Do High-Wage Jobs Attract more Applicants? Directed Search Evidence from the Online Labor Market*

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Abstract

Are workers applying more to high-wage jobs? In the theoretical literature, worker search directed to jobs offering higher wages has strong implications for labor market efficiency, but the evidence supporting this behavior is scarce and murky. In this paper, we provide strong evidence of directed search in online job markets. Since 85% online job ads do not post an explicit wage, selection bias is a huge challenge for estimating a credible impact of wages on applications. In fact, we show that job ads that post an explicit wage require significantly lower education and experience. We surmount this problem thanks to a remarkable feature of our data: wages that employers expect to pay are observable, even if they choose not to make them visible for applicants. When wages are not explicitly declared, we still find a less intense but highly significant directed search evidence, suggesting that the text and requirements of the posted job ad tacitly convey wage information. The evidence suggests that job ads with hidden or implicit wages are noisy signals with high expected wage used to attract skilled applicants and to deter unskilled ones.

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1 Introduction

Nowadays workers routinely search for job opportunities on the internet, facing small costs for applying to jobs through websites such as `www.monster.com` in the US, or `www.trabajando.com` in several countries including Chile and Spain. Typically, applicants take into account wages posted in job ads to direct their search effort. While this may be a commonsensical consideration to some extent, finding convincing evidence of these behaviors is elusive because most employers do not explicitly post wages whatsoever, and if they do, the advertised positions are clearly different from those in which wages are not revealed.

Due to congestions, in labor markets with search frictions, job search efforts negatively impact matching chances of others on the same side of the market, and positively affects the chances of those on the opposite side. Typically, posting vacancies and screening applicants may be strategic substitutes among employers, i.e. the outcome of their effort decreases on the average effort of other employers. In contrast, employers' effort and sending applications are likely strategic complements, i.e. firms' effort returns increase in applicants' effort.

Labor market agents internalize these externalities depending on the way wages are set and how responsive applications are to those wages (Hosios 1990; Moen 1997; Rogerson, Shimer, and Wright 2005), at least in sequential search environments. Usually in random search models, wages are determined via *ex post* bargaining, which leads to inefficient outcomes in most cases. Workers and employers fail to take into account the externalities they generate when splitting the surplus in a bilateral monopoly situation. In contrast, in directed search models workers assess posted wages and their associated likelihood of becoming employed. Applicants direct their search effort to the relevant firm or submarket where employers open positions with specific requirements and announces a take-it-or-leave-it wage schedule (Moen 1997; Menzio and Shi 2010). Some analytic properties of these models ease their use in contexts of cyclical fluctuations (Menzio and Shi 2011) or non-stationary life-cycle environments (Menzio, Telyukova, and Visschers 2012).

More realistically, hiring could be seen as a selection process among heterogeneously productive workers, especially for job positions for skilled workers (van Ours and Ridder 1992; Abbring and van Ours 1994; Oyer and Schaefer 2011; van Ommeren and Russo 2013). In this case, new externalities may arise because screening and recruiting activities affect the composition of the unemployment pool, which in turn impacts the quality of new hirings (Villena-Roldan 2010).

We propose to look for evidence on directed search in the online labor market because it provides rich information regarding the job search process in a context of heterogeneous workers and positions. We use a Chilean database provided by the job search website `www.trabajando.com` that allows us to merge the information of applicants, firms, applications, and positions. In addition, job ads have an offered wage for a vast majority of positions. In some cases, the employers choose to make this information observable for applicants, but sometimes, they choose not to. Thus, for almost all ads, we analysts observe a wage that is declared to be paid to a prospective employee even in cases this information is not observable by applicants. To the best of our knowledge, this is a unique feature among databases of this sort. In other databases some posted wages are also available too, but no wage data are available when the employer decides not to communicate a wage, a likely strategic decision. We also show that ads posting explicit wages receive fewer applications and demand lower requirements. Moreover, the evidence also shows that job ads with explicit wages are more likely to receive applications of low-productivity individuals. Thus, sample selection is generates biased evidence of job search behavior. For us, the availability of expected wage data makes it possible to reliably test whether applicants positively respond to explicit or implicit wages, which is a signal of directed search.

Our main reported results are based on Negative Binomial (NB) models for count data allowing for under- or over-dispersion (See in Cameron and Trivedi 2005). First, we show strong evidence of directed search in the sense that the number of applications increase in the wage paid, even if it is not explicitly posted in the job ad. This impact is significantly larger for ads in which the wage offer is observable for applicants. Second, in line with the available empirical and theoretical work, ads posting explicit wages receive significantly less applications, controlling for the wage offered, position features, firms characteristics and applicants' traits. Third, we find that firms are more likely to post a wage explicitly for low skill jobs. Fourth, workers of low qualifications in terms of education and with potentially lower reservation wages apply for jobs with explicitly posted wage much more frequently. Finally, as suggested by directed search models with heterogeneity on at least one side of the market (e.g. Shi 2002; Menzio, Telyukova, and Visschers 2012), we slice the data in several ways to show that similar workers apply for the same jobs and their qualifications closely meet employers' requirements.

The evidence suggests the employers provide higher uncertainty about the actual wage in equilibrium for higher quality jobs. Hidden or implicit wages are noisy signals that attract skilled applicants, but deter unskilled ones. Explicit wages, on the other hand, are used to achieve the opposite goal. These findings combined suggest that posting a wage is used as a way to pre-screen the market to avoid receiving too many applications for low skilled positions. The empirical study of directed search behavior needs to consider together both application and wage-posting behavior. While applicants sizeably react to information posted (or hidden) by job ads, employers seems to strategically configure ads to attract or to hinder targeted groups of workers.

2 Literature Review

In spite of the importance of search behavior and wage determination mechanism for the efficiency of labor markets, and its potential implications for sound regulation of the labor market, the evidence on the subject is still quite murky. Theoretical models tend to tie committed wage posting and directed search together, but these issues should be seen as two distinct facts, though linked.

Only recently some papers show evidence of directed search behavior. Dal Bó, Finan, and Rossi (2013) focus on the responses of applicants to government sector jobs in Mexico. They find that higher wages attract more and better qualified applicants according to detailed registered screening assessments. They also find that applicants respond to job characteristics such as location, and municipalities' features, showing that job ad features significantly drive workers' search. The facts are thus consistent with premises of directed search: (i) higher wages attract more applicants, and (ii) applicants selectively apply for positions that presumably suit their requirements better.

Marinescu and Wolthoff (2015) use online job ads by *www.careerbuilder.com* and explain ad posted wages mainly thorough job titles. They provide sound evidence of directed search for nearly 20% of job ads with explicitly posted wages. Nevertheless, their data reveal nothing about the larger share of job ads with hidden or implicit wages. These authors show that job titles explain nearly 90% of the variance of explicit wages, and claim that this makes nearly unimportant for applicants whether the wage is explicitly posted or not since it conveys little extra information. If Marinescu and Wolthoff (2015) argument holds, we should have nearly observed a randomization of explicit wage posting decision, leading to similar distributions of job titles for explicit and hidden wage job ads. While there are no systematic comparison between job titles for explicit and hidden wages, it is hard to imagine that costly job advertisement randomly decide being explicit about wages. Our data, which is from a different country and period, is consistent with strategic disclosure of wage offers, which is probably important for most job seekers. We find strong evidence regarding explicit job ads being used in low-requirement positions and predominantly responded by unskilled applicants. Moreover, accepting Marinescu and Wolthoff (2015) rationale leaves unexplained why explicit wage posting is systematically used so little in practice, as the evidence shows (Brenčič 2012; Kuhn and Shen 2013).

Belot, Kircher, and Muller (2015) setup a field experiment by altering original posted wages of real job ads. Their preliminary results support the directed search hypothesis, since high-wage jobs receiving significantly more applications than their low-wage experimental clones. One limitation of their analysis is the limited scale of the experiment, presumably to guarantee that general equilibrium conditions remain unaltered. However, higher wages could convey information unobservable traits of the employer to applicants because posting explicit wages is an endogenous choice of employers, depending on observable and unobservable characteristics. Since our data allow us to observe employers' expected wages even if applicants cannot see them, we can investigate job search behavior even if wages are not explicitly posted. Directed search behavior is also tested in product markets, as in Lewis (2011), who shows that internet seekers for used cars significantly react to posted information regarding automobiles' quality.

Since directed search and committed take-it-or-leave-it offers are key ingredients on theoretical models for delivering efficient competitive equilibrium in labor markets, it is natural to seek evidence on what is the most relevant wage-setting mechanism. Other related Gartner and Holzner (2015) theoretically and empirically investigate wage-posting versus wage-bargaining behavior, measured using declared information by employers for German establishment data. They find no effect of bargaining on wages, and lower number of suitable applicants, especially skilled ones. If we can relate their ex post wage-bargaining to our ex ante measure of hidden or implicit wages, their results seem roughly inconsistent with ours, perhaps because of our highly educated sample. Hall and Krueger (2012) try to distinguish between bargaining and committed wage posting, based on a sample of U.S. recent hires of job-switchers . They find (1) one-third of respondents said they had negotiated their last wage contracting; (2) nearly one-third of workers had a high certainty of the wage paid before applying; and (3) a 47% of respondents reported that current employers found out their previous wages. While knowing wages before hired is not inconsistent with wage-posting, it may simply reflect the fact that the outcome of a bargaining game is rationally anticipated. Thus, while suggestive of a labor market in which wage posting and bargaining coexist, the evidence is inconclusive. Hall and Krueger (2012) also show that the probability of receiving a take-it-or-leave-it offer significantly decays in the level of education, expertise, and experience of the applicant; in contrast, government, unionized, female and unskilled workers more likely face posted wages. These results are in line with Michelacci and Suarez (2006) model, in which employers opt for bargaining wages with skilled workers as a way to attract them, since this wage-setting mechanism makes wages increasing in productivity. To some extent, these behaviors are also consistent with our own findings because relatively unskilled workers apply more frequently to explicit-wage job ads.

Brenzel, Gartner, and Schnabel (2014) study wage posting using survey data from Germany, in which employers are asked whether they bargained wages with their employees or if they made them take-it-or-leave-it offers. A notable shortcoming is that only information of successful matches are recorded, which is likely to be a non-randomly selected sample of all applicants. The authors find that around 70% of labor contacts in the German labor market involve no wage bargaining, although more skilled workers are much more often involved in bargaining, in line with Hall and Krueger (2012). The segmentation hypothesis is supported by the work of Brenčič (2012), who shows that the prevalence of wage posting differs a lot among different kinds of online labor markets, depending on the composition of applicants each website receives. Brenčič (2012) also notices that vacancies posting wages are likely to request workers with lower qualifications. The evidence suggests that firms face a trade-off when announcing a wage: it reduces search costs, but decreases the quality of applicants.

3 Data description

We obtain data on job search behavior from `www.trabajando.com` a job search engine with presence in Latin America, Spain, and Portugal. Our data covers all job ads posted and job searchers between January 1st, 2008 and June 4, 2014 for the Chilean labor market. The company *www.trabajando.com* maintains several job search engines, generating multiple appearances of job ads simultaneously, or repetitions of previously posted ads. If a particular vacancy is posted several times its chances of receiving applicants are likely to be reduced, since that many job searchers look for opportunities in various websites at the same time.

3.1 Applications

The data structure contains three main databases: the first one has applications and personal applicants' data on the applicant; the second one contains employers' information, and the third one gathers information on job ads. Substantial work was done to clean databases. We keep 6,131,626 applications during the mentioned period, after removing nearly 2 millon cases with inconsistencies we refer later.

3.2 Applicants

Individuals are identified in the database by creating an identification code (ID) using years of experience, date of birth, date of entry of the resume, sex, nationality, and profession. The ID code is well defined and generates repeated individuals information in only 9 cases, which are discarded.

We are considering only people ranging from 18 to 69 years old, with the less than 20 years of experience (higher experience is suspected to be typing errors). We also discard individuals reporting monthly net wages higher than 5 million pesos in his/her previous work (9,745 USD per month[1], which is way above the 99th percentile according to CASEN 2011 (Chilean household survey)), which are likely to be typing errors considering the background of the applicant. We

[1]Using average nominal exchange rate over 2008Q1 - 2014Q2.

also exclude individuals with salary expectations over 5 million pesos, and those who did not declare an expected figure.[2] Excluding the last cases, we get 463,495 applicants. Descriptive applicants' statistics are in Tables 1 and 2.

The sample is relatively young (30 years old on average) and mostly single. More than 95% of the population are of Chilean nationality. More than 60% of the applicants are in the Metropolitan Region of Santiago. The sample shows relatively high educational level, so they are often expected to be paid above the legal minimum wage (approximately 377 USD per month). About 42.23% of the population has some kind of college education, followed by technical professionals. We estimate the years of schooling according to highest educational level achieved (8 years primary, 4 years of high school, 5 years of college, or 4 years of technical professionals). The average schooling is 15, with similar averages for males and females. As information regarding the college major or profession of the applicant, we classified them on areas. The gender composition of majors and professions is remarkable in that males are more likely to be in technical or technology related areas, while females are often in sales. A significant share of applicants do not declare an area.

Given the youth of the population, the sample has individuals with few years of work experience. On average, individuals possess 6.5 years of experience, being males slightly more experienced. The years of inactivity is the idle time estimated according a formula[3], which assumes that school starts at age six. Inactive time is not distinct between genders. A large proportion of the sample are self-reported unemployed (47.74%), which are more likely to be females. The rest of applicants should be considered on-the-job searchers.

Finally, there is a large gender gap on wages paid in the previous job, which is close to 44%. These differences were also maintained in wages expected by the applicants. Expected wages for the next job are 3.9% higher than their last or current job. Less than half of the sample chooses to display their wage expectations to be observed by employers.

3.3 Employers

Descriptive statistics are reported in Table 3. Our sample has 6,386 different firms. We use standard industry classifications (CIIU) used by the Central Bank of Chile. A majority of firms are in retail, communications, services, and manufacture sectors. Table 3 shows that the number of ads is increasing in the self-declared size of the employer. A 23.8% of firms is small, but this figure is affected by *recruiting firms* that offer their services to contact and select potential

[2] A customary characteristic of the Chilean labor market is that wages are always often expressed in a monthly rate net of taxes, and mandatory contributions to health (7% of monthly wage), to fully-funded private pension system (10%), to disability insurance (1.2%), and mandatory contribution to unemployment accounts(0.6%)

[3] $\text{inactivity} = \text{age} - \text{schooling} - \text{experience} - 6$

Table 1: Applicants characteristics (I)

	Males	Females	All
Age (%)			
18 - 24	23.25	34.18	28.46
25 - 34	47.61	44.56	46.16
35 - 44	19.59	15.07	17.44
45 - 54	7.60	5.30	6.50
55+	1.95	0.90	1.45
Age (Avg.)	31.25	29.05	30.20
Marital Status (%)			
Married	27.99	19.17	23.79
Partner	2.35	1.39	1.89
Divorced	1.19	1.69	1.43
Separated	1.56	2.73	2.11
Single	66.80	74.75	70.59
Last declared monthly wage (%)			
CLP 70,000 $\leq$	0.82	1.38	1.08
CLP 70,001 - 150,000	3.58	6.50	4.97
CLP 150,001 - 300,000	13.08	23.61	18.10
CLP 300,001 - 600,000	27.41	27.11	27.27
CLP 600,001 - 1,000,000	20.21	13.15	16.85
CLP 1,000,001 - 1,500,000	10.06	5.03	7.66
CLP 1,500,001 - 2,500,000	7.05	2.37	4.82
CLP 2,500,000+	2.70	0.68	1.74
No wage declared	15.18	20.20	17.57
Last declared monthly wage (Avg. / S.D.)	804686	531855	678878
	(684730)	(475868)	(612840)
Wage expectation (%)			
CLP 1 - 70,000	0.17	0.25	0.21
CLP 70,001 - 150,000	2.64	5.50	4.00
CLP 150,001 - 300,000	15.37	30.13	22.40
CLP 300,001 - 600,000	30.89	33.29	32.03
CLP 600,001 - 1,000,000	24.76	18.23	21.65
CLP 1,000,001 - 1,500,000	11.32	5.91	8.74
CLP 1,500,001 - 2,500,000	8.52	3.15	5.98
CLP 2,500,000+	3.26	0.79	2.08
No wage or too high	3.17	2.78	2.98
Wage Expectation (Avg. / S.D.)	838753	559238	705339
	(693009)	(473144)	(614307)
Declare expected wage (%)	48.47	42.77	45.75
Observations	235037	214626	449663

Table 2: Applicants characteristics (II)

	Males	Female	All
Years of experience (%)			
0 - 3	37.08	49.43	42.96
4 - 7	25.38	24.94	25.17
8 - 12	17.86	14.32	16.18
13 - 20	13.60	8.89	11.36
21+	6.08	2.42	4.33
Not mentioned	0.00	0.00	0.00
Experience (Avg / S.D.)	7.44	5.38	6.45
	(7.21)	(5.78)	(6.65)
Estimated inactivity years (Avg. / S.D.)	2.54	2.54	2.54
	(5.25)	(5.68)	(5.46)
Highest attained educ. level(%)			
Primary (1-8 years)	0.39	0.37	0.38
Science & Humanities Secondary (9-12)	11.99	13.44	12.68
Technical Secondary (9-12)	17.09	18.97	17.98
Technical Tertiary	27.17	24.80	26.04
College (Tertiary)	42.62	41.82	42.23
Graduate	0.75	0.61	0.68
Unknown	0.00	0.00	0.00
Estimated Schooling (Avg. / S.D.)	15.25	15.10	15.18
	(2.189)	(2.250)	(2.219)
Major study area (%)			
Commerce & Management	13.95	19.50	16.59
Agriculture	1.19	0.74	0.97
Art & Architecture	1.55	1.77	1.66
Natural Sciences	1.03	1.10	1.06
Social Sciences	2.93	6.93	4.84
Law	1.58	2.21	1.88
Education	1.57	3.80	2.63
Humanities	0.81	1.70	1.23
Health	1.78	5.92	3.75
Technology	33.23	13.05	23.62
No area	36.46	41.18	38.71
Other	3.91	2.09	3.05
Labor status (%)			
Employed	50.09	38.04	44.35
Unemployed	43.12	52.82	47.74
Inactive	6.79	9.13	7.91
Available for work	63.35	35.24	49.96
Observations	242733	220762	463495

applicants for their clients. We define them as those that offer a monthly average job positions higher than the half of the maximum number of the interval[4] of employees they declared to have in operation during the whole period sample[5]. Even though our definition is admittedly *adhoc* and it is not immune to potential misclassification, our results are barely changed by considering this issue.

3.4 Job Ads

Job ads have requirements for applicants in terms of education, major, and an estimated offered wage. The latter is visible by applicants only if the employer chooses so. Descriptive statistics of job ads are shown in Tables 4, 5 and 6.

There is a small number of job ads with no entered offered wage. The sample excludes job with (i) an estimated offered monthly wage below CLP 100,000 and over CLP 5 millions (USD 194-9,745 approximately); (ii) no information of estimated offered wages; and (ii) a requirement of experience over 20 years, or missing experience request. After cleaning, we got 184,920 job ads in our sample, some of them with missing fields.

In the online labor market data, there are both explicit and implicit offered wages. Approximately, 13.4% of job ads posts wages explicitly. Of course, job offers may not represent a real commitment in reality, but it is a signal that may attract or deter potential applicants.

Most of job ads that are available required low labor experience, which is even more noticeable for jobs with explicit wage. The mean and standard deviation of explicit wages is 40% lower than that of implicit the ones. Moreover, fixed-term contracts and non-full-time jobs are slightly more frequent if the job ad posts explicit wage.

Job ads with explicit wage request low educational level more often, particularly completed high school education. Job ads with explicit wage also do not request a particular profession or occupation, and have lower experience requirements. These pieces of evidence showed that jobs with explicit wages are aimed to low skilled workers. As the firms posting them, most job ads concentrate in retail, communications, and services.

Jobs with explicit wage offers have a higher number of vacancies, but receive a lower number of applications, which suggests selectivity on the side of applicants when the wage is observed. Since explicit wage ads request lower education, the number of applicants that fulfill that specific requirement may be scarce in the population of job searchers, as suggested by Kudlyak, Lkhagvasuren, and Sysuyev (2013). A particular posting with the same characteristics may appear in

[4]Intervals reported in Table 3

[5]Dealing with this concern was motivated by informal conversations with managers of trabajando.com who claim these firms exist and are frequent users(clients) of their job search engine.

Table 3: Job Ad Posting by (self-declared) Firm Size

	Self-reported Number of Employees									
	1-10	11-50	51-150	151-300	301-500	501-1000	1001-5000	>5000	NA	Total
Job adds	24.5	34.7	45.5	37.3	110.2	93.9	50.5	163.6	22.4	39.2
	(142)	(319)	(455)	(159)	(575)	(239)	(188)	(340)	(69)	(272)
Wage posting adds	8.6	12.9	14.8	14.9	22.2	25.2	15.8	24.2	5.9	13.0
	(35)	(79)	(69)	(60)	(80)	(97)	(70)	(49)	(12)	(63)
Vacancies	79.8	116.8	427.7	204.8	539.3	551.0	192.2	1021.1	78.8	184.1
	(583)	(1227)	(7800)	(1828)	(4759)	(2427)	(1012)	(2992)	(306)	(2760)
Vacancies per month	10.9	10.8	20.4	12.0	23.1	23.4	10.9	52.6	20.6	14.3
	(81)	(85)	(247)	(107)	(150)	(66)	(39)	(169)	(242)	(138)
Applications	946.6	1057.4	1152.6	1261.8	2243.8	3299.0	2029.2	5845.9	886.1	1284.0
	(6230)	(8256)	(8737)	(5607)	(7899)	(8840)	(8368)	(14106)	(4411)	(7342)
Applications per vacancy	28.6	26.2	26.3	26.7	26.6	21.6	30.8	23.1	24.6	26.9
	(35)	(35)	(31)	(30)	(34)	(24)	(35)	(25)	(32)	(33)
Wage posting adds(%)	17.3	16.4	11.5	13.0	12.8	11.5	13.0	9.2	11.3	14.5
Recruiting firms(%)	16.1	5.5	2.1	0.8	1.6	0.5	0.0	0.0	.	6.5
Sectors (%)										
Agriculture	4.4	4.0	5.3	4.5	7.3	5.2	3.4	5.6	2.9	4.2
Fisheries	0.3	0.5	0.2	1.0	1.6	1.6	0.8	1.9	0.1	0.5
Mining	2.6	3.3	2.6	5.3	4.0	5.8	5.7	9.3	3.0	3.6
Manufacturing	14.5	13.4	20.4	18.3	19.8	15.2	16.3	20.4	13.1	15.4
Electricity, water, gas	1.7	2.0	2.1	1.8	4.0	4.7	3.7	3.7	2.8	2.4
Construction	3.9	4.1	3.1	4.5	6.0	6.8	4.7	3.7	3.2	4.1
Commerce	16.4	19.0	20.1	14.5	16.1	14.7	18.5	11.1	17.8	17.5
Restaurant and Hotels	3.1	3.1	2.7	3.0	3.2	4.2	2.6	1.9	6.3	3.5
Transportation	1.4	2.6	3.8	2.8	2.4	4.2	3.1	1.9	2.8	2.6
Communication	11.1	11.1	9.9	7.7	4.4	5.8	6.2	9.3	6.8	9.2
Financial Serv.	3.7	2.7	2.6	6.0	6.0	3.7	2.9	0.0	2.9	3.4
Business Serv.	10.6	9.8	6.0	6.8	4.4	5.8	7.0	1.9	6.9	8.3
Household Serv.	3.2	2.6	0.7	1.3	0.4	0.5	1.8	1.9	1.6	2.1
Personal Serv.	10.6	8.1	11.5	13.0	8.5	7.3	8.6	7.4	10.8	9.8
Public Admin.	1.8	0.9	0.9	0.5	0.8	0.5	1.3	3.7	1.0	1.1
Others	10.6	12.7	8.2	8.8	10.9	14.1	13.3	16.7	17.9	12.2
Observations	1522	1751	583	600	248	191	615	54	822	6386

different websites powered and maintained by trabajando.com that repeat their contents. Naturally, applicants may not apply through every possible channel, so the number of appearances may negatively impact on the number of applicants a particular vacancy receives.

3.4.1 Job Ads' Titles

Qualitative information of the job may be potentially relevant for applicants, since the job title conveys relevant information on the set of tasks that a worker undertake once hired, the level of responsibility in the organization, relevant qualifications, etc. Marinescu and Wolthoff (2015) use job titles of `www.careerbuilder.com` data to assess their predictive power on the 20% of job ads that post an explicit wage. In `www.trabajando.com`, every job ad has a title with a brief description of the position requested in Spanish.

Our approach to deal with job titles is akin to Marinescu and Wolthoff (2015). We recognize the first four meaningful words of the job title, after deleting articles, connectors, etc., and construct four categorical variables representing a list of words repeated more than 100 times in the whole sample of titles, as one of the first four words. The first word, the most important one, has 140 different categories such as: *analyst* (analista), *chief* (jefe), *manager* (administrador), *assistant* (asistente), *engineer* (ingeniero), *intern* (práctica), etc. The second one considers 290 categories, and the third and fourth have 218 and 67 categories, respectively. If a word in the job title does not appear in the selected list, is listed as *Other*. For the whole sample of job ads in analysis, the first word was catalogued as *Other* only in the 7.04% of the ads' titles. A 17.22%, 27.33% and 12.68% of job ads were categorized into the latter group for the second, third, and fourth words, respectively.

Since most words in Spanish are not gender neutral, we consider male and female words as the same[6]. This entails some loss of information since the employer could succinctly define a desired gender for the applicant. In the Figures 6 and 7 in the appendix, we show "word clouds" with the most repeated words for job ads with implicit and explicit wages, respectively (in Spanish). The larger the word in the cloud, the more repeated it is in our job title sample. A loose inspection of these word clouds suggest that explicit wage job ads are more frequent in low skill jobs.

These categorical variables constructed from the job ads' titles were used as dummy controls in the estimations in the models specified in Tables 7 and 8, and the respective ones in the robustness tests shown in section 5.

[6]For example,"profesor" and "profesora" mean "male school teacher" and "female school teacher", respectively

Table 4: Job Ads Characteristics (I)

	Explicit Wage Posting	Implicit Wage	All
Vacancies per Add (%)			
1 - 5	73.88	85.28	83.74
6 - 10	12.69	8.05	8.68
> 10	13.43	6.66	7.57
Vacancies (Avg / S.D.)	7.14	4.45	4.81
	(17.32)	(12.36)	(13.17)
Max. num. vacancies	200	200	200
Min. num. vacancies	1	1	1
Applications per add (%)			
0	14.44	14.94	14.87
1 - 5	23.08	14.59	15.73
11 - 20	16.23	15.36	15.48
31 - 50	9.88	12.66	12.29
51 - 100	8.52	13.09	12.48
101 - 300	4.39	7.41	7.01
301 - 600	0.39	0.78	0.73
601 - 1000	0.07	0.12	0.11
1001 +	0.01	0.03	0.03
Applications per add (Avg/S.D.)	25.3	36.3	34.8
	(49.68)	(64.52)	(62.84)
Applications/Vacancies (Avg/S.D.)	15.8	27.9	26.2
	(34.05)	(54.16)	(52.07)
Offered Wage (%)			
CLP 100.000 - 150.000	6.93	5.37	5.58
CLP 150.001 - 300.000	47.52	26.49	29.32
CLP 300.001 - 600.000	31.52	29.00	29.34
CLP 600.001 - 1.000.000	9.78	22.32	20.63
CLP 1.000.001 - 1.500.000	2.55	9.78	8.80
CLP 1.500.001 - 2.500.000	1.44	5.58	5.02
CLP 2.500.000 +	0.25	1.47	1.31
Offered Wage (Avg / S.D.)	404887	680704	643614
	(347276.1)	(587200.5)	(568778.1)
Legal contract type (%)			
Fixed-term	26.55	16.28	17.66
Undefined term	60.83	65.20	64.61
Other	12.62	18.52	17.73
Availability (%)			
Commission-earner	0.35	0.70	0.65
Full-time	75.57	85.74	84.37
Part-Time	4.97	3.82	3.98
Shift-work	15.31	7.89	8.89
Internship	3.16	1.35	1.60
Replacement	0.65	0.50	0.52
Observations	24867	160053	184920

Table 5: Job Ads Characteristics (II)

	Explicit Wage Posting	Implicit Wage	All
Required years of experience (%)			
0	21.66	14.62	15.57
1	44.50	31.37	33.14
2 - 3	27.68	39.39	37.82
4 - 7	5.53	12.89	11.90
8 - 12	0.58	1.61	1.47
13 - 20	0.06	0.11	0.10
Years of experience (Avg / S.D.)	1.41	2.05	1.96
	(1.40)	(1.80)	(1.76)
Required educ. level (%)			
Primary (1-8 years)	2.59	1.02	1.23
Science & Humanities Secondary (9-12)	35.15	19.20	21.34
Technical Secondary (9-12)	19.08	14.14	14.81
Technical Tertiary	25.13	28.14	27.74
College (Tertiary)	17.85	36.90	34.34
Graduate	0.20	0.60	0.55
Major study area (%)			
Commerce & Management	23.68	22.24	22.43
Agriculture	0.23	0.43	0.40
Art & Architecture	0.66	0.94	0.90
Natural Sciences	0.68	0.84	0.82
Social Sciences	2.03	2.44	2.39
Law	0.24	0.39	0.37
Education	0.84	0.83	0.83
Humanities	0.66	0.22	0.28
Health	1.34	1.80	1.74
Technology	15.78	29.38	27.55
No area	53.45	40.30	42.07
Other	0.41	0.19	0.22
Observations	24867	160053	184920

Table 6: Job Ads Characteristics (III)

	Explicit Wage Posting	Implicit Wage	All
Sectors (%)			
Agriculture	0.81	1.05	1.02
Fisheries	0.02	0.26	0.22
Mining	0.68	1.98	1.81
Manufacturing	7.76	8.85	8.71
Electricity, water, gas	4.47	2.37	2.66
Construction	1.37	2.59	2.42
Commerce	19.56	19.84	19.80
Restaurant and Hotels	1.49	1.60	1.59
Transportation	6.81	3.13	3.63
Communication	11.12	9.01	9.30
Financial Serv.	4.72	6.33	6.12
Business Serv.	8.57	6.91	7.13
Household Serv.	0.62	1.07	1.01
Personal Serv.	11.99	12.41	12.35
Public Admin.	2.16	1.22	1.34
Others	17.87	21.37	20.90
Firm Size - Num. Employees (%)			
1 - 10	16.12	16.29	16.26
11 - 50	26.11	21.71	22.30
51 - 150	10.66	10.00	10.09
151 - 300	11.69	10.00	10.23
301 - 500	8.45	9.56	9.41
501 - 1000	7.46	7.48	7.48
1001 - 5000	12.84	12.92	12.91
$>$ 5000	1.93	3.68	3.45
N.A.	4.74	8.36	7.87
Add appearances (%)			
1	75.83	80.27	79.67
2 - 3	12.00	10.41	10.62
4 - 6	4.15	3.52	3.61
6 - 10	2.54	1.87	1.96
10 +	5.49	3.93	4.14
Add appearances (Avg/S.D.)	3.31	3.12	3.15
	(10.49)	(12.48)	(12.24)
Adds from Recruiting Firms* (%)	45.72	36.15	37.44
Observations	24867	160053	184920

Note: *Estimated considering the monthly average job ads posted and firms size.

4 Results

4.1 Directed Search

The main goal of the analysis is to assess whether there is directed search or not. If directed search prevails, applicants should react to characteristics of job ads, particularly an explicit or an implicit wage. While the theoretical literature mainly focuses on directed search of wages, it is straightforward to extend this rationale to a multidimensional setting, being jobs a bundle of attributes. If a extreme version of random search prevails, no job ad features should impact application decisions. On the other hand, given the emphasis of wages as signals driving applicants in the literature, one would like to be sure that the attraction of wages is not confounded with other employer or position features, given applicant's characteristics. Our database provides us with an unusually rich set of controls for workers, employers, and jobs.

To empirically study the number of applications we use a count model, since the dependent variable takes non-negative integer values. A Negative Binomial (NB) model suits well our needs, because it relaxes the tight constrain that equals mean and variance in Poisson models. In contrast NB model, allows for either under- or over-dispersion (Cameron and Trivedi 2005; Hilbe 2011).

Table 7 shows the NB model estimates as well as the average marginal effect ($\partial y/\partial x$) of a variable x on the number of applications, y, whereas the Figure 1 summarizes the average marginal effects for ads with explicit and implicit wages at different levels of estimated wages, experience and number of vacancies. The estimates highlight the impact of several features of the job ad on the number of applications received, including whether the wage is actually announced, and the interaction between the posted wage dummy and the estimated wage. Model 1 incorporates a dummy variable for recruiting firm excluding observations when this information not available[7], while Model 2 considers all posted job ads.

The results show that job ads with explicitly posted wage receive significantly fewer applications. Point estimate suggests a marginal effect 2-3 less applications than an ad without explicit wage posted. The estimated wage has both a statistically and economically important effect: doubling the wage (increasing log wage by 1), generates 3-4 more applicants when the wage is not explicit in the ad. This effect roughly doubles when the wage is explicitly posted. Thus, wages have a powerful effect driving applicants' behavior. A posted wage reduces the number of applications, but conditional on being visible, a wage increase is a powerful attractor for more applicants.

[7] In some cases is not possible to list a firm as a recruiting one because the firm did not reported their number of employees

The evidence is consistent with applicants inferring wages from the text and requirements of the job ad because hidden wages generate more applications in spite of being tacit. This finding is consistent with a signal extraction process of the text of the job ad, coupled with directed search. The milder yet important response of applications to implicit wages is consistent with noisy information of the job ad regarding the wage.

The number of vacancies mentioned in the job ad marginally increases the number of applications received, but the magnitude of the effect suggests important decreasing returns to scale in that one extra position induces roughly 0.3 more applications. This finding may constitute evidence of simultaneous search, that is the existence of a selection process of applicants Villena-Roldan (2010). When engaged in sequential search, employers use a productivity reservation optimal strategy that implies that vacancy number and applicants are proportional. Instead, under non-sequential or simultaneous search the impact of more vacancies available increase applications less than proportionally (van Ommeren and Russo 2013), exactly what we see in the data.

Job ad appearances have a negative impact on the total number of applications received it by a particular posting, probably reflecting the fact that searchers look for job opportunities in many websites simultaneously, or may be aware of previous appearances of the same job ad.

Requested experience has a substantial negative impact on the number of applications, which is expected given the youth of the workers participating in this market. The higher the educational level requested, the higher the number of publications received due the composition of workers, where prevail those with high education level, consistent with the findings shown in Faberman and Kudlyak (2013) where workers direct theirs job search to those positions with education requirements similar to their attained level.

Other job characteristics such as availability and legal contract type affect applications in an expected way. Full-time jobs and undefined term contracts seem to attract applicants the most. An specific computer knowledge level seem to deter applicants except if the employee requests user level or advanced user level, which reflects self-selection of applicants into jobs that require usual skill levels. There are also a wealth of results concerning industries and the specific occupations posted in job ads, but these are not presented for the sake of brevity. Finally, the negative binomial model shows over-dispersion as expected.

4.2 Explicit Wage Posting

What would happened if we did not observe implicit or hidden wages when estimating models in the previous section, as it often occurs in other studies of job search on the internet? To answer this, we will investigate factors behind explicit the wage posting by estimating a pro-

Table 7: Wage posting effect on applications using NB Model

	Model 1			Model 2		
	β	SE	$\partial\overline{y}/\partial x$	β	SE	$\partial\overline{y}/\partial x$
Explicit Wage	-2.065***	0.189	-2.930	-2.433***	0.188	-3.899
Ad appearances	-0.031***	0.001	-1.066	-0.034***	0.001	-1.200
Number of vacancies	0.008***	0.000	0.273	0.009***	0.000	0.303
Req. experience	-0.057***	0.002	-1.959	-0.062***	0.002	-2.141
Estimated wage (log)	0.091***	0.006	3.702	0.075***	0.006	3.263
Explicit Wage × Number of vacancies	-0.000	0.001		-0.001**	0.001	
Explicit Wage × Req. experience	0.007	0.006		0.011*	0.006	
Explicit Wage × Estimated wage (log)	0.148***	0.015		0.173***	0.015	
Recruiting firm (=1)	-0.232***	0.006	-8.073			
Highest educ						
Primary (1-8 years)	-0.310***	0.028	-8.514	-0.304***	0.028	-8.517
Tech. High School	-0.007	0.011	-0.235	-0.016	0.011	-0.503
Tech. Tertiary Educ.	0.057***	0.012	1.882	0.061***	0.011	2.059
College	0.181***	0.014	6.321	0.184***	0.013	6.553
Graduate	-0.113***	0.039	-3.410	-0.087**	0.039	-2.706
Legal contract type						
Fixed-term	-0.218***	0.012	-6.874	-0.206***	0.012	-6.627
Undefined term	0.031***	0.011	1.116	0.036***	0.010	1.313
Availability						
Comission-earner	-0.558***	0.034	-14.809	-0.517***	0.034	-14.178
Half time	0.062***	0.022	2.196	0.029	0.021	1.037
Part-time	0.223***	0.022	8.645	0.270***	0.021	10.899
Shift-work	0.015	0.011	0.536	0.029***	0.011	1.048
Internship	0.418***	0.031	17.977	0.414***	0.030	18.010
Replacement	-0.236***	0.040	-7.286	-0.264***	0.038	-8.136
Computer knowledge level						
Low level	-0.019	0.019	-0.637	0.020	0.018	0.694
Expert level	-0.329***	0.024	-9.574	-0.250***	0.024	-7.469
Professional level	-0.230***	0.014	-7.027	-0.172***	0.014	-5.328
Technical level	-0.089***	0.017	-2.921	-0.020	0.017	-0.653
User level	0.058***	0.007	2.036	0.100***	0.007	3.563
Advanced User level	0.049***	0.009	1.715	0.078***	0.008	2.742
Constant	-5.192***	0.189		-5.180***	0.184	
lnalpha	0.064***	0.004		0.099***	0.003	
Observations	170365			184920		
Estimated avg. applications	34.84			35.43		
χ^2	133285.8			141273.5		
Model signif. $P > \chi^2$	0.000			0.000		
pseudo - R^2	0.089			0.087		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.. Omitted groups: *Highest educ:* Science-humanity high-school; *Contract law* Other. *Availabilty:* Full-time. *Computer knowledge level:* None. In both equations, we control for profession/occupation dummies, industry dummies, quarter dummies to capture seasonality, first four words job title dummies, and the number of days the vacancy was open.

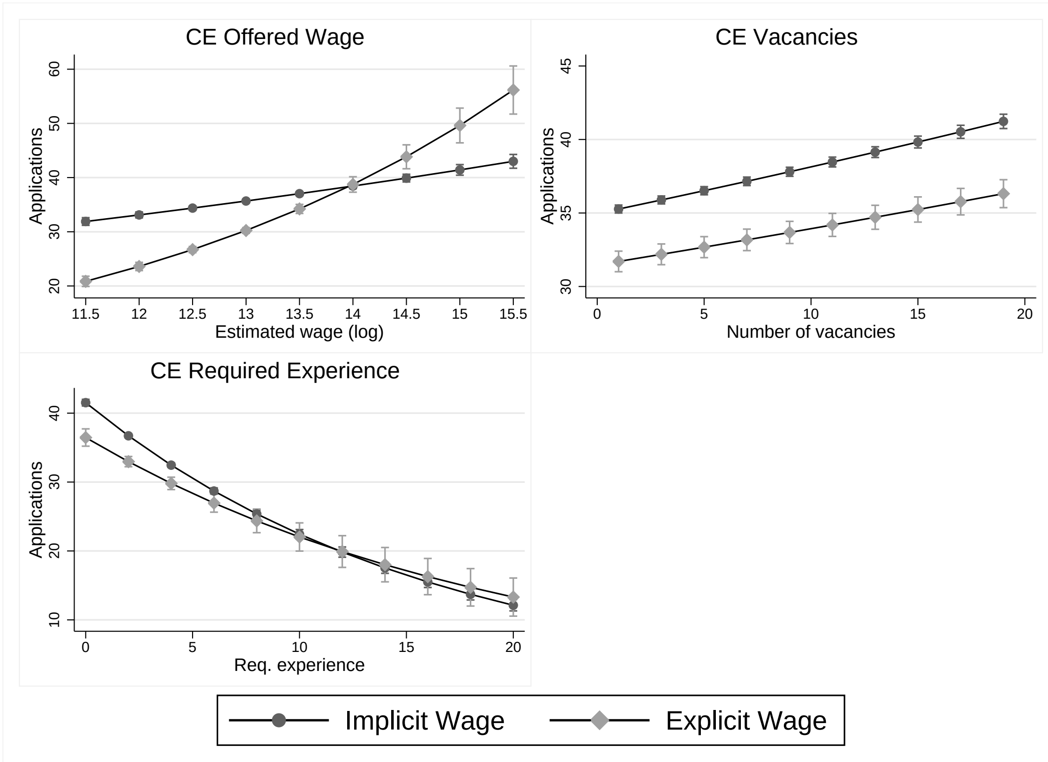

Figure 1: Expected Marginal Effects (EME) on applications, (Table 7, Model 2)

Vertical bars indicate 95% Confidence Intervals.

bit model with two different specifications to learn about the impact of job ad characteristics such as number of vacancies, requested experience, offered wage, educational requirements, profession/occupation, term of contract, industry, etc. In order to control for seasonal effects or trends, we incorporate quarterly binary variables according to the date of the job ad.

Our results in Table 8 contain two specifications. The first one incorporates a dummy variable for recruiting firm, while the second one does not. The most remarkable result is the large impact of the offer wage on the probability of posting an explicit wage. As mentioned before, the wage offered explicitly by employers is roughly 40% lower than that offered implicitly in our sample. In particular, an increase of one log point of offered wage decreases the probability of explicit posting by 5.2%. These results remain virtually unchanged if we do not include recruiting firms control. In Figure 2, we summarize the marginal impact of offered wages on the probability of making wages explicit. For wages close to 100,000 pesos (below the minimum legal monthly wage for full-time workers), the chances are close to 22%. In contrast, for wages close to the top of distribution the chance is close to 3%.

In the literature (Ellingsen and Rosén 2003; Michelacci and Suarez 2006) explicit wage postings are often associated to unskilled job positions. Posting high wages exacerbates adverse selection problems, induces too many unqualified applicants to apply for the position, and increasing the costs of screening of applicants. On the contrary, explicit wage posting deters highly qualified applicants to apply for the position, reducing the total number of applicants, and signaling little room for ex post wage bargaining.

In Table 8, we also observe that higher experience requirements reduce the chances for a job ad to explicitly post a wage. One extra year of experience reduces the probability of wage posting explicitly by 0.6% on average. In the figure 2, we show that ads that do not ask for any experience have 14% of probability of having an explicit wage, while positions with experience requirements over 20 years have a probably close to 6%. Since job complexity is often associated to the level of experience required, firms decide to present a specific wage offer when they are trying to hire skills that are not scarce in the market.

The number of vacancies offered in the job ad does not show a significant impact on the probability the of announcing the wage. We might expect that the larger number of vacancies increases the probability of the wage to be explicit because massive hirings tend to be frequent in low skilled, standardized jobs, as found by Brenčič (2012). In this case, the result is as expected but not statistically significative.

The impact of recruiting firms is increasing the likelihood of announcing an explicit wage by 3.5%. We interpret this result as a potential evidence for a standardized procedure of recruiting, or lower marginal cost of interviewing, given the specialization of these firms. Lower educational requirements are related to larger chances of explicit wage-posting. Moreover, the higher the required education level, the lower the probability of seeing an explicit wage job ad.

Unreported results in Table 8 also show that professions/occupations related to humanities are much more likely to announce an explicit wage. Job ads not requesting a specific profession/occupation or those associate to retailing are also more likely to announce explicit wages. In contrast, professions in technology areas are significantly less likely to announce explicit wages.

There are also important differences across the industry of the employer posting the job ad, being retail industry our reference group (omitted category). In agriculture, utilities (electricity, water, gas), transportation, and public administration clearly prevails explicit wage ads. Hall and Krueger (2012) also show that job ads in the public administration sector exhibit a larger likelihood of explicit wage posting.

The evidence also shows that undefined term jobs, often thought as more stable positions, are less likely to post explicit wages compared with those with fixed-terms. Again, this suggests that lower-quality jobs are the ones showing explicit wages. Somewhat surprisingly, expert and technical level of computation skills required are more likely to be associated to explicit wages

Table 8: Probability of posting an explicit wage using Probit model

	Model 1			Model 2		
	β	SE	$\partial\overline{y}/\partial x$	β	SE	$\partial\overline{y}/\partial x$
Vacancies	0.000	0.000	0.000	0.001$*$	0.000	0.000
Years of experience	-0.031$***$	0.004	-0.006	-0.030$***$	0.003	-0.006
Offered wage (log)	-0.271$***$	0.010	-0.052	-0.258$***$	0.010	-0.049
Recuiting Firm	0.179$***$	0.009	0.035			
Highest educ						
Primary (1-8 years)	0.209$***$	0.035	0.052	0.182$***$	0.033	0.044
Technical Secondary (9-12)	-0.085$***$	0.015	-0.019	-0.096$***$	0.015	-0.021
Technical Tertiary	-0.242$***$	0.016	-0.049	-0.239$***$	0.016	-0.048
College	-0.313$***$	0.020	-0.062	-0.313$***$	0.019	-0.061
Graduate	-0.252$***$	0.076	-0.051	-0.267$***$	0.075	-0.053
Legal contract type						
Fixed-term	0.354$***$	0.017	0.068	0.362$***$	0.016	0.069
Undefined term	0.178$***$	0.016	0.031	0.179$***$	0.015	0.031
Availability						
Comission earner	-0.244$***$	0.061	-0.041	-0.246$***$	0.059	-0.041
Half time	0.076$**$	0.031	0.015	0.128$***$	0.029	0.026
Part-time	-0.122$***$	0.031	-0.022	-0.102$***$	0.030	-0.018
Shift-work	0.095$***$	0.015	0.019	0.068$***$	0.015	0.013
Internship	0.089$**$	0.035	0.018	0.087$***$	0.033	0.017
Replacement	0.041	0.054	0.008	0.080	0.050	0.016
Computer knowledge level						
Low level	0.106$***$	0.023	0.020	0.070$***$	0.023	0.013
Expert level	0.319$***$	0.038	0.066	0.296$***$	0.037	0.061
Professional level	0.101$***$	0.024	0.019	0.081$***$	0.023	0.015
Technical level	0.236$***$	0.025	0.047	0.178$***$	0.024	0.035
User level	0.086$***$	0.012	0.016	0.057$***$	0.011	0.010
Advanced User level	0.133$***$	0.014	0.025	0.103$***$	0.014	0.019
Constant	2.060$***$	0.295		1.886$***$	0.289	
Observations	169487			183997		
Average probability	0.139			0.135		
pseudo - R^2	0.131			0.124		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.. Omitted groups: *Highest educ:* Science-humanity high-school; *Contract law* Other. *Availabilty:* Full-time. *Computer knowledge level:* None. In both equations, we control for profession/occupation dummies, industry dummies, quarter dummies to capture seasonality, first four words job title dummies, and the number of days the vacancy was open.

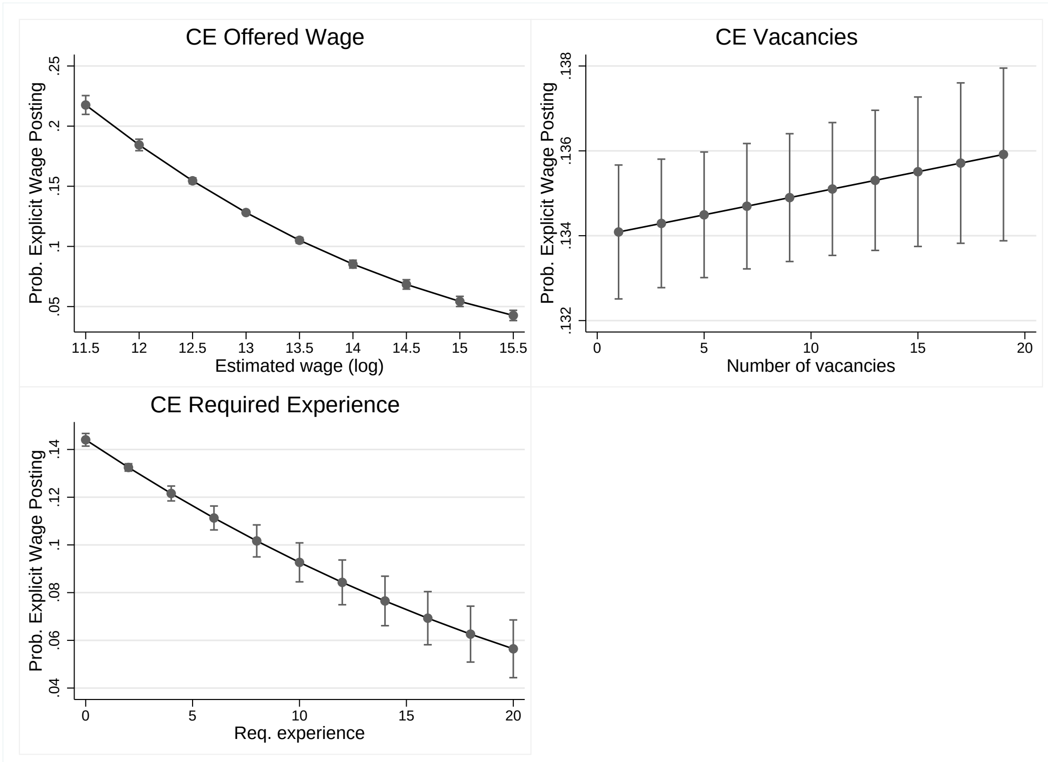

Figure 2: Expected Marginal Effects (EME) on Prob. of Explicit Offered Wage Posted (Table 8, Model 2)

Vertical bars indicate 95% Confidence Intervals.

job ads.

Putting together this evidence regarding experience, we can see that explicit wage ads typically target low productivity workers. Our hypothesis is that explicit wage posting works as a deterrence device to reduce recruiting costs of the firm. It may also reflect the fact that firms avoid hiring overqualified workers, probably reflecting the fact of an expensive foreseen turnover. This concern often shows up in qualitative evidence (Bewley 1999).

All in all, the fact that the explicit job ads are used to target low skilled workers indicates that the use of evidence solely based on explicit wages to assess the importance of directed search may lead to inaccurate results, overestimating the sensitivity of the job search to wages. While explicit wages are important signals for job seekers, there are more information available for them to direct their search.

4.3 Application to ads with explicit wage

In the previous subsection, we investigate determinants of explicit wage posting from employers. The evidence shows that this kind of job ads often target low-educated, unexperienced, low-wage expectation workers. In turn, we can also analyze the way job seekers respond to those posted wages and other characteristics of the ads. Do targeted workers respond to the job ads in the way presumably intended the employer? To answer this, we estimate the effect of several applicants traits on the probability that a given application of job seeker is directed to an explicit-wage job ad.

We estimate three different specifications shown on Table 9. The first model includes all the available variables including applicants features, last employment duration (the number of days in his/her previous job, i.e. last tenure reported), and unemployment duration (the time he/she has been unemployed according to self-reported employment history). The second model includes all the variables concerning the applicant, but omits durations. The third model excludes wage expectations and the wage in the previous job. By discarding the aforementioned variables, we are able to expand the sample size for our estimations. In all three models, we control for seasonal effects. The results are quite similar across models.

The last employment duration or last tenure is calculated as the number of days between the starting and ending dates the job seeker declares for their previous job. Likewise, we compute the unemployment spell of the job seeker as the number of days between the last day in his previous work and the date of the application. For those who are working on the time of the application (on the job searchers) we attach a value of zero for this variable.

Table 9 shows that males have between 0.3-1.3% lower probability of applying to explicit wage job ad. While the relative impact seems reduced, in absolute terms matters because the average applying probability is close to 9.5%.

The evidence also shows that as the expected wage increases, the probability of applying to explicit wage job ad decays. An increase of one log point of expected wage approximately reduces by 4.7% the probability of application to an explicit wage job ad given the worker applies. A qualitative similar impact is generated by an increase of the log of the previous wage job, but the magnitude here is much lower (1.1%). It is interesting to notice that the sensitivity to expected wages is higher than it is for previous job wages, suggesting that expectations may be revised due to idiosyncratic shocks affecting the prospects in the labor market of the applicant.

A higher educational level of applicants negatively impacts the chances of applying to a job with explicit wage. A partial exception to this behavior occurs for individuals with just primary education, which may happen due to the low number of these individuals in the sample and potential errors of this groups of workers when dealing with the job search engine. On the other

Table 9: Probability of applying for an explicit wage using probit model

	Model 1			Model 2			Model 3		
	β	SE	$\partial\overline{y}/\partial x$	β	SE	$\partial\overline{y}/\partial x$	β	SE	$\partial\overline{y}/\partial x$
Sex (Male = 1)	-0.02***	0.00	-0.003	-0.02***	0.00	-0.003	-0.08***	0.00	-0.013
Available for working	-0.03***	0.00	-0.004	-0.03***	0.00	-0.004	-0.08***	0.00	-0.013
Years of Experience	0.00**	0.00	0.000	-0.00	0.00	-0.000	-0.01***	0.00	-0.001
Wage expectation (log)	-0.30***	0.00	-0.047	-0.30***	0.00	-0.047			
Wage last job (log)	-0.07***	0.00	-0.011	-0.07***	0.00	-0.011			
Last job duration (log)	-0.01***	0.00	-0.001						
Unemploy. duration (log)	0.00***	0.00	0.001						
Highest educ									
Primary (1-8 years)	-0.07***	0.01	-0.011	-0.07***	0.01	-0.011	-0.15***	0.01	-0.028
Tech. High School	-0.03***	0.00	-0.005	-0.03***	0.00	-0.005	-0.05***	0.00	-0.009
Tech. Tertiary Educ.	-0.03***	0.00	-0.006	-0.03***	0.00	-0.006	-0.08***	0.00	-0.015
College	-0.15***	0.00	-0.024	-0.15***	0.00	-0.024	-0.31***	0.00	-0.053
Graduate	-0.17***	0.01	-0.027	-0.17***	0.01	-0.027	-0.45***	0.01	-0.070
Not declared	-0.07	0.19	-0.011	-0.06	0.19	-0.009	-0.09	0.14	-0.017
Profession/Occup.									
Commerce and Management	0.04***	0.00	0.005	0.04***	0.00	0.005	0.08***	0.00	0.011
Agropecuary	-0.02**	0.01	-0.003	-0.02**	0.01	-0.003	0.05***	0.01	0.007
Art and Architecture	0.14***	0.01	0.023	0.14***	0.01	0.023	0.24***	0.01	0.040
Natural Sciences	0.07***	0.01	0.011	0.07***	0.01	0.011	0.18***	0.01	0.028
Social Sciences	0.05***	0.00	0.008	0.05***	0.00	0.008	0.14***	0.00	0.021
Law	0.13***	0.01	0.021	0.13***	0.01	0.021	0.21***	0.01	0.034
Education	0.07***	0.01	0.011	0.07***	0.01	0.011	0.28***	0.01	0.048
Humanities	0.05***	0.01	0.007	0.05***	0.01	0.007	0.15***	0.01	0.023
Health	0.02***	0.01	0.003	0.02***	0.01	0.003	0.15***	0.01	0.023
Non-declared	0.14***	0.00	0.023	0.14***	0.00	0.023	0.33***	0.00	0.058
Other	-0.04***	0.00	-0.006	-0.04***	0.00	-0.006	-0.10***	0.00	-0.014
Labor Status									
Contracted	-0.05***	0.00	-0.008	-0.05***	0.00	-0.007	-0.13***	0.00	-0.021
Student	-0.03***	0.01	-0.005	-0.03***	0.01	-0.005	0.13***	0.01	0.024
Self-employed	-0.05***	0.01	-0.008	-0.05***	0.01	-0.008	-0.07***	0.00	-0.011
Just graduated	-0.03***	0.01	-0.004	-0.03***	0.01	-0.004	0.07***	0.01	0.012
Unemployed	-0.00	0.00	-0.000	-0.01*	0.00	-0.001	0.04***	0.00	0.007
Temporary job	-0.04***	0.01	-0.006	-0.04***	0.01	-0.006	-0.01	0.00	-0.001
Constant	4.20***	0.10		4.19***	0.10		-0.62***	0.09	
Observations	5348646			5348646			6059709		
Average probability	0.093			0.093			0.096		
pseudo - R^2	0.058			0.058			0.045		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.. Omitted groups: *Highest educ:* Science-humanity high-school; *Profession/Occupation* Technology. *Labor status:* Other. *Marital status:* Single. In all equations, we control for quarterly dummies to capture seasonality and marital status dummies.

hand, years of experience have a low practical relevance for explaining this behavior.

In model 1 of Table 9, we observe the impact of both last tenure and unemployment duration on the likelihood of applying to wage-explicit jobs. The likelihood of applying for explicit-wage jobs increases with unemployment duration, in line with a literature showing a decreasing quality of jobs accepted over the unemployment spell. In the presence of a stigma effect of unemployment duration, or human capital depreciation that lead to negative duration dependence of the job finding rate (Kroft, Lange, and Notowidigdo 2013), one would expect that applicants start considering jobs for which they are probably overqualified if they remain unemployed for too long. Since we are controlling for expected wage as well as previous job wage, this is probably not just a matter of reduction of reservation wages. This fact may constitute evidence that workers are searching for nonpecuniary job characteristics that tend to be absent in positions that explicitly advertise their wages. This result is similar to the one obtained by Kudlyak, Lkhagvasuren, and Sysuyev (2013).

Interestingly, the results also show a negative impact of the duration in the previous job (previous tenure). Workers who have stayed in previous positions for longer times may have capabilities that are less likely to be demanded in job positions of low-quality, which are the ones that typically explicitly communicate wages. In Figure 3, we show the impact of expected wages, previous wages, years of experience, previous tenure, and unemployment duration on the probability of application to a job ad with an explicit wage.

The profession/occupation of an applicant also matters for his/her proclivity to apply for explicit-wage jobs. Individuals with no specific profession/occupation are substantially more likely to apply for these jobs. Other areas such as education, social sciences, and art and architecture are also more likely to apply. Applicants on technology areas, on the other hand, have a lower tendency to apply for these jobs.

The labor status of the applicant also affects the decision to apply. Individuals who have currently a job, or are self-employed are substantially less likely to apply for explicit-wage positions. This seems to be consistent with the idea that individuals with less urgency to find a job are pickier, because being employed is likely to increase the reservation wage of applicants, or other nonpecuniary aspects valued by job seekers. On the other hand, the students and unemployed applicants are more likely to apply, probably because they need to find a job more urgently.

4.4 Segmentation

In directed search models with heterogeneity on one or two sides of the market, i.e. applicants direct their search effort to a particular submarket where employers are posting offers to specif-

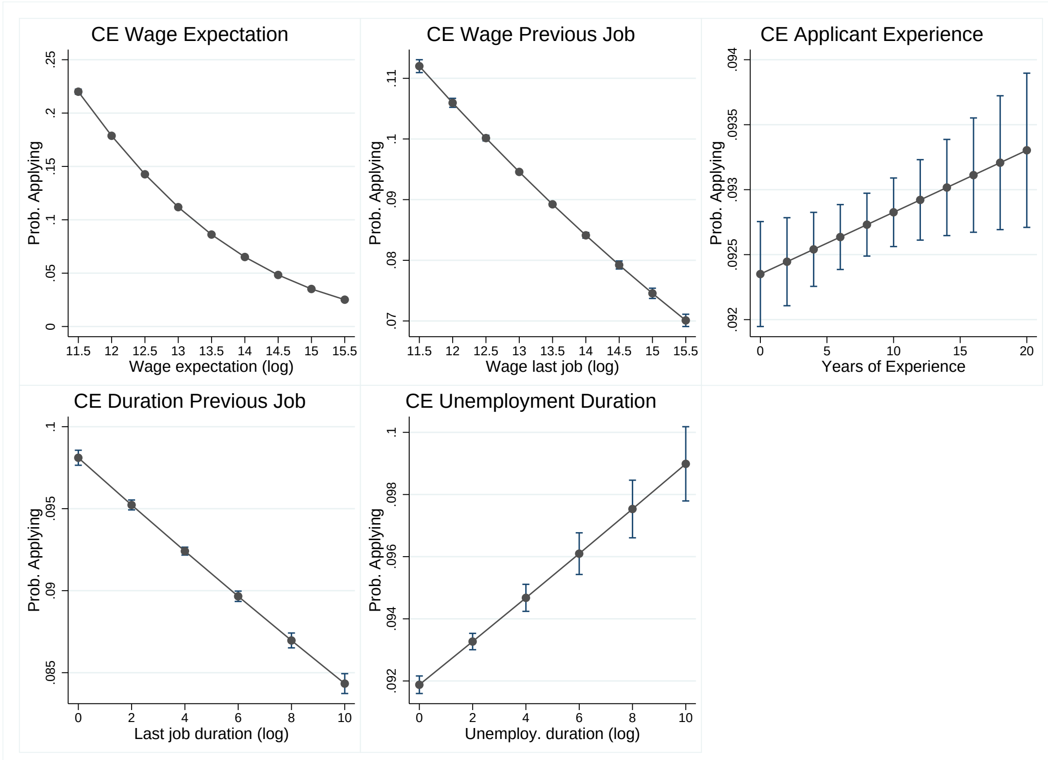

Figure 3: Expected Marginal Effects (EME) on Prob. of Application to Explicit Wage Ad (Table 9, Model 1)

Vertical bars indicate 95% Confidence Intervals.

ically attract them (Shi 2002; Menzio, Telyukova, and Visschers 2012). Thus, directed search mechanism generates endogenous segmentation of the labor market. We assess the relevance of this prediction in several complementary ways.

First, we ask if several job ads' requirements or characteristics such as experience and schooling etc. are correlated with the average corresponding attribute of the applicants they receive. In the upper-left panel of Figure 4, the correlation between the required experience of the job ad and the average experience of the applicants to job ads posting such experience requirement is very high. A thin 99% horizontal confidence interval surrounding the local polynomial curve indicates that the average pool of candidates applying to jobs of a given level of required experience shows little variance. We interpret this evidence as evidence of applicants directing their applications to job ads requiring the experience level they possess.

A similar segmentation phenomenon appears when we look at the applications to job ads according their required educational level. On the vertical axis of the upper-right panel of Figure 4, we have ordered level of educational requirements (Primary, High-School, Technical

High-School (T1), Technical Tertiary (T2), College, Graduate). For job ads requiring high-school (Scientific-Humanistic or Technical), there is no clear relation between years of schooling and requirements.[8] Thus, jobs that require high school or less receive applications from individuals ranging between 8 to 12 years of schooling, and there is a large variation on educational level across job ads requiring these low levels of education. Therefore, the educational requirement does not segment the market in this particular and small subset of applicants (nearly 30% of the applicants, according to Table 2). For higher levels of schooling requirements, we see that applicants tend to apply for jobs that match their own educational attainment approximately. To understand the upper portion of the panel, consider we have imputed five years of education to a college degree on top of the 12 years of primary and secondary education. Since individuals with 18 or more years of schooling as shown in Table 2 account only for 0.68% of applicants and graduate degree requirements are rare in job ads, there is a very large confidence interval surrounding the point estimate.

Focusing on the three remaining panels of Figure 4, we observe a clear positive correlation between the job ad offered log wage (implicit, explicit, and both) and the average log expected wage of individuals applying for those jobs. For implicit wages, the polynomial local regression flattens at $\exp(12.5) \approx 270,000$ CLP ≈ 523 USD per month, i.e, employers are rarely offering wages lower than this level. The 99% horizontal confidence interval along the local regression has a similar width for different levels, showing a degree of variation of average log expected wages of applicants around the log offered wage of the employer. We interpret this evidence directed search because applicants tend to apply for jobs that intend to pay them relatively close to what they expect. Moreover, this evidence shows a relatively precise signal extraction because the average log expected wage of applicants is quite close to the offered implicit wage on average. This constitutes evidence that the applicants accurately read and interpret features of the job ad, and make application decisions based of this information. In the case of explicit wages, the picture shows a somewhat different pattern. While there is a clear positive relation between log offered wages and average log expected wages, the confidence intervals widen as the explicit offered log wage increases. Therefore, low explicit wages generate lower variance of average expected log wages across job ads. We interpret this as employers posting high precision signals of wages when choosing to be explicit. However, explicit wage posting for high-wage jobs seem to attract pools of applicants that are quite heterogeneous in terms of their log wage expectations.

Table 10 portrays a matrix of major educational areas of applicants. On the vertical axis,

[8] The Chilean educational system has 8 years of primary school, and 4 years of secondary or high school education that can be either scientific-humanistic (mostly leading to tertiary education) or technical.

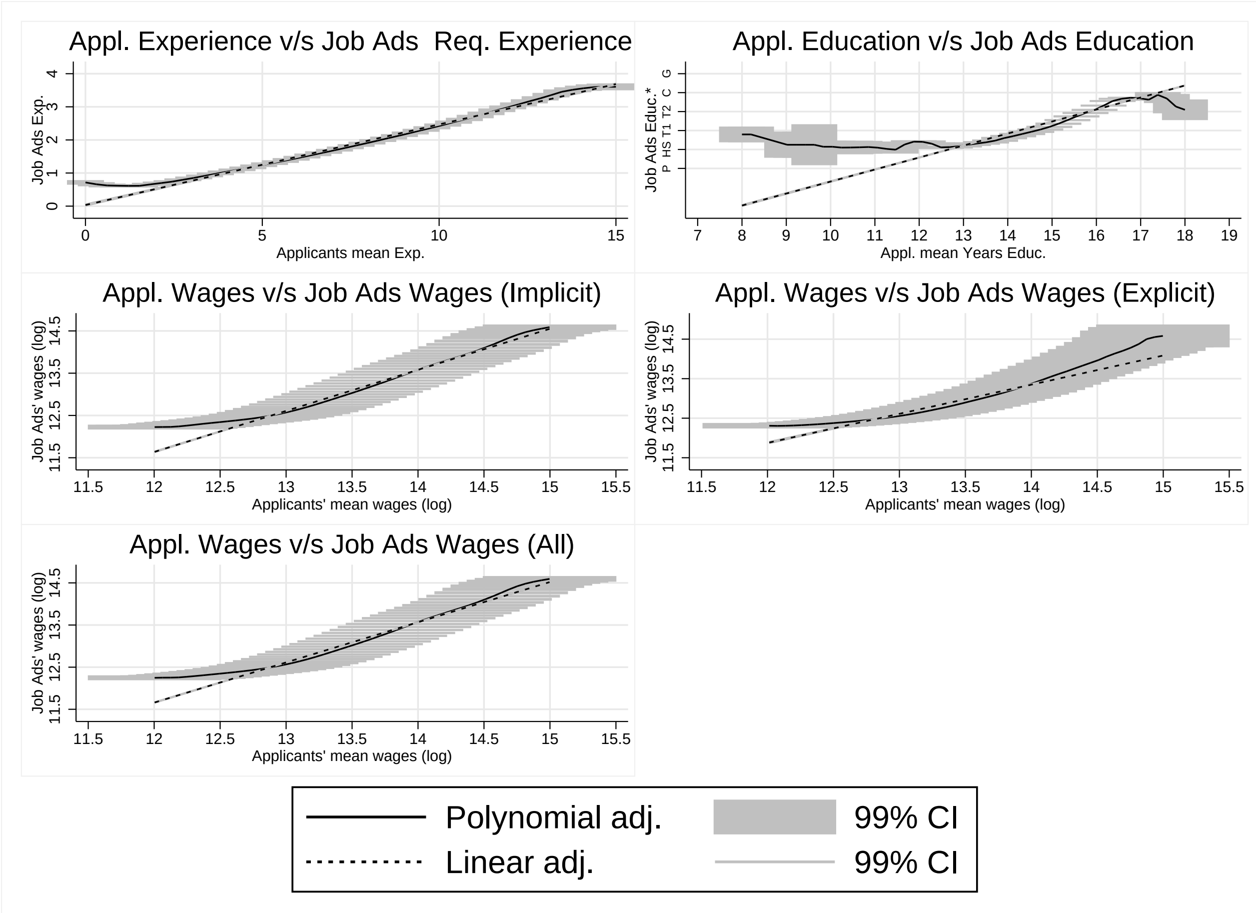

Figure 4: Correlations between job ad requirements and average applicants' characteristics

there are educational majors required by job ads, while the horizontal one lists the educational major possessed by applicants. At each entry, the table displays the share of applicants possessing a particular educational major who apply for jobs requiring a given educational major. A great deal of segmentation is observed since the main diagonal of the matrix shows high percentages, showing that applicants tend to apply more for jobs explicitly requiring a specialized worker. Among the most specialized segments, we have jobs requiring law, health, and social sciences majors. More than 60% of the applicants for these jobs have the same kind of major required by the employer. There is some dispersion across applicants majors for every specific requirement, but in all cases, the mode is applying for a job with the same requirement that the applicant possesses. There is also a roughly uniform distribution across applicants' majors that are not a coincidental match, which suggests that reasons for applying to non-matching major ads are unrelated to other aspects of the job search process.

Table 10: Segmentation Education Area

		Applicants Mean Distribution											
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Job Ads Requirements	(1) Commerce and Management	**48,38**	0,53	0,99	0,34	3,52	1,17	0,92	2,16	0,56	18,73	17,85	5,25
	(2) Agropecuary	13,25	**44,96**	0,36	1,06	0,88	0,14	0,22	0,47	2,13	25,29	4,49	6,97
	(3) Art and Architecture	11,92	0,20	**29,17**	0,42	13,38	0,62	1,41	1,26	0,59	27,11	8,09	6,17
	(4) Natural Sciences	7,76	2,95	0,39	**26,30**	0,95	0,20	1,64	0,55	6,80	34,81	13,00	5,66
	(5) Social Sciences	9,72	0,11	2,53	0,13	**68,32**	0,30	1,05	0,98	0,13	4,24	4,41	8,26
	(6) Law	3,85	0,03	0,09	1,24	1,09	**82,11**	0,14	0,48	0,05	2,23	3,78	5,15
	(7) Education	6,70	0,27	1,28	1,41	7,22	0,47	**44,18**	5,03	1,46	5,89	16,98	10,63
	(8) Humanities	12,31	0,24	1,96	0,54	8,70	2,06	7,64	**39,42**	0,75	6,74	14,15	6,22
	(9) Health	3,50	0,74	0,24	1,26	0,83	0,10	1,14	0,27	**70,60**	8,86	11,37	2,84
	(10) Technology	23,38	0,89	0,84	0,55	2,69	0,19	0,25	0,57	0,40	**53,74**	7,41	9,36
	(11) Non-declared	21,84	0,74	1,47	0,79	3,75	1,52	1,58	1,23	1,81	19,34	**44,67**	2,91
	(12) Other	17,86	1,88	3,07	1,26	6,52	1,92	6,68	2,66	2,13	21,53	23,06	**12,13**

Table 11: Segmentation Education Level

		Applicants Mean Distribution					
		(1)	(2)	(3)	(4)	(5)	(6)
Job Ads Req.	(1) Primary (1-8 years)	**1,94**	42,24	26,02	20,76	17,91	0,13
	(2) Science-humanity High School	1,15	**24,13**	24,32	27,22	25,21	0,19
	(3) Tech. High School	0,73	8,49	**26,49**	36,44	28,74	0,31
	(4) Tech. Tertiary Educ.	0,47	2,44	17,20	**37,34**	42,46	0,63
	(5) College	0,25	0,31	6,82	14,94	**76,11**	1,67
	(6) Graduate	0,43	0,26	6,52	6,40	82,45	**4,10**

An additional way to show segmentation on the online labor market, is to look at the relative similarity of workers applying for the same job ad. We construct a similarity measure as the gap between the percentile 1 and 99 for key variables such as log of applicants' expected wage, log of last wage, age, and experience within each group applying for a job ad. To put this similarity in relative terms, we compute the same for the whole sample of applicants. The Relative Similarity Ratio (RSR) is defined as the ratio of the former and the latter. Thus, the RSR varies across job ads. A RSR value below 1 indicates that individuals applying for the same job are more similar to one another regarding one variable than they are in the whole sample. Figure 5 depicts histograms showing the shape of distributions of RSRs of the four key variable aforementioned. In all cases, a substantial share of the RSR is below 1, showing a large set of job ads have a pool of applicants that is substantially less diverse than is the average sample. We compute the same ratios splitting the sample between explicit-wage and implicit-wage job ads, reporting the histograms in the appendix. While the shape of the distribution of the RSR for both group of ads is somewhat different, they still have a very large part of their distribution way below 1. This shows that there is a sorting of applicants on jobs on characteristics, a clear signal of segmentation. We also repeat these exercises computing relative similarity ratios for other percentile gaps (5/95, 10/90, 25/75), min/max, and standard deviation within individuals applying for the same job ad, which are available upon request. The main findings on segmentation remain intact regardless of the similarity measure used.

Figure 5: Relative Similarity Ratio p1/p99 for all ads

All in all, the three illustrations provide evidence supporting that applicants self-select into job ads for which similar others apply, and that approximately meet employers' requirements in terms of wage expectations, experience, and majors.

5 Robustness Tests

When workers are searching for a job, they often have idiosyncratic preferences for different firms. An applicant could direct their search to a particular firm if she can figures out the employer's identity. Sometimes this information is conveyed explicitly in the ads, sometimes remains hidden. For example, workers may have preferences for particular firms due to known fringe benefits, status, location, organizational climate, and other features which are unobservable for the econometrician. In our previous estimates, these preferences are not considered, and therefore there is a potential omitted variable bias if unobserved features are correlated with observable characteristics. To test the robustness of our results, we estimate our models adding firm fixed effects.

The numerical accuracy for computing maximum-likelihood estimations, such as the negative binomial model, is increasing in the number of parameters of the model. Essentially any maximization algorithm needs to approximate and invert a Hessian matrix with dimension equal to the number of parameters, leading to a large loss of accuracy in case of using nearly 6,000 firm fixed effects. If instead, we rely on a random effects model, this imposes that unobservable individual level variables are uncorrelated with observables, a constrain that may not hold. Hence, we rely on a simple linear regression with fixed firm effects, using the logarithm of applications received by ad as dependent variable and keeping the independent ones. Results are reported in the Table 12. The main conclusions remain.

The findings can be interpreted in at least two ways: (i) variables which are observable for us contain enough information for applicants to direct their job searches; or (ii) applicants cannot generally recognize which firm are applying for, because most job ads present generic descriptions without mentioning specific firms. The results also show that applicants are more sensitive to changes in required experience when wage is explicitly posted in comparison to the baseline case, but the reaction is still lower than those ads with implicit wages.

We check robustness to probability estimations as well, simply using a linear probability model. We maintain the same specifications but add fixed effect on firms. Again, less-skilled jobs present a higher likelihood to post an explicit wage. Overall, the results in Table 13 are very similar to the ones obtained before, showing that idiosyncratic unobservable features are not driving wage-posting strategies in their job ads. Finally, introducing firm fixed effects to the probability of applying to an explicit wage ad, we find similar results between this model and the ones we estimated before, as shown in Table 14. The main difference is on the effect of applicant's experience in the likelihood of applying to an explicit wage ad: in the probit model, we have a positive effect, but the sign is reversed for the linear probability estimation with fixed effects. However, in both cases, the coefficient is not statistically relevant.

6 Discussion (work in progress)

The findings in the preceding sections could be summarized as follows:

- Applicants direct their search to high-wage jobs (and other job traits) regardless if wages are posted explicitly or hidden (implicit).

- Applicants are more sensitive to wages when explicit and less sensitive to other job characteristics. The opposite pattern occurs when wages are implicit since other job characteristics become more important to drive applications.
- Workers apply more on average for implicit-wage jobs, particularly at low wage levels.
- Employers target low-skill workers through explicit wages and high-skill workers through implicit wages.
- Applicants comply to employers' wage posting strategies: unskilled tend to apply to explicit-wage ads, and skilled go for implicit-wage ones.

To the best of our knowledge, there is no theoretical model capable of accounting for all these stylized facts. Theoretical models such as Ellingsen and Rosén (2003) and Michelacci and Suarez (2006) assume that wages that are not posted explicitly necessarily imply ex post bargaining. In the first paper, search is not directed in these models, contradicting a clearly established fact in our data. Under certain parameterizations, the second model allows for separating equilibria, that is positively assortative applications: good workers apply for good jobs and bad workers go for bad jobs. However, there is no explanation in either model for the fact that, ceteris paribus, job ads with explicit wage receive less applications than do their implicit-wage counterparts.

The fact that applicants are more reactive to explicit wages denotes a clear directed search behavior, after controlling for several observed features of the job, such as specific requirements. Job seekers significantly react to implicit wages, but the sensitivity of their response is substantially lower. We interpret this fact as evidence for an applicant signal extraction of the expected wage from job requirements and text of ads, since the application behavior may be dampen by the noisiness of the wage information.

That implicit wage ads attract more applicants than their explicit counterparts may seem as a strange result at first sight. The explanation we advocate entails with a natural property in many search models, starting with McCall (1970): a noisier wage signal implies a higher expected outcome because applicants can always turn down low wage realizations. We hypothesize that higher uncertainty in implicit wages –perhaps due to a ex post bargaining– may be more valuable for workers, and therefore attract more applicants.

If this argument holds, then why would ever employers use explicit wages? Posting explicit wages is a strategy of the employer for reduce the expected number of costly applications. This is just another disguise for a common congestion problem in online markets. Given that the marginal cost of application is so low, job seekers may apply for positions that poorly meet employers' requirements. Employers devote considerable effort for recruiting activities as documented in previous research (Barron, Bishop, and Dunkelberg 1985; Barron and Bishop 1985; Villena-Roldan 2010; Oyer and Schaefer 2011) so receiving less applications reduces their processing, screening, and interviewing costs. This is particularly important when employers intend to recruit workers for basic jobs, they often need just a small set of resumes to find the right one. Evaluation of resumes in many basic jobs is not nuanced, variety has no intrinsic value: any worker is a very good substitute for another. Hence, explicit-wage strategies are focused on low-skill jobs for which receiving a large number of applications increases recruiting costs and provides little additional value to the employer.

The previous argument points out why employers use explicit wages to marginally discourage applications. But the evidence clearly shows that unskilled workers are much more likely to apply for these positions. Something about unskilled applicants may be different from their high-skilled counterparts in order to direct their searches to explicit-wage ads. The most plausible hypothesis relies on applicants' risk-aversion. Noisier ads entail higher expected wages if applicants rationally use a reservation-wage decision, but also imply higher uncertainty regarding the job search process. Naturally, risk-averse applicants face a trade-off: they dislike uncertainty on one hand, but they appreciate larger expected wages. Due to the higher marginal utility of consumption of low-wage, unskilled applicants, the first motive outweighs the second, leading to a greater frequency of application for explicit-wage job that offer low mean but low variance. In contrast, the high-skilled can afford the pain of the extra uncertainty provided the expected return if sufficiently appealing.

The above reasoning portrays an equilibrium in which employers can post explicit wages to attract unskilled workers, and implicit wages to receive high-skilled applications. If there are unknown aspects of a job that must be inferred by applicants, the strategy played by the employer may convey information regarding job features not directly observed by the applicant. Hence, explicit wages may signal "bad" positions, reinforcing the screening due to self-selection of applicants based on the explicitness of the wage in the ad. In equilibrium, each type of worker tends to apply to the ads that are precisely targeting the corresponding type.

Environment and matching

We propose a relatively simple model to highlight the aspects of the wage-posting and application process on the online labor market.

Consider a one-period economy populated with applicants of type t who are either skilled ($t = 1$) or unskilled ($t = 0$). There are two types of jobs, with high ($k = 1$) and low ($k = 0$) productivity. Applicants of type t send a total number of $a_{t,k}$ applications to job ads of type k. Employers of type k announce v_k vacancies through job ads to attract applicants. Applicants meet vacancies according to a constant-returns-to-scale matching function described by $m(a_{t,k}, v_k) \equiv v_k m(q_{t,k}, 1)$ with $q_{t,k} \equiv a_{t,k}/v_k$.

The probability of hiring an applicant of type t, if strictly preferred to type $1-t$, is $h(q_{t,k}) \equiv m(q_{t,k}, 1)$. In case the vacancy k strictly prefers the type $1-t$, the probability of hiring a type t applicant is $(1 - h(q_{1-t,k})h(q_{t,k})$. If vacancies are indifferent between types t and $1-t$, then there is a probability of vacancy k to prefer applicants of type t, $p_{t,k} \in (0, 1)$. Naturally, $p_{t,k} = 1 - p_{1-t,k}$. Generalizing, the probability of hiring a worker of type t is

$$H(q_{t,k}, q_{1-t,k}) = p_{t,k}h(q_{t,k}) + (1 - p_{t,k})(1 - h(q_{1-t,k}))h(q_{t,k}) \tag{1}$$

On the other hand, the probability that an applicant t finds a job is $h(q_{t,k})/q_{t,k}$ if strictly preferred. The job finding probability if type $1-t$ is preferred to t is $(1 - h(q_{1-t,k})h(q_{t,k})/q_{t,k}$. Considering the probability of being preferred by a type k vacancy, the chance of finding a job is

$$F(q_{t,k}, q_{1-t,k}) = p_{t,k}\frac{h(q_{t,k})}{q_{t,k}} + (1 - p_{t,k})(1 - h(q_{1-t,k}))\frac{h(q_{t,k})}{q_{t,k}} = \frac{H(q_{t,k}, q_{1-t,k})}{q_{t,k}}. \tag{2}$$

Applicants

Individuals of type t applying to job ads of type k obtain expected utility

$$\bar{u}_t(\theta_k) \equiv \mathbb{E}[u(w)|\theta_k, w \geq r_t] = \int_{r_t}^{\infty} u(w)\frac{g(w, \theta_k)}{1 - G(r_t, \theta_k)}dw,$$

derived from a posted noisy signal of an employer $k = 0, 1$ that follows a distribution with cumulative distribution function (cdf) $G(w, \theta_k)$ with density $g(w, \theta_k)$. The employer sets the parameter vector θ_k determining the shape of the distribution of wages to attract (or deter) applicants.

Applicants are risk-averse and their preferences over wage realizations of the signal are represented by an utility function $u(\cdot)$ twice-continuously differentiable, increasing and concave. The expected utility obtained by an applicant t takes into account that she will reject realizations of the signal below her reservation wage r_t. Therefore, if applicants differ in their reservation wage, they receive different utility values from the exactly same signal.

A worker of type t finds a job with probability $\frac{h(q_{t,k})}{q_{t,k}}$ if the employer strictly prefers the type t in equilibrium. If the applicant fails to get a job, he receives his exogenous outside option providing utility $u(r_t)$. Hence, the value an applicant t gets by applying to a job ad k is

$$A_t(\theta_k) = F(q_{t,k}, q_{1-t,k})\bar{u}_t(\theta_k) + (1 - F(q_{t,k}, q_{1-t,k}))u(r_t).$$

The preference probability $p_{t,k}$ is given from the viewpoint of the applicant, but it becomes endogenously determined later. Applicants direct their search to both sectors by spending some fraction of time applying for jobs of each type. In equilibrium, both application choices should generate the exact same expected utility, i.e $A_t(\theta_k) = A_t(\theta^*_{1-k})$ considering that what is obtained from applying to $1-k$ is exogenous for the applicant.

Job ads

We assume that a skilled applicant is more productive in a high-type job, ($y_{11} > y_{10}$) and is also more productive that an unskilled applicant in a high-type job, ($y_{11} > y_{01}$). We will consider cases in which skilled workers have absolute advantage in each job type ($y_{10} > y_{00}$), and a case in which there is specialization, in which the latter inequality is reversed.

The hiring problem for a employer of type $k = 0, 1$ consists on optimally posting a signal, i.e. choosing a shape of the distribution $G(w, \theta_k)$ that yields expected utility $\bar{u}_t(\theta_k)$ to applicants of type $t = 0, 1$. Employers take into consideration that applicants are indifferent between applying for positions k and $1-k$ given their type t. The noisy signal $G(w, \theta_k)$ imply a expected wage of

$$\bar{w}_t(\theta_k) \equiv \mathbb{E}[w|\theta_k, w \geq r_t] = \int_{r_t}^{\infty} w \frac{g(w, \theta_k)}{1 - G(r_t, \theta_k)} dw$$

for a worker with reservation wage r_t. Note that employers can only post one signal $G(w, \theta_k)$ that is visible for both kinds of applicants. However, the same signal yields different expected utilities to both types, given their different reservation wages and equilibrium outside options in the other market of employers of type $1-k$.

Employers also decide on the optimal hiring strategy $p_{t,k}$: they may have a strict preference for some type ($p_{t,k} \in \{0, 1\}$) or may be indifferent between them ($p_{t,k} \in (0, 1)$).

$$J_k = \max_{q_{t,k}, q_{1-t,k}, \theta, p_{t,k}} \{H(q_{t,k}, q_{1-t,k})(y_{t,k} - \bar{w}_t(\theta_k)) + H(q_{1-t,k}, q_{t,k})(y_{1-t,k} - \bar{w}_{1-t}(\theta_k)) - \xi(q_{t,k} + q_{1-t,k})\} \tag{3}$$

s.t. $A_t(\theta_k) = A_t(\theta^*_{1-k})$

$A_{1-t}(\theta_k) = A_{1-t}(\theta^*_{1-k})$

$q_{t,k}, q_{1-t,k} \geq 0$

$p_{t,k} \in [0, 1]$

Using applicants conditions, we obtain that

$$\bar{u}_t(\theta_k) = \frac{A_t(\theta^*_{1-k}) - u(r_t)}{F(q_{t,k}, q_{1-t,k})} + u(r_t) \tag{4}$$

$$\bar{u}_{1-t}(\theta_k) = \frac{A_{1-t}(\theta^*_{1-k}) - u(r_{1-t})}{F(q_{1-t,k}, q_{t,k})} + u(r_{1-t}) \tag{5}$$

Rearranging, we can rewrite the problem into (3) as

$$J_k = \max_{q_{t,k}, q_{1-t,k}, \theta_k, p_{t,k}} \{q_{t,k}\left(\Delta_t(\theta_k) - \xi\right) + q_{1-t,k}\left(\Delta_{1-t}(\theta_k) - \xi\right)\} \tag{6}$$

$$\text{with } \Delta_t(\theta_k) \equiv \left(\frac{A_t(\theta^*_{1-k}) - u(r_t)}{\bar{u}_t(\theta_k) - u(r_t)}\right)(y_{t,k} - \bar{w}_t(\theta_k))$$

$$\Delta_{1-t}(\theta_k) \equiv \left(\frac{A_{1-t}(\theta^*_{1-k}) - u(r_{1-t})}{\bar{u}_t(\theta_k) - u(r_{1-t})}\right)(y_{1-t,k} - \bar{w}_{1-t}(\theta_k))$$

$$\text{subject to } H(q_{t,k}, q_{1-t,k}) = \Delta_t(\theta_k) q_{t,k}$$

$$H(q_{1-t,k}, q_{t,k}) = \Delta_{1-t}(\theta_k) q_{1-t,k}$$

Equilibrium

Equilibrium definition is a collection of queue lengths $\{q_{1,1}, q_{1,0}, q_{0,1}, q_{0,0}\}$, noisy signals $\{G(w, \theta_0), G(w, \theta_1)\}$, and hiring strategies $\{p_{1,1}, p_{1,0}\}$ such that

- Applicants observe signals $\{G(w, \theta_0), G(w, \theta_1)\}$ and optimally decide to apply to job ads so that they become indifferent between applying to sector $k = 0$ or $k = 1$, i.e. $A_t(\theta_1) = A_t(\theta_0)$ for $t = 0, 1$.
- Employer optimally choose signals $\{G(w, \theta_0), G(w, \theta_1)\}$ and hiring decision $\{p_{1,1}, p_{1,0}\}$, considering applicants' behavior.
- Applicants' decisions are consistent with the aggregate fixed supply of job ads and applicants such that condition (**??**) holds.

(To be completed)

7 Conclusions

Our evidence shows that directed search is a prevalent behavior in the the online labor market studied. Applicants react to signals given by employers as, for example, offered wages. Those ads that offer higher wages, receive more applications than those with lower ones, giving insights of a conscious job search behavior, sending their applications to ads with more attractive characteristics. An important finding is, even an ad doesn't explicit a wage on it, applicants can infer which jobs offer better conditions with the additional information present in the ad as the text present in the job ad or other specified requirements. An important issue is applicants are more sensitive to changes in wage when it is explicit and less when this information is hidden. Explicit a wage provides more relevant information to applicants, making easier their job search and reacting more to changes in wages.

Another relevant finding is workers apply more for implicit-wage jobs. Firms have a trade-off when are looking for workers, because more applicants give more options, but have to fall into higher selection costs, therefore some firms, especially those dedicated to recruitment, prefer explicit a wage in way to filter applicants and reduce the pool. But, as has been shown, explicit a wage attracts less productive workers, in that way firms should target their jobs to low-skill workers through explicit wages and target to high-skill ones through implicit wages.

Applicants also react to other signals as specific requirements. Jobs that require more experience tend to receive less applications, because workers know they don't have a high probability to been contracted if they don't fulfill the requirements.

Finally, we have tested if applicants also direct their job search distinctively among firms. We tested if the attained conclusions change if we include firms as fixed effect in simple linear regressions. Our results didn't changed considerably, supporting our findings, and also, giving insights of some difficult to identify firms characteristics by workers in job ads, due many firms present themselves anonymously.

References

Abbring, J. and J. van Ours (1994). Sequential or Non-Sequential Employers' Search? *Economic Letters 44*, 323–328.

Barron, J. and J. Bishop (1985). Extensive Search, Intensive Search, and Hiring Costs - New Evidence on Employer Hiring Activity. *Economic Inquiry 23*(3), 363–382.

Barron, J. M., J. Bishop, and W. C. Dunkelberg (1985). Employer search: The interviewing and hiring of new employees. *The Review of Economics and Statistics 67*(1), 43–52.

Belot, M., P. Kircher, and P. Muller (2015, May). How Wage Annoucements Affect Job Search Behaviour: a Field Experimental Investigation. 2015 Annual Search and Matching Gruoup Meeting. Aix-en-Provence, France.

Bewley, T. F. (1999). *Why wages don't fall during a recession*. Harvard University Press.

Brenčič, V. (2012). Wage Posting: Evidence from Job Ads. *Canadian Journal of Eco-*

nomics/Revue canadienne d'économique 45(4), 1529–1559.

Brenzel, H., H. Gartner, and C. Schnabel (2014). Wage bargaining or wage posting? Evidence from the employers' side. *Labour Economics 29*(0), 41 – 48.

Cameron, A. C. and P. K. Trivedi (2005). *Microeconometrics - Methods and Applications*. Cambridge University Press.

Dal Bó, E., F. Finan, and M. A. Rossi (2013). Strengthening state capabilities: The role of financial incentives in the call to public service. *The Quarterly Journal of Economics 128*(3), 1169–1218.

Ellingsen, T. and Å. Rosén (2003). Fixed or Flexible? Wage-setting in Search Equilibrium. *Economica 70*(278), 233–250.

Faberman, R. J. and M. Kudlyak (2013). The Intensity of Job Search and Search Duration. mimeo, Federal Reserve Bank of Richmond.

Gartner, H. and C. Holzner (2015, May). Wage Posting as a Positive Selection Device: Theory and Empirical Evidence. 2015 Annual Search and Matching Gruoup Meeting. Aix-en-Provence, France.

Hall, R. E. and A. B. Krueger (2012, May). Evidence on the Incidence of Wage Posting, Wage Bargaining, and On-the-Job Search. *American Economic Journal: Macroeconomics 4*(4), 56–67.

Hilbe, J. (2011). *Negative Binomial Regression*. Cambridge University Press.

Hosios, A. J. (1990). On the Efficiency of Matching and Related Models of Search and Unemployment. *The Review of Economic Studies 57*(2), 279–298.

Kroft, K., F. Lange, and M. J. Notowidigdo (2013). Duration Dependence and Labor Market Conditions: Evidence from a Field Experiment. *The Quarterly Journal of Economics 128*(3), 1123–1167.

Kudlyak, M., D. Lkhagvasuren, and R. Sysuyev (2013). Systematic job search: New evidence from individual job application data. mimeo, Federal Reserve Bank of Richmond.

Kuhn, P. and K. Shen (2013). Gender Discrimination in Job Ads: Evidence from China. *The Quarterly Journal of Economics 128*(1), 287–336.

Lewis, G. (2011). Asymmetric Information, Adverse Selection and Online Disclosure: The Case of eBay Motors. *The American Economic Review 101*(4), 1535–1546.

Marinescu, I. E. and R. P. Wolthoff (2015, May). Opening the Black Box of the Matching Function: The Power of Words. Discussion Paper 9071, IZA.

McCall, J. J. (1970, Feb). Economics of Information and Job Search. *The Quarterly Journal of Economics 84*(1), 113–126.

Menzio, G. and S. Shi (2010). Block recursive equilibria for stochastic models of search on the job. *Journal of Economic Theory 145*(4), 1453 – 1494. Search Theory and Applications.

Menzio, G. and S. Shi (2011). Efficient Search on the Job and the Business Cycle. *Journal of Political Economy 119*(3), 468–510.

Menzio, G., I. A. Telyukova, and L. Visschers (2012, January). Directed Search over the Life Cycle. Working Paper 17746, National Bureau of Economic Research.

Michelacci, C. and J. Suarez (2006). Incomplete Wage Posting. *Journal of Political Economy 114*(6), 1098–1123.

Moen, E. R. (1997). Competitive Search Equilibrium. *The Journal of Political Economy 105*(2), 385–411.

Oyer, P. and S. Schaefer (2011). Personnel Economics: Hiring and Incentives. *Handbook of Labor Economics 4*, 1769–1823.

Rogerson, R., R. Shimer, and R. Wright (2005). Search-Theoretic Models of the Labor Market: A Survey. *Journal of Economic Literature 43*(4), 959–988.

Shi, S. (2002). A directed search model of inequality with heterogeneous skills and skill-biased technology. *The Review of Economic Studies 69*(2), 467–491.

van Ommeren, J. and G. Russo (2013). Firm Recruitment Behaviour: Sequential or Non-sequential Search? *Oxford Bulletin of Economics and Statistics*, 1–24.

van Ours, J. and G. Ridder (1992). Vacancies and the Recruitment of New Employees. *Journal of Labor Economics 10*(2), 138–155.

Villena-Roldan, B. (2010). Aggregate Implications of Employer Search and Recruiting Selection. Working Paper 271, Center for Applied Economics, University of Chile.

Appendix

Word cloud for job titles

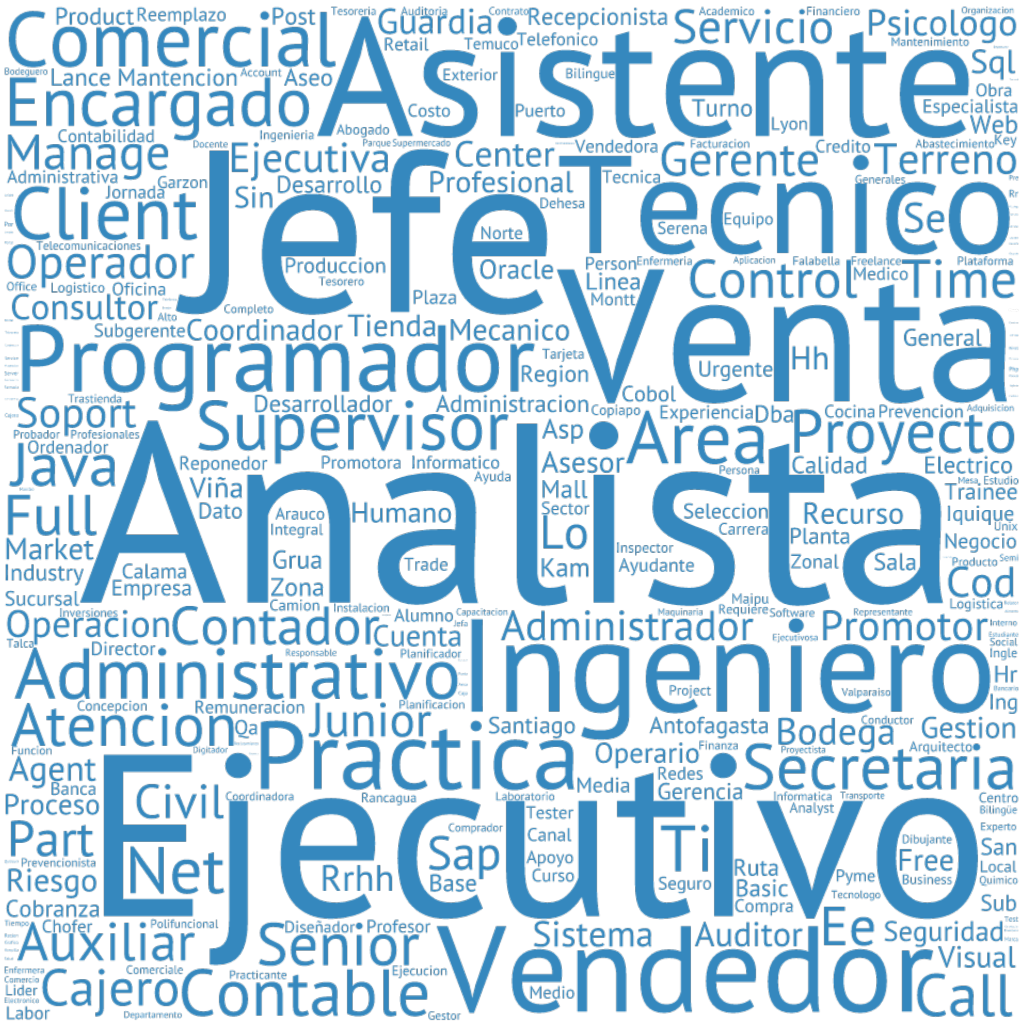

Figure 6: Job Ads' Titles with Implicit Wages

Generated in www.tagul.com.

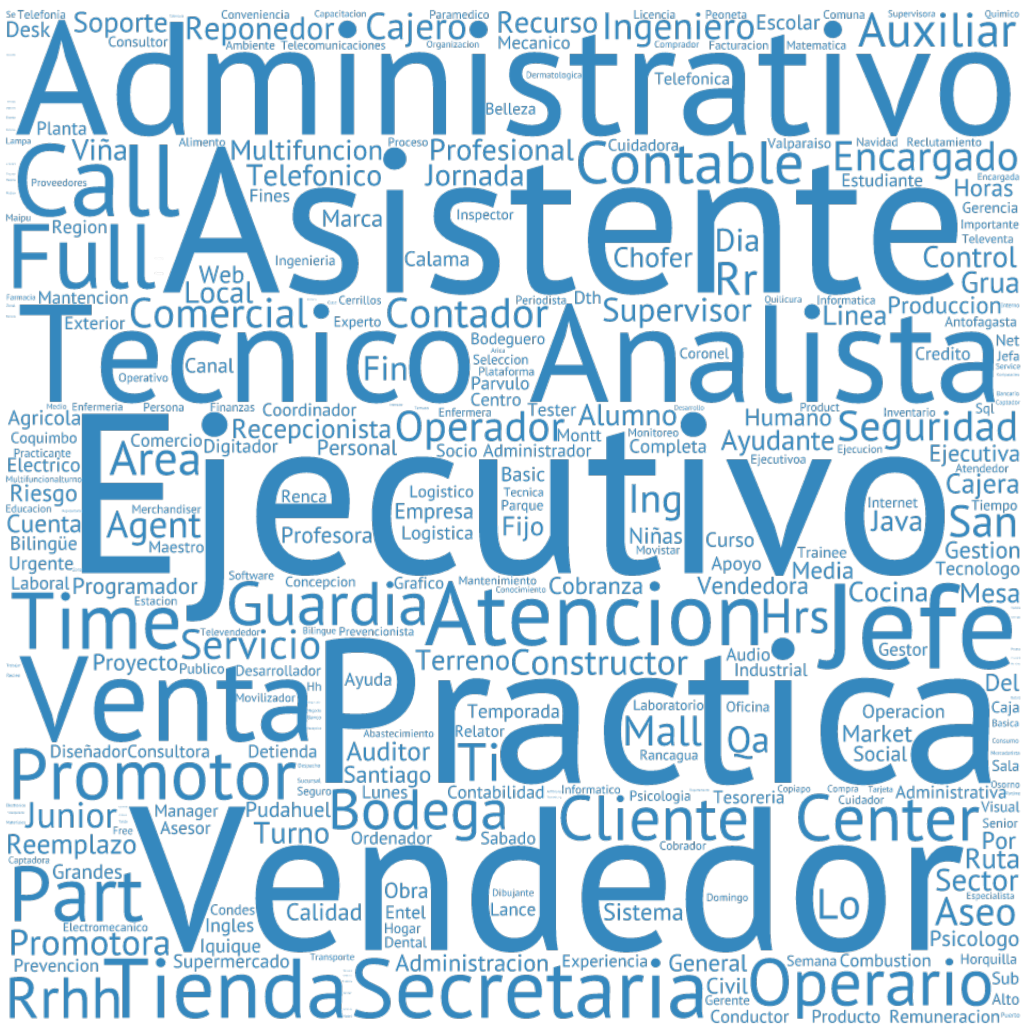

Figure 7: Job Ads' Titles with Explicit Wages

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Segmentation figures

Figure 8: Relative Similarity Ratio p1/p99 for explicit wage ads

Figure 9: Relative Similarity Ratio p1/p99 for implicit wage ads

Robustness checks

Table 12: Wage posting effect on applications (log) using Linear Regression and Firms Fixed Effect

	Model 1			Model 2		
	β	SE	$\partial\overline{y}/\partial x$	β	SE	$\partial\overline{y}/\partial x$
Explicit Wage	-2.268∗∗∗	0.179	-0.037	-2.184∗∗∗	0.175	-0.038
Ad appearances	-0.008∗∗∗	0.000	-0.008	-0.008∗∗∗	0.000	-0.008
Number of vacancies	0.005∗∗∗	0.000	0.005	0.005∗∗∗	0.000	0.005
Req. experience	-0.047∗∗∗	0.002	-0.047	-0.047∗∗∗	0.002	-0.047
Estimated wage (log)	0.055∗∗∗	0.006	0.078	0.060∗∗∗	0.006	0.082
Explicit Wage × Number of vacancies	-0.000	0.000		-0.001	0.000	
Explicit Wage × Req. experience	0.001	0.006		-0.001	0.006	
Explicit Wage × Estimated wage (log)	0.171∗∗∗	0.014		0.164∗∗∗	0.014	
Recruiting firm (=1)	0.000	.	0.000			
Highest educ						
Primary (1-8 years)	-0.287∗∗∗	0.028	-0.287	-0.297∗∗∗	0.027	-0.297
Tech. High School	0.020∗	0.011	0.020	0.019∗	0.010	0.019
Tech. Tertiary Educ.	0.086∗∗∗	0.011	0.086	0.083∗∗∗	0.011	0.083
College	0.160∗∗∗	0.013	0.160	0.159∗∗∗	0.013	0.159
Graduate	-0.030	0.037	-0.030	-0.022	0.036	-0.022
Legal contract type						
Fixed-term	-0.113∗∗∗	0.012	-0.113	-0.113∗∗∗	0.011	-0.113
Undefined term	0.065∗∗∗	0.010	0.065	0.074∗∗∗	0.010	0.074
Availability						
Comission-earner	-0.314∗∗∗	0.035	-0.314	-0.299∗∗∗	0.034	-0.299
Half time	-0.020	0.021	-0.020	-0.017	0.020	-0.017
Part-time	0.097∗∗∗	0.020	0.097	0.128∗∗∗	0.019	0.128
Shift-work	-0.046∗∗∗	0.011	-0.046	-0.055∗∗∗	0.010	-0.055
Internship	0.358∗∗∗	0.029	0.358	0.361∗∗∗	0.027	0.361
Replacement	-0.242∗∗∗	0.036	-0.242	-0.253∗∗∗	0.033	-0.253
Computer knowledge level						
Low level	0.071∗∗∗	0.016	0.071	0.077∗∗∗	0.016	0.077
Expert level	-0.239∗∗∗	0.023	-0.239	-0.238∗∗∗	0.022	-0.238
Professional level	-0.069∗∗∗	0.014	-0.069	-0.061∗∗∗	0.013	-0.061
Technical level	-0.008	0.016	-0.008	0.008	0.016	0.008
User level	0.041∗∗∗	0.008	0.041	0.043∗∗∗	0.007	0.043
Advanced User level	0.076∗∗∗	0.009	0.076	0.077∗∗∗	0.008	0.077
Constant	-1.261∗∗∗	0.164		-1.316∗∗∗	0.159	
Observations	170365			184920		
Estimated avg. applications (log)	2.59			2.59		
R^2	0.606			0.611		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.. Omitted groups: *Highest educ:* Science-humanity high-school; *Contract law* Other. *Availabilty:* Full-time. *Computer knowledge level:* None. In both equations, we control for profession/occupation dummies, industry dummies, quarter dummies to capture seasonality, first four words job title dummies, and the number of days the vacancy was open.

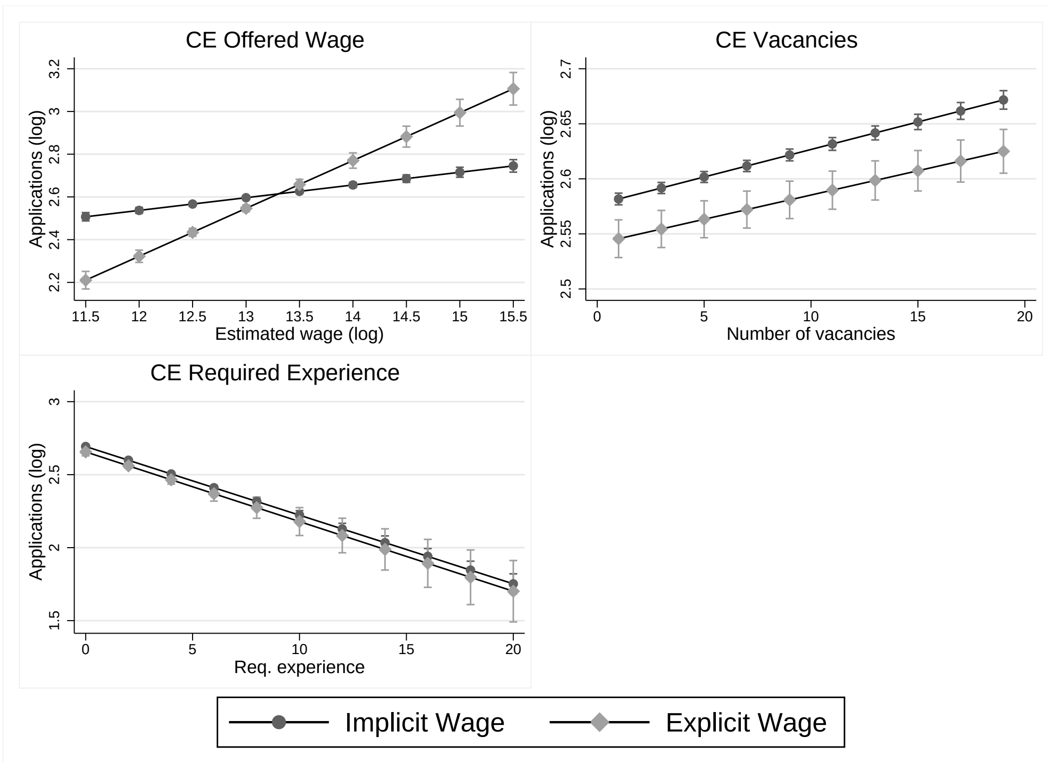

Figure 10: Expected Marginal Effects (EME) on applications (log), (Table 12, Model 2)

Vertical bars indicate 95% Confidence Intervals.

Table 13: Probably of posting an explicit wage using probit model (OLS Firms Fixed Effect)

	Model 1			Model 2		
	β	SE	$\partial\overline{y}/\partial x$	β	SE	$\partial\overline{y}/\partial x$
Vacancies	0.000*	0.000	0.000	0.000	0.000	0.000
Years of experience	-0.005***	0.001	-0.005	-0.005***	0.001	-0.005
Offered wage (log)	-0.029***	0.002	-0.029	-0.028***	0.002	-0.028
Recuiting Firm	0.000	.	0.000			
Highest educ						
Primary (1-8 years)	0.024***	0.008	0.024	0.022***	0.008	0.022
Tech. High School	-0.022***	0.003	-0.022	-0.022***	0.003	-0.022
Tech. Tertiary Educ.	-0.043***	0.003	-0.043	-0.041***	0.003	-0.041
College	-0.049***	0.004	-0.049	-0.048***	0.004	-0.048
Graduate	-0.044***	0.011	-0.044	-0.043***	0.011	-0.043
Legal contract type						
Fixed-term	0.032***	0.003	0.032	0.032***	0.003	0.032
Undefined term	0.026***	0.003	0.026	0.026***	0.003	0.026
Availability						
Comission earner	-0.060***	0.011	-0.060	-0.058***	0.010	-0.058
Half time	0.005	0.006	0.005	0.006	0.006	0.006
Part-time	-0.015**	0.006	-0.015	-0.019***	0.006	-0.019
Shift-work	0.023***	0.003	0.023	0.021***	0.003	0.021
Internship	0.021**	0.009	0.021	0.010	0.008	0.010
Replacement	-0.012	0.011	-0.012	-0.004	0.010	-0.004
Computer knowledge level						
Low level	0.033***	0.005	0.033	0.028***	0.005	0.028
Expert level	0.015**	0.007	0.015	0.011*	0.006	0.011
Professional level	-0.017***	0.004	-0.017	-0.020***	0.004	-0.020
Technical level	0.015***	0.005	0.015	0.009**	0.005	0.009
User level	0.012***	0.002	0.012	0.011***	0.002	0.011
Advanced User level	0.010***	0.003	0.010	0.008***	0.002	0.008
Constant	0.457***	0.048		0.429***	0.046	
Observations	170365			184920		
Avg. Probability	0.139			0.134		
R^2	0.314			0.316		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.. Omitted groups: *Highest educ:* Science-humanity high-school; *Contract law* Other. *Availabilty:* Full-time. *Computer knowledge level:* None. In both equations, we control for profession/occupation dummies, industry dummies, quarter dummies to capture seasonality, first four words job title dummies, and the number of days the vacancy was open.

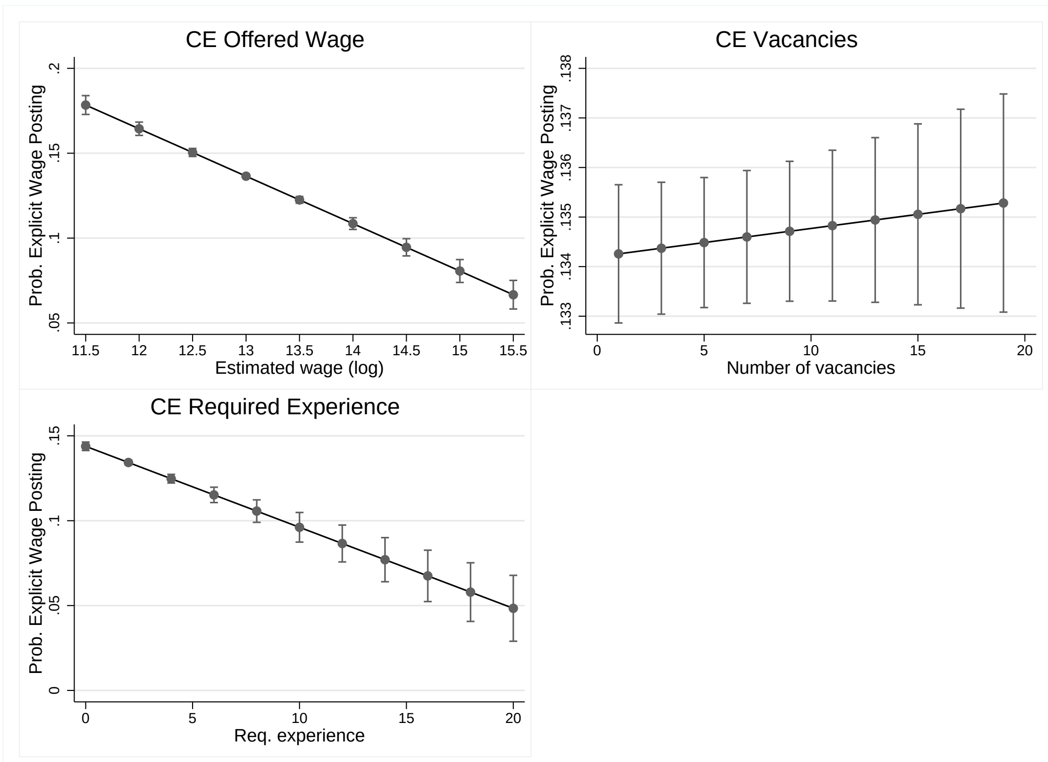

Figure 11: Expected Marginal Effects (EME) on Prob. of Explicit Offered Wage Posted estimated with OLS and Firms Fixed Effect (Table 13, Model 2)

Vertical bars indicate 95% Confidence Intervals.

Table 14: Probability of applying for an explicit wage using OLS with Firms Fixed Effect

	Model 1			Model 2			Model 3		
	β	SE	$\partial\overline{y}/\partial x$	β	SE	$\partial\overline{y}/\partial x$	β	SE	$\partial\overline{y}/\partial x$
Sex (Male = 1)	-0.00***	0.00	-0.003	-0.00***	0.00	-0.003	-0.01***	0.00	-0.008
Available for working	-0.00***	0.00	-0.004	-0.00***	0.00	-0.004	-0.01***	0.00	-0.008
Years of Experience	-0.00***	0.00	-0.000	-0.00***	0.00	-0.000	-0.00***	0.00	-0.001
Wage expectation (log)	-0.03***	0.00	-0.028	-0.03***	0.00	-0.027			
Wage last job (log)	-0.01***	0.00	-0.006	-0.01***	0.00	-0.006			
Last job duration (log)	-0.00***	0.00	-0.001						
Unemploy. duration (log)	0.00***	0.00	0.001						
Highest educ									
Primary (1-8 years)	-0.02***	0.00	-0.016	-0.02***	0.00	-0.015	-0.02***	0.00	-0.022
Tech. High School	-0.01***	0.00	-0.011	-0.01***	0.00	-0.011	-0.01***	0.00	-0.011
Tech. Tertiary Educ.	-0.02***	0.00	-0.016	-0.02***	0.00	-0.016	-0.02***	0.00	-0.017
College	-0.02***	0.00	-0.023	-0.02***	0.00	-0.023	-0.04***	0.00	-0.036
Graduate	-0.02***	0.00	-0.024	-0.02***	0.00	-0.024	-0.04***	0.00	-0.044
Not declared	-0.03	0.03	-0.027	-0.03	0.03	-0.027	-0.02	0.02	-0.018
Profession/Occup.									
Commerce and Management	0.00***	0.00	0.004	0.00***	0.00	0.004	0.01***	0.00	0.007
Agropecuary	-0.01***	0.00	-0.006	-0.01***	0.00	-0.006	0.00	0.00	0.000
Art and Architecture	0.00***	0.00	0.004	0.00***	0.00	0.004	0.01***	0.00	0.012
Natural Sciences	-0.00	0.00	-0.001	-0.00	0.00	-0.001	0.01***	0.00	0.007
Social Sciences	0.00	0.00	0.000	0.00	0.00	0.000	0.01***	0.00	0.007
Law	0.01***	0.00	0.014	0.01***	0.00	0.014	0.02***	0.00	0.021
Education	0.01***	0.00	0.007	0.01***	0.00	0.007	0.02***	0.00	0.024
Humanities	0.00***	0.00	0.004	0.00***	0.00	0.004	0.01***	0.00	0.013
Health	0.01***	0.00	0.006	0.01***	0.00	0.006	0.02***	0.00	0.017
Non-declared	0.02***	0.00	0.017	0.02***	0.00	0.017	0.03***	0.00	0.032
Other	0.00**	0.00	0.001	0.00**	0.00	0.001	-0.00***	0.00	-0.004
Labor Status									
Contracted	-0.00***	0.00	-0.003	-0.00***	0.00	-0.002	-0.01***	0.00	-0.010
Student	0.00***	0.00	0.003	0.00***	0.00	0.003	0.02***	0.00	0.015
Self-employed	-0.01***	0.00	-0.005	-0.01***	0.00	-0.006	-0.01***	0.00	-0.007
Just graduated	0.00***	0.00	0.003	0.00***	0.00	0.004	0.01***	0.00	0.012
Unemployed	0.00**	0.00	0.001	0.00*	0.00	0.001	0.01***	0.00	0.005
Temporary job	-0.00***	0.00	-0.004	-0.00***	0.00	-0.004	-0.00*	0.00	-0.001
Marital Status									
Married	-0.00***	0.00	-0.003	-0.00***	0.00	-0.003	-0.01***	0.00	-0.008
Partner	-0.00	0.00	-0.001	-0.00	0.00	-0.001	-0.00***	0.00	-0.002
Divorced	-0.00***	0.00	-0.004	-0.00***	0.00	-0.004	-0.01***	0.00	-0.006
Separated	-0.00*	0.00	-0.001	-0.00*	0.00	-0.001	-0.00***	0.00	-0.003
Widow	0.00*	0.00	0.005	0.00*	0.00	0.005	0.01***	0.00	0.007
Constant	0.62***	0.02		0.62***	0.02		0.18***	0.02	
Observations	5348646			5348646			6059709		
Average probability	0.093			0.093			0.096		
R^2	0.307			0.307			0.310		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.. Omitted groups: *Highest educ:* Science-humanity high-school; *Profession/Occupation* Technology. *Labor status:* Other. *Marital status:* Single. In all equations, we control for quarterly dummies to capture seasonality and marital status dummies.

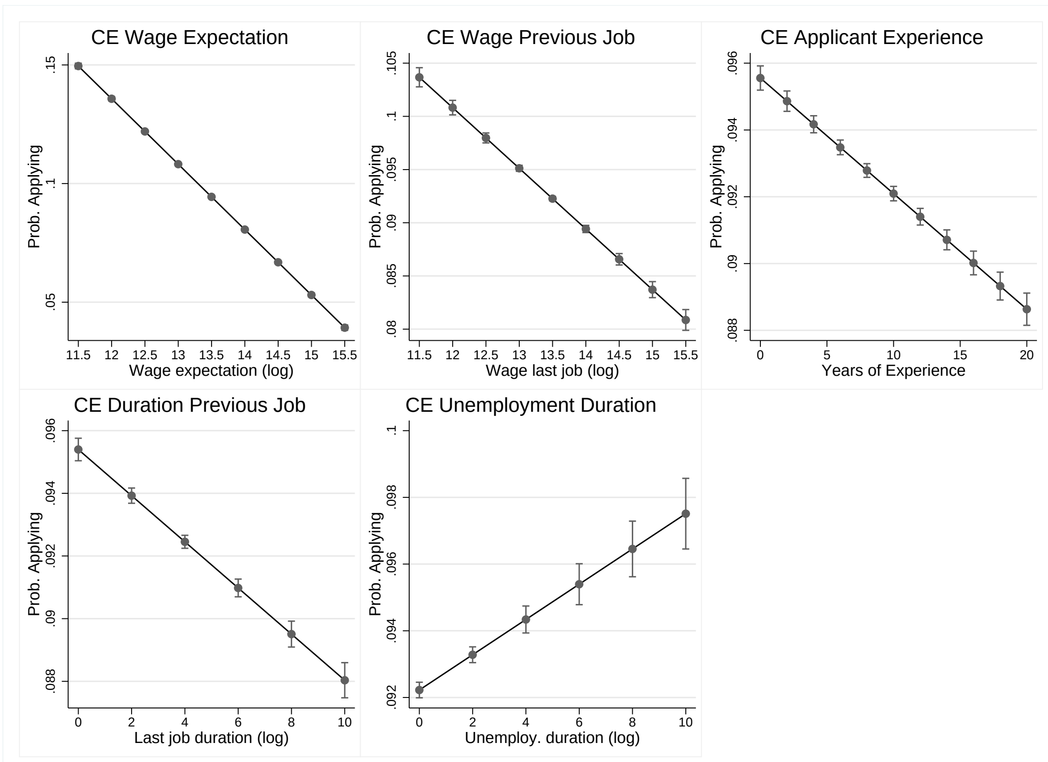

Figure 12: Expected Marginal Effects (EME) on Prob. of Application to Explicit Wage Ad using OLS with Firms Fixed Effect (Table 14, Model 1)

Vertical bars indicate 95% Confidence Intervals.