. Two reasons support our choice: first, in Chile there is a very strong focal point in monthly wages. Indeed, trabajando.com and the *Encuesta Nacional de Empleo* (ENE henceforth, a national employment survey) explicitly ask for wages referring to a monthly basis. Second, there is also a very strong focal point in a 45-hour workweek, the maximum allowed without incurring overtime premiums under Chilean labor law. In the ENE, 60% of full-time private sector jobs report a usual 45-hour workweek (even more after COVID). Hence, the assumption of uniform workweek and period of reference for full-time jobs approximately holds, leading to low measurement error. Moreover, tables A6 and A7 show that the majority of workers in most groups and industries adhere to a 45-hour week.

[14] 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)

[15] We present HP filtered trends just for visual reference. In the next section, we use more flexible time controls in our estimations.

In other datasets, harmonizing hours from diverse industries/occupations with varying pay structures is more challenging. For instance, in handling Lightcast data Hazell and Taska (2024) presumably assume a 40-hour workweek or 2000-hour annual hours in the US. While this strategy seems the most commonsense given data limitations, the 40-hour focal point observed in the US is much less pronounced, as shown by Bick et al. (2022).

2.2 How individuals react to job ad requirements?

In terms of how individuals using the job portal respond to job posting requirements, in the following tables we present some descriptive statistics using the joint information for job positions along with the information on applicants to those positions. For individuals using the website to find jobs, we observe year of birth, gender, location of residence, current employment status, education, years of experience and monthly salary expectations. The information is provided by individuals at the time of creating or updating their online profile.

Table 2: Correlation between Job and Applicant's information

Wage	0.605
Technical degree	0.324
Years of experience	0.378

Information from job advertisements and job applicants in www.trabajando.com, for the period March 1st 2010 to March 31st 2020, for full-time jobs. Statistics for job ads weighted by number of positions. See the main text for a description of the rows.

In table 2 we present correlations between the information posted in job ads with the information from the median applicant to the position. The *Wage* row shows the correlation between the nominal advertised wage and the median salary expectation of applicants; the *Technical degree* row does the same for a dummy variable that indicates whether the job requires, or the median applicant has, an education beyond high school; *Years of experience* is the correlation between required years of experience at the position with (self reported) years of experience of the median applicant. We perform all calculations for data weighted by number of vacancies reported in the job ad. From the table we see that correlations are high, which shows that there is sorting of job positions and job seekers in these different dimensions. This result is also present in Banfi et al. (2022), who show that there is evidence of considerable sorting.

Table 3 shows information from the median job applicant to the different job positions, given the latter's characteristics. For example, if a job requires a technical degree (or above), 99.8% of job applicants possess one. The table also shows that on average, job seekers possess more experience than the requirement on job positions, and the median applicant does conform to higher experience requirements (second part of the table).

Table 3: Applicant's characteristics given job requirements

Job requires technical degree or above	
Mean applicant	0.984
Median applicant	1
Job Requires X years of experience	
Median applicant's years, if $X = 0$	5
Median applicant's years, if $X = 1$	6
Median applicant's years, if $X = 2$	8
Median applicant's years, if $X \geq 3$	10

Information from job advertisements and job applicants in www.trabajando.com, for the period March 1st 2010 to March 31st 2020, for full-time jobs. Statistics for job ads weighted by number of positions.

2.3 Representativeness

A natural question that arises is how accurate is the information on the website: does it represent the entire labor market or only a self-selected group? In the appendix (see section A.3), we provide some analysis comparing our dataset with information from aggregate labor surveys on several educational categories. The short of it is that the aggregate economy is well represented by the information in the website (with some minor caveats).

One could argue that representativeness of wage information is more critical for the analysis. Since ad wages in www.trabajando.com are associated with job creation in the short term, in order to assess representativeness of our data we compare them to 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, an ENE supplement) 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.[16]

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 for full-time jobs in the 2010-2019 waves of the ESI (we do not consider 2020 because of COVID-19 pandemic effects).

Figure 2 depicts cumulative probability function estimators of log real wage distributions. On the left, we show the comparison for all job ads/workers (excluding outliers and missing data). On the right, we exclude job ads requiring primary or no educational attainment and recently hired workers with no secondary schooling. Both plots show that the information in the website lines up accurately to wages

[16] 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.

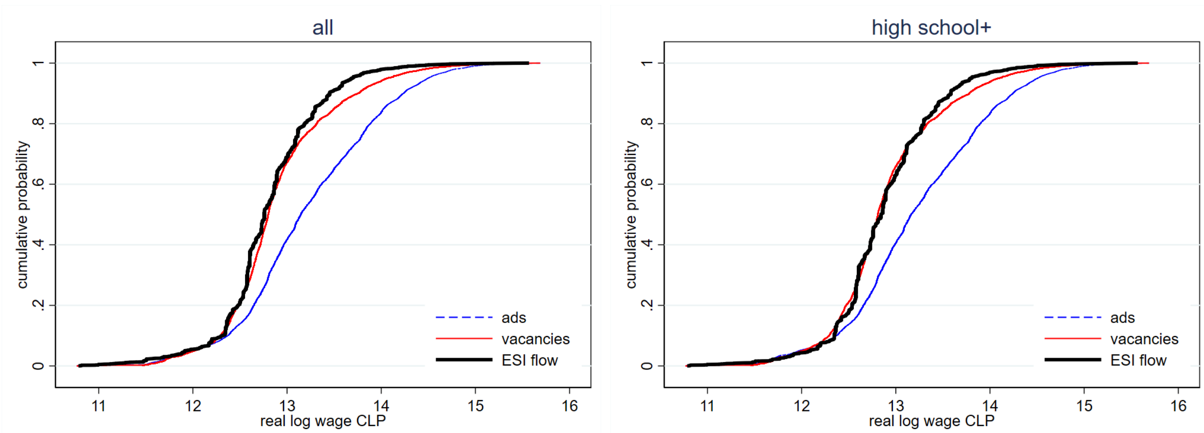

Figure 2: Cumulative probability function (CDF) of log real wages March 2010 - March 2020 in real Chilean Pesos (CLP) of 2018, for trabajando.com data and information from newly hired workers from the ESI supplement of the *Encuesta Nacional de Empleo* (ENE) dataset. For ESI data, we use the 2017 Census correction of weights, as recommended by INE. The left panel considers all workers and all ads whereas the right panel excludes workers with schooling below high school level and job ads with primary or no educational requirement.

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.[17]

3 The facts

3.1 Methodology

Our analysis is based on estimating linear regressions relating the log offered real 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

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

where X_a is a set of characteristics of the job, $T_{t(a)}$ contains a linear trend and seasonal monthly binary variables at the time of posting $t(a)$, and $\varphi_{f(a)}$, $\lambda_{j(a)}$, and $\zeta_{m(a)}$ represent firm, job title, and required major fixed effects, respectively. The empirical setup resembles 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 semi-elasticity between wages and aggregate unemployment, $\partial \log w_a / \partial U_{t(a)}$.

More specifically, the use of job titles 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 pre-processing of texts,[18] we detect the first four meaningful words of the job title and the first three of the required educational degree (major) description.[19] Then, we construct a set of binary variables for the first job title word with a share greater than

[17]Note that there is a caveat in this comparison because there is no guarantee that posted and realized wages are the same for a given match due to wage bargaining or ex post compensations.

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

[19]This description in job ads does not focus on university degrees only, given the educational system in Chile, as

0.1% of the whole sample, assigning those that do not reach the threshold as a "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 requirement description.

Our setup considers the behavior of hiring standards, as in Modestino et al. (2020), but applied to the case of wage cyclicality. Hence, X_a include posted requirements in the form of years of experience, a categorical variable for required education (technical/tertiary and university/postgraduate, with high school as the base variable) and any form of knowledge (general, specific, and language) requirements (See the appendix for details on the construction of these variables). Note that we do not control for region, industry, and firm size, as these variables are absorbed into firm fixed effects.

Our identification strategy leverages a dataset with an unusually rich array of covariates, allowing us to assume *ignorability*: that unobserved factors influencing wages are uncorrelated with observed ones. By controlling for firm, job title, and required major fixed effects, we isolate the cyclical wage response for a specific job within a given firm and requirements. Further incorporating detailed hiring standards from job ads allows us to hold constant expected applicant qualifications. While this causal interpretation, like much of the literature, hinges on some form of the ignorability assumption, we acknowledge potential confounders. If firms adjust unobserved aspects of job ads, like implicit training or non-firm-specific promotion prospects, in response to economic conditions, our estimates may be biased. However, unlike matched employer-employee studies, our focus on posted wages ameliorate concerns about match-specific effects, as employers set wages before any worker- or match-specific factors come into play. Our estimation yields a more accurate semi-elasticity of wages to unemployment, for the same job, firm, and requirements, and is less susceptible to bias than existing estimates.

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 taking into account the supply side as well, 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 choosing the composition of jobs and workers in 2017, one point in our sample when the unemployment rate was close to the average of the entire period. We run a logit model[20] estimating the probability of being part of the 2017 sample as a function of observables on the average characteristics of applicants for a job and on the job ad side. For individuals, we use 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. For ads, we use required experience categories; dummy for explicit wage posted; area; industry; general, specific, and language knowledge; and educational level requirement categories. We then compute a predicted probability of a job ad being present in the target year.

Our dataset also contains unusual information regarding the number of positions or vacancies each job advert announces. Our discussion in section 2 highlights that key descriptive statistics remarkably

noted above.

[20] 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.

change once we weight job ads by the number of vacancies. This is the case for Lightcast (Tsvetkova et al., 2024) and Adzuna (Office for National Statistics UK, Office for National Statistics UK) datasets, arguably the most used ones for research purposes. In what follows, unless stated otherwise, we weight each job ad using the product of the predicted probability DFL odds and the number of vacancies in the job ad, to appropriately represent the job creation with a composition of job ads and applicants at the reference year.

Our data as shown in section 2 offers other key advantages which help us avoid potential pitfalls. The prevalence of standardized monthly contracts with a strong 45-hour workweek in Chile largely reduces wage rate measurement error. Employer reported point-estimated wages, instead of bracket midpoints, are likely to understate cyclical responses as wages may still lie within a bracket after an adjustment. We can also reduce sample selection since `www.trabajando.com` has a small fraction of hidden wages compared to most online job boards (Brenčič, 2012; Banfi and Villena-Roldán, 2019).

Our focus on posted wages, while a strength, also presents a limitation. We cannot directly observe the realized wages that result from the interplay of labor demand and supply. To some extent, this prevents direct comparison with studies employing realized wage data, which, while potentially better at controlling for worker traits, often lack comparable controls for job characteristics and match quality. To bridge this gap, we also include an exercise imputing wages for job seekers and find qualitative support for our main findings.

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 (*Base*). In this case, we find a semi-elasticity of -1.08. Our preferred specification which controls for job characteristics and requirements (hiring standards) in X_a (*Full* column), produces an estimate of -1.67. Thus, measured wage cyclicality is significant and the estimated cyclicality is higher when we *include* controls for hiring standards.

In figure 3, we show a visual comparison between the *full* specification and an alternative one where we emulate, as close as possible, what is usually present in related papers. In the *No controls* model we consider an empirical specification with only explicit wages (wage information is present in the job advert), along with no controls for job requirements and no sample weights (no DFL nor vacancy weights). The estimate for the semi-elasticity in this specification is of -0.09, with an associated standard deviation of 0.206 (from a sample of $192,330$ job ads). Interestingly, this estimate is close to the one in Hazell and Taska (2024).[21]

The main takeaway from the figure is the vast heterogeneity of estimates, given different empirical setups and restrictions imposed by idiosyncratic datasets. For example, in most job boards only a small fraction of ads contain wage information (Batra et al., 2023) or may misrepresent actual labor demand when information on number of positions each job ad represents is unclear (Office for National Statistics

[21] They find a comparable estimate of -0.65. Table 4, column (4).

Table 4: Estimation results

	Dependent variable: log real ad wage	
	Base	*Full*
Unemployment rate	-1.079	-1.674
	(0.077)	(0.076)
Job ad characteristics	N	Y
Adjusted R2	0.589	0.626
R2	0.604	0.636
Sample size (ads)	1,030,163	1,030,163
Sample size (vacancies)	3,946,107	3,946,107

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 a monthly trend and month-of-year dummies and firm, job title, and major fixed effects. Observations are weighted using number of posted vacancies and the DFL methodology (see text). Standard errors in parenthesis.

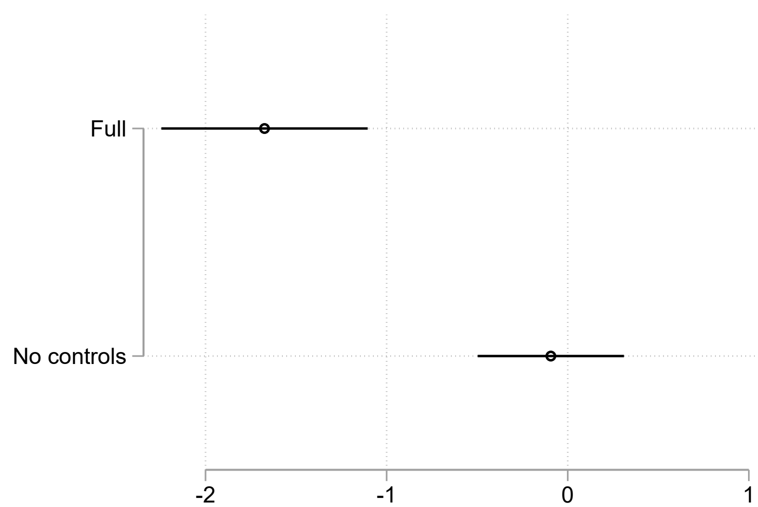

Figure 3: Regression coefficient comparison between our Full model (**Full**) and an alternative emulating the rest of the literature: **No controls** represent results from a model considering job ads with explicit wage information, we do NOT use any weights in the regression and no hiring standards.

UK, Office for National Statistics UK; Tsvetkova et al., 2024). Other cases may present poor or no job title information and rarely there is enough information to properly control for job market conditions as we do with the DFL weighting.

In table 5, we present further estimates for different specifications. The first row labelled *Full*, represents estimates from the last column of table 4. Each successive row presents empirical models where we alter one thing at a time only.

The row labelled *Explicit wage* shows results for the semi-elasticity for a model where we consider only jobs where salary information was explicitly available to job seekers in the text of the job advertisement, but maintain all other controls as in the *Full* specification. Note that the number of observations drops dramatically in this case and the cyclicality of these wages is substantially higher than those for the rest of the economy.

In the next two rows, *Only vacancy weights* and *No weights*, we consider specifications where we alter the weighting variable used. The results there show that both the DFL and vacancy weights are important to explain our baseline results, since the estimated cyclicality of real wages decreases when we do not consider them.

The next two rows of the table show that how we identify jobs and which jobs we consider play an important role to understand our results. The *No Job Title FE* row presents the estimation of equation (1) when we remove job title and major fixed effects from our *Full* specification. The estimate for the semi-elasticity in this case is not statistically different from zero, which suggests that the composition of the types of jobs present in any moment in time matters for the estimated cyclicality of wages. On the other hand, when we include all jobs in the estimation (not only full-time jobs) we see that the semi-elasticity increases dramatically, showing that wages at full-time jobs are relatively less cyclical than part-time, seasonal, and other types of jobs.

The last two rows of the table show an alternative model where we use the *Full* specification, but we replace aggregate unemployment with a monthly indicator for aggregate economic activity in Chile, the IMACEC (*Indice Mensual de ACtividad EConomica*) which is a proxy for GDP at the monthly frequency.[22] Given the change in the variable used for aggregate conditions, we present the estimates for the *elasticity* (instead of semi-elasticity) of log real wages to log(IMACEC). The table shows that this elasticity is positive: higher economic activity is significantly associated to higher wages, controlling for linear trend and seasonal monthly dummies.[23] Moreover, the difference between *Full* and *Base* specifications remains, in that controlling for hiring standards produces estimates associated with higher cyclicality of wages.

3.3 Hiring standards and wage cyclicality

The main result from table 4 is that our estimates *without* job requirements (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 4, where we ignore information on job characteristics, is due to the co-movement 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). Note that 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 4. 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

[22] See https://www.bcentral.cl/en/cuentas-nacionales-imacec-excel

[23] The Frisch-Waugh-Lovell theorem implies that we are estimating the response of detrended non-seasonal log real wages to either detrended non-seasonal log GDP (or unemployment rate).

Table 5: Semi-elasticity estimation results: different specifications

	Semi-elasticity*	std. error	N ads
Full	-1.674	(0.291)	$1,030,163$
Explicit wage	-2.571	(0.570)	$157,831$
Only vacancy weights	-1.339	(0.237)	$1,194,445$
No weights	-0.482	(0.083)	$1,194,445$
No Job Title Fixed Effect	0.451	(0.317)	$1,030,163$
All jobs (beyond full-time)	-3.927	(0.282)	$1,287,980$
models using output instead of unemployment:			
Full	0.219	(0.062)	$1,030,163$
Base	0.108	(0.065)	$1,030,163$

Estimation results for alternative specifications. Sample period is March 1st 2010 to August 31st 2023. All regressions control for **time effects** by way of a monthly trend and month-of-year dummies to control for seasonality. * For the last two rows, the estimates are for the *elasticity* between log real wages and log(IMACEC), the indicator for aggregate output.

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

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 $\log$ real 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 6 we present a summary of the results for the decomposition exercise. The variables in X_a which we identify as hiring standards are: required years of experience, indicator variables for technical/tertiary education and university degree (or above), and indicator variables for language requirement, general knowledge, and specific knowledge of some kind.[24]

Estimates in this second column (β_{X_a}) follow intuitive patterns: jobs requiring higher experience, education and some form of knowledge, pay more than their counterparts. The third column in table 6

[24]See A.4 for details on the construction of this variable.

Table 6: Decomposition: cyclical variation of hiring standards

Job ad characteristic	β_{X_a}	$\partial X_a/\partial U$	pct. of $\hat{\beta}^{\text{base}} - \hat{\beta}^{\text{full}}$
Years of experience	0.057	0.738	0.042
Ed. Requirement: Technical/Tertiary	0.152	−0.706	−0.107
Ed. Requirement: University or above	0.404	0.909	0.367
Foreign language	0.155	0.356	0.055
General knowledge	0.044	1.858	0.081
Specific knowledge	0.040	3.936	0.157

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

$(\partial X_a/\partial U)$, shows how job characteristics (at specific firm-job title combinations) change when aggregate unemployment changes. The numbers in that column show that all categories, except the technical educational requirement, react positively to an increase in aggregate unemployment, i.e., labor demand tends to become more *picky* when labor market conditions worsen for the labor supply. The negative correlation for technical education (-0.706) paired with the positive value for university education requirements (0.909) suggest that job positions try to upgrade from technical to university degrees when unemployment increases.

The last column in table 6 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 $-1.079 - (-1.674) = 0.595$. From the table we observe that all requirements are important to explain the difference in estimates, with university education being the most important characteristic in relative terms.

The bottom line is that 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 more productive workers (given the evidence in β_{X_a}) for a lower wage to do the same job (firm id and job title) and this leads to an important conclusion: not accounting for countercyclical upgrade of requirements (on the firm's side) leads to underestimating the true cyclicality of posted wages.

3.4 Heterogeneous cyclical hiring standards

Which type of job changes hiring standards during the business cycle? To answer this question empirically and give some context to our results, in what follows we contrast posted job requirements with the aggregate unemployment rate for different parts of the posted salary distribution. More specifically, we construct a dummy variable that takes the value of one if either the job requires at least one year of experience or requires above a technical/tertiary degree of education (inclusive) or requires any type of knowledge (as described above). Next, in table 7 we report regressions similar to equation (1) but with the described indicator as a dependent variable. For specifications in all the columns except the first one, we also include as a regressor the interaction between the aggregate unemployment level and indicator variables for the job ad salary belonging to the second and third terciles of wages. The base category is the first (lowest) tercile.

Table 7: Standards, unemployment, and wages

	Dependent variable: job ad has requirements				
	All	All	Experience	Education	Knowledge
Unemployment rate (U)	0.745	0.091	-0.668	-0.864	1.256
	(0.276)	(0.275)	(0.341)	(0.180)	(0.347)
Wage in T2 × U		1.088	1.367	0.307	1.056
		(0.052)	(0.058)	(0.028)	(0.062)
Wage in T3 × U		1.302	2.033	2.358	1.602
		(0.059)	(0.068)	(0.042)	(0.071)
R^2	0.460	0.466	0.459	0.694	0.402
Adjusted R^2	0.439	0.445	0.439	0.682	0.379

Linear regressions between an indicator variable on existence of job requirements (see main text) and explanatory variables. Regressions include fixed effects for job titles, educational requirements and firm identifiers. Time effects controlled using a monthly trend and month of the year dummies. Jobs posted between March 1st 2010 and August 31st 2023. $N = 1,030,163$ (ads) for all columns. Standard errors in parenthesis.

The table shows that the probability of a job ad presenting hiring standards increases (ceteris paribus) with the aggregate unemployment rate. This effect is strong and significant: an increase of 1 percentage point (p.p.) in the unemployment rate increases the probability of an ad showing a requirement by 0.745%. The second column of table 7 shows that this effect is heterogeneous in different regions of the wage distribution. We report a positive (0.091) non-significant reaction to a 1 p.p. raise of the unemployment rate for the first (lowest) tercile, a significant increase of 1.088% of the likelihood of exhibiting a requirement for the second (middle) tercile, and an even larger effect of 1.302% for the upper tercile. A similar picture is observed when studying specific requirements such as experience and education, which are procyclical for the lowest tercile of the distribution of wages, but strongly countercyclical for the middle and third terciles of these requirements. The binary knowledge requirement is countercyclical for all terciles, with reactions more similar across terciles.

The main takeaway from the last four columns of table 7 is that each individual requirement reacts more strongly to aggregate unemployment the higher the salary paid at the position is. This means that better paid jobs are the ones which typically see more cyclical changes in requirements. Our interpretation is that more complex jobs that are paid better depend more decisively on certain qualifications, whereas basic jobs tend to be less dependable of a fine-tuning of the requirements, because the performance is scarcely affected by worker accomplishments.

3.5 Other exercises

In this section we consider some further empirical exercises to check on robustness and how our results compare with the rest of the literature.

COVID. As a first exercise, we extend the analysis to include all job ads and job seeker information up to March 31, 2023. As seen in figure A1, the aggregate unemployment rate experienced a hike in years 2020 and 2021 due to pandemic contagions and lockdowns in Chile. In table A3, we present the results of extending our analysis to include this time period, where we show that the main qualitative results of the previous section hold: the model with full controls exhibits higher cyclicality of wages than the model without hiring standards. Moreover, the semi-elasticity estimates increase significantly. However, these results should be taken with caution: while unemployment increased, the main driver of these changes were not cyclical productivity declines but health related restrictions, with changes in other dimensions (selection, labor force participation, and worker mobility) that may make the interpretation of results less clear. Exploration of the overall effects of the COVID-19 pandemic on hiring decisions, and overall market equilibrium is a topic beyond the scope of the current paper.

Job Seekers. In the second exercise, we consider the information of job seekers using the website to apply for jobs. Estimates of wage cyclicality from individuals rather than job ads can show how comparable our results are to the literature that uses worker surveys and distinguishes between wage cyclicality of those employed versus those unemployed (Haefke et al., 2013; Gertler et al., 2020). This exercise attempts to bridge our intrinsically ex ante demand-side measurement of marginal cost of labor and the literature using realized wages from either household surveys or administrative records, which typically have more worker-side controls. In this way, we can compare wage cyclicality when measured from the side of individuals versus job positions or demand. The results also highlight how job position information can be used to avoid issues with composition of the labor market (i.e., fraction of unemployed in the job seeker pool, for example).

In our exercise, for each job seeker we consider a search window of seven days starting from the time of an online profile creation or the most recent update of their online profile if one already exists. Over this reference period, we consider the real wages of all job ads included in the sample of our *Full* specification to which individuals applied to. We set the wage for job seekers at the median of their applications. In a similar way, we obtain the mode of job titles and business areas of jobs to which individuals apply.[25] Applicants using the website also report their labor force status during the reference period, which allows us to compare how wage cyclicality behaves for unemployed versus employed job seekers. In table A4 (appendix A.2) we present results for the semi-elasticity of $\log$ real wages for job seekers on the aggregate unemployment rate during their reference month, controlling for a monthly trend and month-of-year dummies. In models under column *(1)*, we further control for age (using

[25] Each job ad has a non-standardized employer declared area of business, which does not conform to NAICS or ISIC classifications.

a quartic polynomial), self-reported experience (quadratic polynomial), and a categorical variable on highest achieved education level. In models under column *(2)*, we also control for geographic location of the job seeker and characteristics of the jobs individuals applied to in the form of fixed effects for job titles and majors required (modes of two main words) and firm area of applied ads. To refine our demand-side controls, column *(3)* replaces the fixed effects of modal words with a more nuanced measure. For each applicant, we calculate the relative frequency of the first two words in the job title, required major, and firm business area description within the set of ads (s)he applied to. This captures the intensity of their focus on specific keywords within their job search scope and also avoids the random choice of the mode when it is not unique.

The table A4 shows a qualitatively similar result as those found in Gertler et al. (2020). Columns *(1)* show very strong procyclicality. Given the lack of geographical and demand-side controls, this suggests that during downturns, applicants target relatively worse jobs and locations (in terms of match quality), not only worse wages. Once we introduce information such as job titles, required majors, and firm business areas, procyclicality is reduced. Notably, the effects reported in columns *(2)* and *(3)*, both capturing demand-side information in different ways, show a procyclicality of wages for unemployed seekers that is quite close to our *Full* model from the previous section.

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 fairly 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 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 shocks are i.i.d. across matches and time periods and are distributed according to the cumulative distribution function (cdf) $F(x)$. Although this is a strong assumption, its relaxation (e.g., x being persistent for the worker) creates quantitative complications without adding much to the intuition and analysis.

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

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 if low draws of the idiosyncratic shock x occur.

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 functions 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. For a given cyclical productivity z, some matches of idiosyncratic productivity x below a threshold $\underline{x}$ may generate a negative surplus. If this is the case, a profit-maximizer employer cut off losses by forgoing matches for an x below $\underline{x}$. Therefore, surplus is only defined by shocks above the threshold or hiring standard $\underline{x}$. The hiring standard $\underline{x}$ if existing for a given value of z is defined as

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

Hence, the hiring standard $\underline{x}$ is a function on the aggregate productivity shock, z. Notice that if the cyclical stance of the economy in z is good enough, there is no idiosyncratic shock that may generate a negative surplus and employers keep every match, i.e., $S(z,x) > 0$ for all 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:

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

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 z 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

[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 17 points to approximate the process.

grid of 201 points, with 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 flow 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 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. 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. The statistic in the Chilean data is 0.926.

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 4 for the specification without job ad characteristics (*base* semi-elasticity of -1.079). 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

[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.

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.

Table 8: Parameter Values

parameter	description	value
ϕ_0	constant, matching function	0.458
ϕ_1	elasticity matching fcn wrt unemployment	0.629
s	exogenous separation rate	0.028
σ_x	std. dev. idiosyncratic shock	0.247
c_v	flow cost vacancy	0.159
η	worker's bargaining weight	0.369
b	flow value of unemployment	0.846
ρ	autocorrelation AR(1)	0.972
σ_ϵ	std. dev. AR(1)	0.007

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 US economy. Note that we find a relatively 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 9, 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] In the table we also show the business cycle behavior of the (vacancy weighted) average wage in the job platform (row *TC wages*).

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 9 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 left (minimum value) boundary

[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`.

Table 9: Business cycle statistics

	Data			Model		
x	σ_x	σ_x/σ_{output}	$\rho_{x,output}$	σ_x	σ_x/σ_{output}	$\rho_{x,output}$
Output	0.040	1.000	1.000	0.026	1.000	1.000
Unemployment	0.140	3.790	-0.920	0.119	4.542	-0.861
Vacancies	0.400	10.610	0.890	0.120	4.606	0.493
Job Finding	0.100	2.670	0.770	0.063	2.400	0.956
Job Separations	0.150	3.860	-0.690	0.107	4.085	-0.517
TC wages	0.070	1.970	0.040	0.017	0.654	0.905

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 aggregate 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 10 below, we show the results from this exercise, where we estimate both $\hat{\beta}^{base}$ and $\hat{\beta}^{full}$ from model simulated data.

Table 10: Model Experiments

	Data	Model
$\hat{\beta}^{\text{base}}$	-1.079	-1.080
$\hat{\beta}^{\text{full}}$	-1.674	-2.211

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 previous empirical results section. The point estimate of the semi-elasticity is higher (-2.211) in the model, 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 omitted variable bias mechanism 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 real 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 by means of a higher job finding probability.

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 market tightness, it is key to understand what influences the elasticity of this variable with respect to productivity. Ljungqvist and Sargent (2017) summarize well the issue, showing that the magnitude 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 similar to the standard one, but exhibits an adjusted *fundamental surplus*, given the presence of idiosyncratic productivity shocks. As employers can set 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 favor some potential explanations for the cyclical behavior of unemployment. Through the lens of our model, a relatively small surplus calibration, as in Hagedorn and Manovskii (2008) is a natural way to simultaneously explain both facts. In the vein of Sedláček (2014), the model also exhibits endogenous procyclical matching productivity, which reflects countercyclical hiring norms. Matches are generated more easily during upturns because employers find more matches acceptable, reflecting a lower hiring threshold.

In the appendix A.5 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 relatively small in our model.

To provide further support to our argument, in figure 4 we show two facts related to our model: first, the job finding rate is always increasing with the level of the productivity shock: if productivity is high, firm's expected profits are higher and there is more incentive for them to post vacancies, increasing job matches. Second, for low levels of the productivity level, separations increase, while they are constant for higher levels of z. This implies that there are no minimum idiosyncratic productivity requirements for vacancies/jobs when productivity is high, but there are binding requirements when it is low. Taken

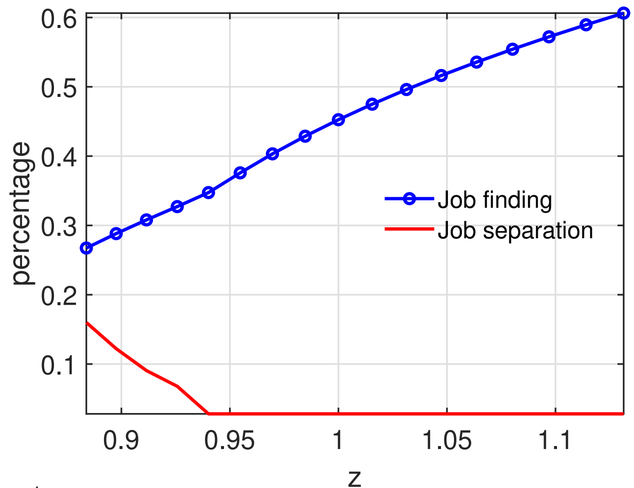

Figure 4: Endogenous job finding and separation rates in the model.

as a whole, hiring standards are counter-cyclical in the model as they bind and change more frequently 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 or continue matches.

More formally, consider the surplus equation from section 4 in steady state (we make z constant and omit it as a state variable):

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

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 the 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, if the calibration allows the model to have realistic job finding and separation probabilities, in appendix A.5 we show that the market tightness cyclicality is typically magnified when hiring standards are binding and vary over the cycle. A more complete list of predictions is as follows:

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.
5. The unemployment rate is more countercyclical under hiring standards compared to the model without this feature.
6. The model dampens the wage-unemployment semi-elasticity in comparison to a model without hiring standards. The more countercyclical the hiring standards, the larger the attenuation.

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 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

[32] For details, see section A.5.

matches are created, and the acceptability (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 *acceptability 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 and even could turn negative in rare cases.

Unemployment sensitivity to productivity shocks in our model with hiring standards is larger, in absolute terms, than that of a standard DMP model with no hiring standards. This may seem unexpected due to the similarity of our model with the endogenous separation case studied by Fujita and Ramey (2012), which delivers a counterfactual positively sloped Beveridge curve. A key difference in our model is that the hiring standard is also a firing standard, so a productivity drop leading to a higher threshold diminishes hiring and increases firing at the same time. A negative productivity shock reduces market tightness by increasing unemployment through separations and by reducing vacancies. That is, a well-behaved Beveridge curve.

We also seek to understand more in-depth the cyclical wage sensitivity generated in our model (and the standard one, as a particular case), a topic scarcely discussed in the literature. In appendix A.5 our analysis shows a fundamental trade-off in the model: a large unemployment income b plays a large role in wage determination, leading to an intuitively low sensitivity of wages to productivity. On the other hand, as earlier discussed, a small fundamental surplus, associated with a high b, raises the cyclical sensitivity of market tightness. A demand-supply analogy illustrates this result further. Whenever labor demand is very elastic, a productivity shock generates low variation in wages and large movements in labor quantities. The opposite occurs when labor demand is inelastic: sensitive wages and barely reactive quantities. Although our model exhibits this trade-off as well, the calibration we adopt happens to be enough to deliver realistic, rightly-signed sensitivities to market tightness and wages, provided that hiring standards behave countercyclically.

The worker bargaining power η plays a nuanced role in the cyclical behavior of wages. Intuitively, a low η dampens wage cyclicality because wage is very close to the outside option b. However, a very high η also results in nearly acyclical wages. This is because high bargaining power needs low market tightness to maintain employer search with almost no profit to gain. A marginal productivity increase in this scenario leads to a strong market tightness response due to the large *proportional* increase in profits, but a tiny wage response since the bargaining process transfers almost all the productivity gains to workers. Hence, an intermediate bargaining power and a mid-small surplus in our calibration generates realistic cyclical responses of wages, market tightness, and hiring standards. These theoretical considerations are illustrated in some simulation exercises in figures A2 and A3 in the appendix.

In the appendix, section A.6 we generate two additional exercises to highlight the empirical implications of the main mechanisms behind wage cyclicality. First, we inquire how an efficient labor market, in the sense of Hosios (1990), would behave in our setting. As the bargaining power η is equalized to the unemployment matching elasticity, wage cyclicality becomes higher and unemployment volatility lower than the baseline results, as shown in table A9. The result is expected as the worker's bargaining share η is larger than in the baseline, reducing the Υ quantity accompanying the fundamental share $\frac{zy}{zy-b}$ in equation (16).

A second exercise is devised to better understand the role of idiosyncratic shocks in generating cyclical volatility. To this end, in section A.6, table A10 we set the variance of idiosyncratic shocks to zero, e.g., we shut down the hiring standard channel. The simulations reveal that endogenous hiring standards actually reduce the volatility of quantities in the model but increase its comovement with aggregate output. Wages, on the other hand, behave similarly since endogenous countercyclical hiring standards partially ameliorate cyclical shocks.

5 Conclusions

We use a decade of internet data to study the cyclicality of real posted wages at new positions which provides evidence of a highly procyclical marginal cost of labor for firms. The richness of our dataset and methodological choices allow us to get close to the theoretical experiment: we want to learn how real wages at the same firm, position, and requirements vary over the business cycle. We compare real wages for full-time jobs after controlling for job composition, using the DiNardo et al. (1996) method, and hiring standards. We also minimize concerns about cyclical mismatch (Hagedorn and Manovskii, 2013; Bellou and Kaymak, 2021) due to the ex ante nature of posted wage data compared to realized wages and our controls for hiring standards. The institutional strong focal point in a 45-hour workweek and standard monthly salaries, as well as data of open positions per ad also ameliorate an often overlooked source of measurement error.

Moreover, we document that hiring standards are counter-cyclical and that ignoring them biases estimates downward. We also show that ignoring how many actual job positions an ad represents biases results towards finding less procyclical wages. An additional exercise estimating cyclicality of applied-for wages on the supply side (applicants) helps to better understand different estimates in the literature and the effect of different controls on the labor demand side. While our analysis uses Chilean data, the findings apply to other economies exhibiting countercyclical hiring standards, as documented for the US in Modestino et al. (2020), and similar cyclical dynamics in fundamental labor market variables.

To rationalize our empirical findings, we extend a standard DMP model (Mortensen and Pissarides, 1994) to incorporate both idiosyncratic and aggregate shocks that affect match productivity. We allow employers to set a hiring standard that varies with business cycle conditions. We calibrate our model to the Chilean labor market and demonstrate its ability to replicate the observed cyclical patterns of both wages and hiring standards. 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 relatively small, as noted by Hornstein et al.

(2005), Hagedorn and Manovskii (2008), and Ljungqvist and Sargent (2017), among others. Thus, we report new facts that equilibrium models of the labor markets should match to deliver realistic dynamics of wages, quantities, and hiring standards. While our deliberately simple theoretical framework may not do justice to more nuanced aspects of the rich empirical findings we provide here and in other papers (Banfi and Villena-Roldán, 2019; Banfi et al., 2022), we achieve the primary goal of reliably estimating the marginal cost of labor dealing with multiple challenges arising with this kind of wage data (Batra et al., 2023; Hazell and Taska, 2024) and establish a clear linkage with a well-known family of models explaining the cyclical behavior of labor markets.

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A Appendix

A.1 Descriptive statistics for ALL jobs

Table A1: Characteristics of Job Postings

	Ads (ALL)	Vacs. (ALL)	Ads (FT only)	Vacs. (FT only)
Observations	1,515,013	7,565,102	1,194,445	4,745,918
Average:				
Real wages (thousand CLP, 2018=100)	723	469	802	543
Years of experience	1.71	0.96	1.88	1.13
Share of jobs:				
Ed. Requirement: Technical/Tertiary	0.28	0.16	0.29	0.17
Ed. Requirement: University or above	0.34	0.13	0.37	0.16
Foreign language	0.08	0.03	0.09	0.04
General knowledge	0.65	0.54	0.69	0.59
Sepcific knowledge	0.19	0.19	0.20	0.20
Big firm ($\geq$ 51 Employees)	0.44	0.46	0.44	0.47
Explicit wage	0.17	0.24	0.16	0.23
Full time contract	0.79	0.63	1.00	1.00

Information from job advertisements in www.trabajando.com, for the period March 1st 2010 to March 31st 2020, for individual job ads (Ads) and job ads weighted by number of positions (Vacs). We also categoriza by offered contract all contracts (ALL) versus full time jobs (FT only).

A.2 Expanded Sample and Other Exercises

Table A2: Characteristics of Job Postings (Including COVID)

	Ads (ALL)	Vacs. (ALL)	Ads (FT only)	Vacs. (FT only)
Observations	2,316,064	10,412,749	1,713,966	6,464,140
Average:				
Real wages (thousand CLP, 2018=100)	712	499	764	547
Years of experience	1.68	0.98	1.79	1.09
Share of jobs:				
Ed. Requirement: Technical/Tertiary	0.28	0.17	0.29	0.17
Ed. Requirement: University or above	0.33	0.13	0.35	0.15
Foreign language	0.07	0.03	0.08	0.04
General knowledge	0.66	0.56	0.68	0.59
Specific knowledge	0.20	0.20	0.20	0.20
Big firm ($\geq$ 51 Employees)	0.41	0.43	0.41	0.43
Explicit wage	0.17	0.24	0.17	0.24
Full time contract	0.74	0.62	1.00	1.00

Information from job advertisements in www.trabajando.com, for the period March 1st 2010 to August 31st 2023, for individual job ads (Ads) and job ads weighted by number of positions (Vacs). We also categoriza by offered contract all contracts (ALL) versus full time jobs (FT only).

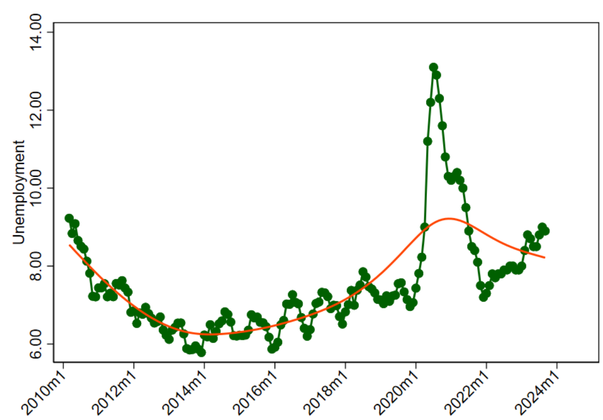

Figure A1: Aggregate unemployment rate including COVID period (March 1st 2010 to August 31st 2023). Hodrick-Prescott smoothed trend with parameter $\lambda = 14,400$ as a reference (red line).

Table A3: Estimation results (Including COVID)

	Dependent variable: log real ad wage	
	Base	*Full*
Unemployment rate	-1.923	-2.082
	(0.041)	(0.040)
Job ad characteristics	N	Y
Adjusted R2	0.554	0.577
R2	0.570	0.592
Sample size (ads)	1,469,826	1,469,826
Sample size (vacancies)	3,800,056	3,800,056

Estimation results of equation (1), between log of real posted wages and the aggregate unemployment rate. Sample period is March 1st 2010 to August 31st, 2023. 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.

Table A4: Estimation results for JOB SEEKERS

	(1)		(2)		(3)	
	Employed	Unemployed	Employed	Unemployed	Employed	Unemployed
Unemployment rate	-3.282***	-3.211***	-2.368***	-1.877***	-2.367***	-1.858***
	(0.206)	(0.155)	(0.185)	(0.164)	(0.176)	(0.153)
Municipality FE	N	N	Y	Y	Y	Y
Modal words FE	N	N	Y	Y	N	N
Frequency of words	N	N	N	N	Y	Y
Adjusted R2	0.291	0.244	0.609	0.569	0.634	0.604
R2	0.291	0.244	0.61	0.571	0.636	0.606
N	249398	337964	162608	168126	162626	168142

Estimation results of for a regression between the log of real wages for **job seekers** and the aggregate unemployment rate (see main text for definitions). Sample period is March 1st 2010 to March 31st, 2020. All regressions control for a monthly trend and month-of-year dummies. Municipality fixed effects (FE) refer to the reported residence of the applicant. Modal words FE refer to dummy variables for mode words describing the first two meaningful words of the job title, the first two describing the required major of applied job ads, and the category describing the mode firm area of applied job ads. Frequency of words refer to the relative frequency of each word appears within the set of words describing job title, major, and firm area. Standard errors in parenthesis.

A.3 Results on data representativeness

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. 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. (2022) and Banfi et al. (2019). In terms of educational levels, there are two 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 (from the ESI dataset) matches the distribution of educational requirements for workers in www.trabajando.com for those with at least a high school education, thus the website data misses job creation for very low-educated workers. Leaving aside primary school requirements, 68.5% of vacancies target high-school level workers, compared to 71.2% of the ESI flow and 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 A5 shows these results in the appendix.

Table A5: 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).

Table A6: Distribution of usual weekly hours worked in ENE data 2010-23

	Usual weekly hours worked (%)							
	1-29	30-39	40-44	45	46-50	51-60	60+	obs
stock of workers								
before April 2020	6.90	4.18	7.34	58.43	12.62	4.22	6.31	893,656
after April 2020	6.86	4.59	13.92	62.10	7.90	1.83	2.81	255,734
All	6.89	4.30	9.19	59.46	11.29	3.55	5.32	1,149,390
recently hired workers								
before April 2020	13.93	5.50	6.74	52.02	11.65	4.10	6.06	71,685
after April 2020	14.83	5.51	12.38	54.60	7.61	2.07	3.00	19,265
All	14.17	5.50	8.25	52.71	10.56	3.56	5.24	90,950

Data are self-reported usual weekly hours worked by private salaried workers from the *Encuesta Nacional de Empleo* (ENE) from March 2010 - December 2023. We use survey inverse probability weights adjusted according to the 2017 Census. We discard individuals reporting null or more than 168 hours per week. Since 2005 the Chilean Labor Law establishes a maximum of 45 hours worked every week for jobs working under supervision, with some exceptions. For hours worked between 46 and 60 hours, employers must pay overtime overcharge. Supervised workers cannot work more than 60 hours per week.

Table A7: Distribution of usual weekly hours worked in ENE data 2010-23 by industry

	Usual weekly hours worked (%)							
	1-29	30-39	40-44	45	46-50	51-60	60+	obs
Stock of workers								
Agriculture	6.6	3.9	5.9	70.1	8.0	2.3	3.2	61,384
Mining	1.4	2.1	40.7	25.9	16.4	10.1	3.4	13,671
Manufacturing	3.3	1.7	7.3	73.3	9.7	2.3	2.6	56,167
Electricity	1.2	1.6	14.5	72.4	6.6	2.2	1.7	2,595
Water	4.7	2.3	9.4	66.7	11.7	2.7	2.5	5,253
Construction	3.4	2.2	10.1	72.4	6.5	2.7	2.6	53,035
Retail	9.4	4.7	5.4	65.2	9.6	2.3	3.4	82,061
Transport	6.3	4.5	8.2	52.5	11.8	4.1	12.6	36,612
Hotel/Food	11.0	6.2	8.4	51.0	13.6	4.0	5.7	27,667
Communications	3.3	3.0	8.9	76.9	4.6	1.0	2.5	9,011
Financial	1.8	2.4	11.4	80.4	2.4	0.5	1.1	10,765
Real State	8.6	3.0	10.7	63.4	10.1	1.4	2.8	4,368
Professional / Scientific	6.1	3.6	13.0	70.1	4.3	1.4	1.6	14,543
Managerial	6.0	3.2	13.6	59.1	12.8	2.6	2.7	37,328
Public Administration	7.1	4.7	32.8	44.3	6.6	1.2	3.4	3,131
Education	11.9	13.1	24.9	47.2	1.9	0.4	0.6	36,316
Health	10.5	5.9	13.6	51.7	13.3	2.3	2.8	16,893
Art & Entertainment	19.4	9.0	8.7	47.7	9.9	2.2	3.1	4,220
Other Services	10.3	4.8	11.2	50.8	14.6	2.9	5.4	9,082
All	6.9	4.4	10.9	62.8	9.0	2.5	3.6	484,102
Recently hired workers								
Agriculture	15.6	6.6	7.4	59.5	6.5	2.1	2.3	8,920
Mining	3.1	5.0	37.2	26.3	14.0	7.0	7.5	677
Manufacturing	9.0	3.7	8.4	63.9	9.1	3.0	3.0	3,205
Electricity	4.6	1.0	16.2	67.2	5.4	3.6	2.0	119
Water	7.4	3.2	8.5	67.9	9.2	2.9	1.0	232
Construction	9.1	3.3	9.3	66.5	6.4	2.3	2.9	6,829
Retail	18.7	5.9	6.3	54.0	8.5	2.9	3.8	4,603
Transport	15.7	5.9	8.1	42.5	11.9	3.6	12.3	2,306
Hotel/Food	23.1	9.6	9.2	38.3	10.9	3.7	5.2	2,386
Communications	5.5	1.9	9.3	71.6	6.5	2.7	2.5	432
Financial	2.4	1.5	8.8	83.7	1.4	1.3	0.9	305
Real State	20.4	2.7	9.9	55.3	7.6	2.3	1.7	209
Professional / Scientific	13.2	4.3	13.0	61.4	4.0	1.7	2.5	749
Managerial	10.9	4.1	12.3	52.9	13.7	3.2	3.0	2,871
Public Administration	12.4	7.8	20.2	43.7	9.8	1.5	4.7	129
Education	24.7	13.1	16.3	41.7	3.4	0.8	0.1	985
Health	19.6	7.8	10.9	44.0	12.3	1.1	4.4	794
Art & Entertainment	25.6	10.1	8.1	45.9	3.9	2.2	4.3	281
Other Services	19.0	5.3	9.9	38.7	19.2	2.4	5.6	514
All	14.1	5.4	9.5	56.0	8.6	2.7	3.8	36,546

Data are self-reported usual weekly hours worked by private salaried workers from the *Encuesta Nacional de Empleo* (ENE) from March 2010 - December 2023. We use survey inverse probability weights adjusted according to the 2017 Census. We discard individuals reporting null or more than 168 hours per week. Since 2005 the Chilean Labor Law establishes a maximum of 45 hours worked every week for jobs working under supervision, with some exceptions. For hours worked between 46 and 60 hours, employers must pay overtime overcharge. Supervised workers cannot work more than 60 hours per week.

A.4 Description of variable construction

As in Banfi and Villena-Roldán (2019) and Banfi et al. (2022), we construct variables related to whether a job requires some form of additional knowledge. The set of words we use to create these variables are *"exper"*, *"conocim"*, *"capacit"*, which are Spanish roots/stems related to *experience*, *knowledge* and *training* and we use to create a *general knowledge* requirement.

For *specific knowledge* requirements, we search for *"estudio"*, *"especiali"*, *"dominio"* which relate to *studies*, *specialty* and *mastery/proficiency*.

For language requirements, we search for terms *"habla"* (speaks) and the most common requested languages: *"francés"*, *"alemán"*, *"portug"*, *"italia"*, *"chino"*, *"japo"*, *"ingles"*, *"inglés"*, *"engl"* (French, German, Portuguese, Italian, Chinese, Japanase and English).

A.5 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

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

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

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

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

$$\left(\frac{zy}{zy-b}\right)\left(1 + \epsilon_{y,\underline{x}}\epsilon_{\underline{x},z}\right) = \epsilon_{\theta,z}\Upsilon^{-1} - \epsilon_{F_+,\underline{x}}\epsilon_{\underline{x},z}\Lambda \tag{A1}$$

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

market tightness cyclical elasticity: $\epsilon_{\theta,z} \equiv \dfrac{d\log\theta}{d\log z} = \dfrac{z\theta'}{\theta}$

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

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

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

From equation (A1) 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).

$$\epsilon_{\theta,z}\Big|_{\underline{x}'=0} = \left(\frac{zy}{zy-b}\right)\Upsilon \tag{A2}$$

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 (A1) we present below the elasticity of tightness to aggregate conditions z when hiring standards are not constant.

$$\epsilon_{\theta,z} = \epsilon_{\theta,z}\Big|_{\underline{x}'=0} \left(1 + \epsilon_{y,\underline{x}}\epsilon_{\underline{x},z}\right) + \Lambda\Upsilon\epsilon_{F_+,\underline{x}}\epsilon_{\underline{x},z} \tag{A3}$$

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

$$\left(\frac{1-\eta}{c_v}\right)(b - z\underline{x}) = F_+ \left(\frac{1-s}{q} - \eta\theta\right) \tag{A4}$$

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, (A4) 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 studying comparative statics in steady state. To achieve that goal, we differentiate equation (A4) with respect to z, to obtain

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

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

$$\epsilon_{\underline{x},z} = -\frac{\Delta-\Psi\epsilon_{\theta,z}}{\Delta-\Gamma} \tag{A5}$$

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 (A5) into expression (A3), we can solve for the market tightness elasticity as

$$\epsilon_{\theta,z} = \frac{(\Delta-\Gamma)\,\epsilon_{\theta,z}\Big|_{\underline{x}'=0}-\nu\Delta}{\Delta-\Gamma-\nu\Psi} \tag{A6}$$

where

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

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 acceptability when employers raise the bar, i.e. $\epsilon_{F_+,\underline{x}} < 0$. As long as $\chi < 0$, i.e the acceptability 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 acceptability 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

$$\epsilon_{\theta,z} = \epsilon_{\theta,z}\Big|_{\underline{x}'=0}\left(\frac{1-\frac{\chi}{\Delta-\Gamma}\frac{\underline{x}}{y}\Upsilon^{-1}}{1-\frac{\nu}{\Delta-\Gamma}\Psi}\right) \tag{A7}$$

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

$$\underline{x} > F_{+}y\left(\frac{\eta p-(1-\phi_1)(1-s)}{\eta p+(1-\phi_1)(1-s)}\right) \tag{A8}$$

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 $F_{+}y$ lies 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 (A8) 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 (A5) and (A6)

$$\epsilon_{\underline{x},z} = -\frac{\Delta}{\Delta-\Gamma}\left(\frac{\Delta-\Gamma-2\nu\Psi}{\Delta-\Gamma-\nu\Psi}\right) - \epsilon_{\theta,z}\Big|_{\underline{x}'=0}\left(\frac{\Psi}{\Delta-\Gamma-\nu\Psi}\right) \tag{A9}$$

A simple inspection of the formula tells us that if the acceptability effect offsets the average productivity effects of raising hiring standards, i.e. $\nu < 0$, the hiring standards are always countercyclical. If that's not the case, the countercyclicality still holds unless the acceptability 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

$$\epsilon_{\underline{x},z} = -\epsilon_{\theta,z}\Big|_{\underline{x}'=0}\left(\frac{\frac{\underline{x}}{y}\Upsilon^{-1}}{\Delta-\Gamma}\left(\frac{\Delta-\Gamma-2\nu\Psi}{\Delta-\Gamma-\nu\Psi}\right)+\left(\frac{\Psi}{\Delta-\Gamma-\nu\Psi}\right)\right) \tag{A10}$$

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.

On the semi-elasticity of wages with respect to unemployment:

In this subsection we analyze the implied semi-elasticity of the average wage with respect to the unemployment rate, i.e. the theoretical counterpart of the main quantity measured in our empirical framework. First, let us remember that the unemployment rate in the model equals $u = \frac{s^*(\underline{x})}{s^*(\underline{x})+p(\theta)}$ with $s^*(\underline{x}) = 1-(1-s)F_+(\underline{x})$. Hence, we could rewrite is as

$$u(z) = \frac{1/F_+(\underline{x}(z)) - 1 + s}{1/F_+(\underline{x}(z)) - 1 + s + p(\theta(z))}$$

where we highlight that since both θ and $\underline{x}$ are functions of z, so it is the unemployment rate, u.

Thus, it is possible to take u as the cyclical variable and $z(u)$ as the shock consistent with the equilibrium u. Hence, we can write the average wage equation as

$$w(\theta(z(u)), \underline{x}(z(u))) = \eta\left(zy(\underline{x}(z(u))) + c_v\theta(z(u))\right) + (1-\eta)b \tag{A11}$$

Taking derivatives of (A11), we obtain

$$\frac{dw}{du} = \frac{dw}{d\theta}\frac{d\theta}{dz}\frac{dz}{du} + \frac{dw}{d\underline{x}}\frac{d\underline{x}}{dz}\frac{dz}{du}$$

Doing some algebra, we obtain

$$\frac{u}{w}\frac{dw}{du} = \left(\left(\frac{\theta}{w}\frac{dw}{d\theta}\right)\left(\frac{z}{\theta}\frac{d\theta}{dz}\right) + \left(\frac{\underline{x}}{w}\frac{dw}{d\underline{x}}\right)\left(\frac{z}{\underline{x}}\frac{d\underline{x}}{dz}\right)\right)\left(\frac{z}{u}\frac{du}{dz}\right)^{-1}$$

Hence, expressing the latter in terms of elasticities, we obtain

$$\epsilon_{w,u} = (\epsilon_{w,\theta}\epsilon_{\theta,z} + \epsilon_{w,\underline{x}}\epsilon_{\underline{x},z})\epsilon_{u,z}^{-1} \tag{A12}$$

We can compute all the terms in (A12)

$$\frac{d\log(1-u)}{dz} = \frac{d\log p}{dz} + \frac{d\log(1/F_+ - 1 + s + p)}{dz}$$

Computing derivatives, we obtain

$$-\frac{u}{1-u}\left(\frac{z}{u}\frac{du}{dz}\right) = \left(\frac{d\log p}{d\log\theta}\right)\left(\frac{d\log\theta}{d\log z}\right) - \frac{p\left(\frac{\theta}{p}\frac{dp}{d\theta}\right)\left(\frac{z}{\theta}\frac{d\theta}{dz}\right) + \left(\frac{\underline{x}}{F_+}\frac{dF_+}{d\underline{x}}\right)\left(\frac{z}{\underline{x}}\frac{d\underline{x}}{dz}\right)\frac{1}{F_+}}{1/F_+ - 1 + s + p}$$

where $\frac{d\log p}{d\log\theta} = \phi_1$. Reorganizing terms, and replacing elasticity notation yields

$$\epsilon_{u,z} = -(1-u)\left(\phi_1\epsilon_{\theta,z} + \frac{\epsilon_{F_+,\underline{x}}\epsilon_{\underline{x},z}}{1-F_+(1-s)}\right)$$

o the extent that $\epsilon_{\underline{x},z} < 0$, $\epsilon_{F_+,\underline{x}} = -\frac{f(\underline{x})\underline{x}}{F_+} < 0$ and $\epsilon_{\theta,z} > 0$, clearly $\epsilon_{u,z} < 0$. As highlighted above, the countercyclical hiring standard, $\epsilon_{\underline{x},z} < 0$, occurs when the acceptability effect dominates the average productivity effect, i.e., there is substantial mass around $\underline{x}$. Moreover, this proves that the unemployment rate is more sensitive to productivity shocks in a model with countercyclical hiring standards than in a model without them, in which $\epsilon_{\underline{x},z} = 0$. The intuition for these results is clear: as employers raise the bar in recessions, the endogenous separation probability increases and generates more unemployment. This result is different in our model compared to those in Mortensen and Pissarides (1994) and Fujita and Ramey (2012) because the productivity of a match at the beginning is stochastic in our case rather than fixed. This issue entails that hiring and firing standards typically increase as productivity declines, resulting in both less job creation and more job destruction. In this way, our model avoids generating a counterfactual positive correlation between unemployment and vacancies.

To compute the wage-tightness elasticity $\epsilon_{w,\theta}$, we just need to differentiate and obtain

$$\frac{dw}{d\theta} = \eta c_v$$

$$\epsilon_{w,\theta} = \frac{\theta}{w}\frac{dw}{d\theta} = \eta c_v\frac{\theta}{w} > 0$$

We can also compute

$$\frac{dw}{d\underline{x}} = \eta c_v\frac{d\theta}{dz}\frac{dz}{d\underline{x}}$$

$$\epsilon_{w,\underline{x}} = \frac{\underline{x}}{w}\frac{dw}{d\underline{x}} = \eta c_v\frac{d\theta}{dz}\frac{dz}{d\underline{x}}\frac{\underline{x}}{w} = \eta c_v\frac{\theta}{w}\frac{\epsilon_{\theta,z}}{\epsilon_{\underline{x},z}}$$

Replacing the different elements in (A12), we obtain an expression for the wage-unemployment semi-elasticity $\xi_{w,u} = \frac{d\log w}{du} = \epsilon_{w,u}/u$.

$$\xi_{w,u} = \epsilon_{w,u}/u = -\frac{2\eta c_v(\theta/w)\epsilon_{\theta,z}}{u(1-u)\left(\phi_1\epsilon_{\theta,z} + \frac{\epsilon_{F_+,\underline{x}}\epsilon_{\underline{x},z}}{1-F_+(1-s)}\right)}$$

We define $\gamma = b/zy \in (0,1)$, i.e. the ratio between unemployment income and labor productivity. Using the wage equation and the entry condition we obtain that

$$zy(1-\gamma) = \frac{\eta c_v\theta}{(1-\eta)\Omega}$$

where

$$\Omega \equiv \frac{\eta p}{\eta p + 1/\delta F_+ - 1 + s} \in (0,1)$$

Similarly, working out the wage equation renders

$$w = (\eta + (1-\eta)\Omega)(zy - b) + b = zy((\eta + (1-\eta)\Omega)(1-\gamma) + \gamma)$$

Replacing the previous expressions, we obtain

$$\frac{\eta c_v \theta}{w} = \left(\frac{(\eta + (1-\eta)\Omega)(1-\gamma)}{(\eta + (1-\eta)\Omega)(1-\gamma) + \gamma}\right)\left(\frac{(1-\eta)\Omega}{(1-\eta)\Omega + 1}\right) \in (0,1)$$

For the standard model with no hiring standards (or non-binding ones), the result is

$$\xi_{w,u}\Big|_{\underline{x}'=0} = -\frac{2\eta c_v(\theta/w)}{u(1-u)\phi_1}$$

Therefore, it is possible to write the wage-unemployment semi-elasticity as

$$\xi_{w,u} = \left(\xi_{w,u}\Big|_{\underline{x}'=0}\right)\frac{\phi_1\epsilon_{\theta,z}}{\phi_1\epsilon_{\theta,z} + \frac{\epsilon_{F_+,\underline{x}}\epsilon_{\underline{x},z}}{1-F_+(1-s)}}$$

The fraction accompanying $\xi_{w,u}\Big|_{\underline{x}'=0}$ lies between 0 and 1 as long as the hiring standards are countercyclical, i.e., $\epsilon_{\underline{x},z} < 0$, since $\epsilon_{F_+,\underline{x}}$ is always negative. This implies that countercyclical hiring standards *reduce* the absolute value of the semi-elasticity of wages with respect to unemployment. Thus, if we measure this quantity while allowing hiring standards to vary endogenously over the business cycle, we will measure a lower absolute semi-elasticity than if the hiring standards were fixed.

In summary, there is a trade-off between the sensitivity of market tightness to productivity shocks and the wage sensitivity to productivity shocks. The presence of endogenous hiring standards amplifies the former and dampens the latter. However, for a realistic calibration that generates countercyclical hiring standards as observed, a relatively small surplus calibration closely replicates the observed sensitivities of market tightness, hiring standards, and wages.

To demonstrate this, we use the calibrated parameters from Table 4.1 and compute the wage-unemployment semi-elasticity implied by varying η, the worker bargaining power, and the share of unemployment income with respect to average income, γ, in different ways. For all combinations of (η, γ) considered, we adjust the cost of entry such that the unemployment rate, the job finding probability, and the separation probability match the sample values for the period March 2010 - March 2020. Figure A2 depicts the results of these calculations.

On the left panel, we compute the wage-unemployment semi-elasticity, $\xi_{w,u}$, as a function of γ for different levels of η. All functions are negative and increasing, indicating that the model predicts procyclical wages whose responsiveness to unemployment declines as the fundamental surplus decreases (as γ increases). The intuition is likely clear: as γ increases, the equilibrium wage becomes increasingly dependent on the value of b and, therefore, less reactive to changes in unemployment or the underlying productivity. The functions' positions change noticeably with varying levels of η, reaching higher values

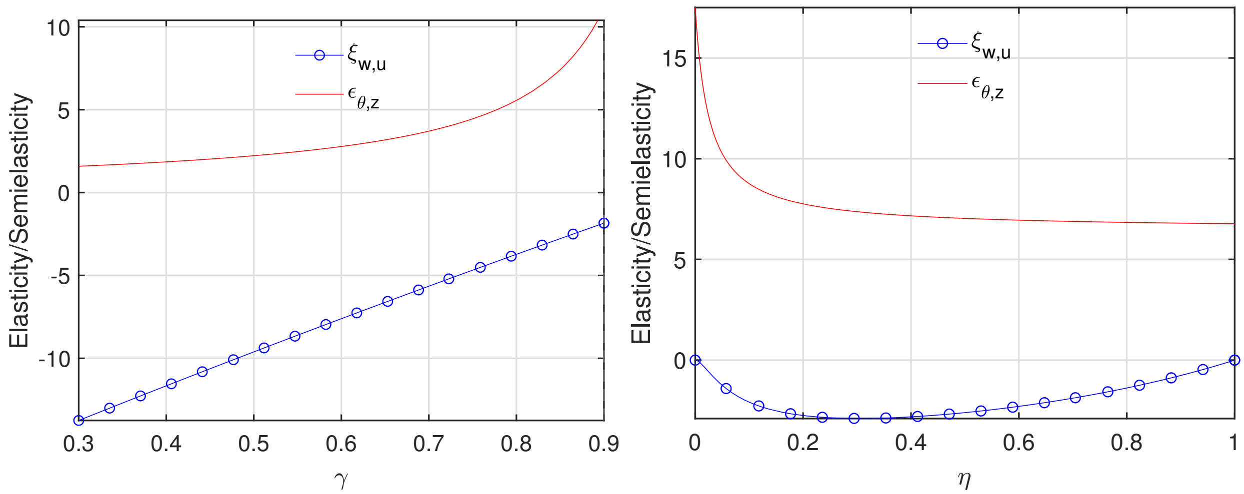

Figure A2: Wage-unemployment semi-elasticity, $\xi_{w,u}$, at different levels of unemployment income share, γ, varying over worker bargaining power, η (left figure). The right figure depicts the wage-unemployment semi-elasticity, $\xi_{w,u}$, at different levels of worker bargaining power, η, varying over unemployment income share, γ. The figures depict steady-state magnitudes consistent with average March 2010 - March 2020 unemployment rate, and quarterly job finding and separation probabilities by adjusting entry costs accordingly.

for the calibrated value of $\eta = 0.369$.

This result is explained by the right panel, which computes the wage-unemployment semi-elasticity as a function of η for different levels of γ. The functions exhibit a U-shape, reaching their minimum at an intermediate value between 0.2 and 0.4. This pattern is explained by a trade-off that is clearer when considering extreme values for η, either 0 or 1. When $\eta \to 0$, the wage equals the outside option b, making it insensitive to productivity shocks or their induced variation in unemployment. When $\eta \to 1$, the wage equals the productivity of the match, making profits unresponsive to productivity shocks or to its associated unemployment variations. Only for intermediate values does the response of wages to unemployment variation become substantial. Consistent with the right panel, larger values of γ are associated with higher values of wage-unemployment semi-elasticity, i.e., less procyclical wages.

Figure A3 depicts the implied wage-unemployment semi-elasticity and the market tightness-productivity elasticity depending on η (left panel) and γ (right panel). The figures are computed in the same vein as in the previous figures: we adjust vacancy-posting costs so that key magnitudes such as the unemployment rate, job finding probability, and separation probability match their empirical counterparts. These figures show that, although there is a trade-off in simultaneously generating high absolute values for $\xi_{w,u}$ and $\epsilon_{\theta,z}$, the model can generate empirically plausible values for these quantities for intermediate values of worker bargaining power, η. The exercises in the left panel, varying the quantities of interest by γ, also show that a not high enough value renders too low sensitivity of market tightness to productivity (Shimer (2005) result) but also wages that are too reactive to unemployment, if we try to match key variables as explained above. If $\gamma = 0.4$, the computation suggests a value for $\epsilon_{\theta,z}$ in the ballpark of $[1, 2]$ but a value of $\xi_{w,u} < -10$, a number at odds with any empirical result in the literature. This

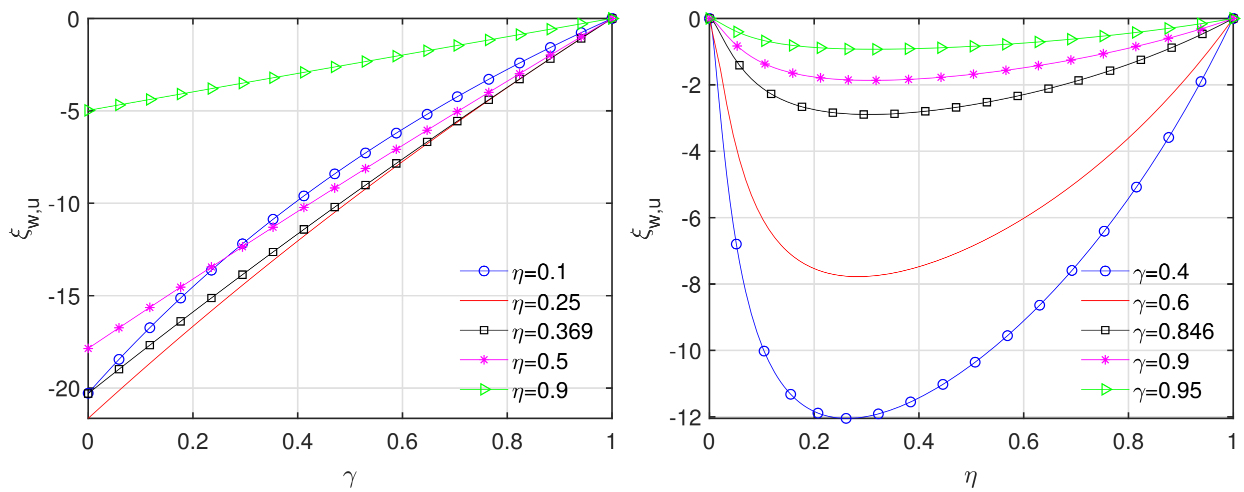

Figure A3: Wage-unemployment semi-elasticity, $\xi_{w,u}$, and market tightness-productivity elasticity, $\epsilon_{\theta,z}$, at different levels of worker bargaining power, η (left figure) and unemployment income share, γ (right figure). The figures depict steady-state magnitudes consistent with average March 2010 - March 2020 unemployment rate, and quarterly job finding and separation probabilities by adjusting entry costs accordingly.

simulation reinforces the need for a smaller surplus to match the behavior of key variables in the labor market.

A.6 Model: Extras

In table A.6 we show the calibration when we impose the Hosios (1990) condition ($\eta = \phi_1$, i.e., worker's bargaining share equal to the elasticity of the matching function with respect to unemployment), maintaining all calibration targets, but dropping the target on semi-elasticity of wages to unemployment. The results are similar to those of the baseline calibration. Figure A4 shows the reaction of hiring standards under different values of cyclical productivity. Simulations show that wages are substantially more volatile and somewhat more procyclical than the baseline calibration. Unemployment and vacancies exhibit slightly higher volatility. Their volatility in relative terms with respect to output is substantially larger than is the baseline calibration, as shown in table A9. Overall, the procyclical behavior of wages become more pronounced that observed in the data under this alternative calibration. The whole exercise shows how standard calibration choices could entail quantitatively important consequences for the behavior of labor markets over the cycle. Taking into count than the semi-elasticity OLS estimate using simulated data is basically $\hat{\beta} = \frac{cov(\log w, U)}{var(U)} = \frac{corr(\log W, U) sd(\log W)}{sd(U)}$ the higher volatility of wages dominates and increases the measured semi-elasticity under the Hosios calibration. Thus, higher efficiency would entail a more volatile economy in our setting.

Table A8: Parameter Values (imposing Hosios condition)

parameter	description	value
ϕ_0	constant, matching function	0.467
s	exogenous separation rate	0.029
σ_x	std. dev. Idiosyncratic shock	0.391
c_v	flow cost vacancy	0.121
b	flow value of unemployment	0.711
ρ	autocorrelation AR(1)	0.984
σ_ϵ	std. dev. AR(1)	0.013
ϕ_1	elasticity matching fcn wrt unemployment	0.629
η	worker's bargaining weight	0.629

In table A10 we consider an additional exercise to understand the role of idiosyncratic productivity shocks in generating cyclical fluctuations. We keep all the parameters of the original in table 4.1 calibration constant except for equation to zero the standard deviation of idiosyncratic shocks σ_x. As a result, quantities such as output, unemployment, and vacancies become less volatile and more correlated with output. Wage volatility becomes only marginally less volatile. In consequence, the cyclical negative comovement between wages and unemployment increases in absolute terms, but the variance of unemployment declines. This combination yields a more negative coefficient between log-wages and unemployment in the simulated data as it is clear from the semi-elasticity OLS estimate $\hat{\beta} = \frac{cov(\log w, U)}{var(U)} = \frac{corr(\log W, U) sd(\log W)}{sd(U)}$. These findings quantitatively illustrate the main forces driving key labor market variables in the model. Idiosyncratic shocks may actually assuage labor market volatility since endogenous hiring standards provide an extra margin for employers to partially offset the impact of cyclical shocks.

Table A9: Business cycle statistics (Baseline vs. Hosios)

	Baseline			Hosios		
$\hat{\beta}^{\text{base}}$		-1.080			-2.211	
$\hat{\beta}^{\text{full}}$		-1.883			-4.349	
x	σ_x	σ_x/σ_{output}	$\rho_{x,output}$	σ_x	σ_x/σ_{output}	$\rho_{x,output}$
Output	0.026	1.000	1.000	0.043	1.000	1.000
Unemployment	0.119	4.542	-0.861	0.124	2.865	-0.755
Vacancies	0.120	4.606	0.493	0.148	3.436	0.649
Job Finding	0.063	2.400	0.956	0.072	1.668	0.976
Job Separations	0.107	4.085	-0.517	0.114	2.654	-0.304
TC wages	0.017	0.654	0.905	0.038	0.881	0.949

Table A10: Business cycle statistics (Baseline vs. model with no idiosyncratic shocks (hiring standards))

	Baseline			no idiosyncratic shocks		
$\hat{\beta}^{\text{base}}$		-1.080			-5.759	
$\hat{\beta}^{\text{full}}$		-1.883			-5.759	
x	σ_x	σ_x/σ_{output}	$\rho_{x,output}$	σ_x	σ_x/σ_{output}	$\rho_{x,output}$
Output	0.026	1.000	1.000	0.022	1.000	1.000
Unemployment	0.119	4.542	-0.861	0.045	2.068	-0.974
Vacancies	0.120	4.606	0.493	0.088	4.048	0.980
Job Finding	0.063	2.400	0.956	0.048	2.238	0.992
Job Separations	0.107	4.085	-0.517	0.000	0.000	-0.159
TC wages	0.017	0.654	0.905	0.016	0.743	0.999

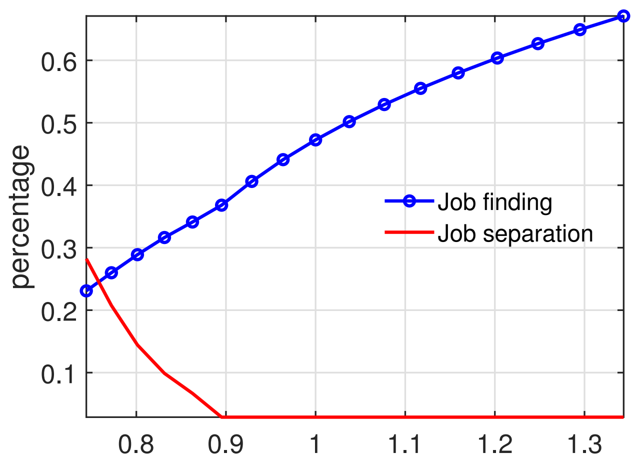

Figure A4: Endogenous job finding and separation rates in the model (imposing Hosios condition).