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DO HIGH-WAGE JOBS ATTRACT MORE APPLICANTS? DIRECTED SEARCH EVIDENCE FROM THE ONLINE LABOR MARKET

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

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Abstract

If workers direct their search to better jobs, the labor market becomes more efficient in theory. We provide novel evidence of directed search for an online job board using data on offered wages, even if employers hide them from applicants. Since explicit-wage ads often target unskilled workers, selection bias affects estimates ignoring hidden-wage ads. We find significant but milder evidence for directed search for hidden (or implicit) wages, suggesting that ad texts and requirements tacitly convey wage information. Moreover, job ad requirements are aligned with their applicants' traits, as predicted in directed search models with heterogeneity.

Keywords: directed search, wage posting, online job board, segmentation.
JEL codes: J64, J22, J42, E24.

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1 Introduction

Nowadays workers routinely search for job ads on websites such as `www.monster.com` in the US, or `www.trabajando.com` in several countries, including Chile and Spain. Applicants consider wages and other features posted in job ads to direct their search effort. On the other side, employers post to attract the appropriate kind and number of applications. Theoretical models of the labor market in the search and matching tradition typically propose a precise way in which workers seek jobs or employers seek and select applicants. With few exceptions, existing models advocate either *random search*, in which wages are determined *ex post* in a bargaining setting and play no role in driving applications, or *directed search*, in which wages do drive applications and impact the probabilities of obtaining positions.

Researchers often pick random or directed search based on analytical convenience and theoretical implications rather than the alignment between theory and evidence. However, characterizing deep underlying behavior matters for prescribing policies in counterfactual scenarios. Since it is often possible to construct models generating similar predictions based on different premises, evaluating competing models based solely on indirect empirical implications is often insufficient.

The prevalence of random or directed search in frictional markets implies different normative policy implications. Job search efforts negatively impact the matching chances of others on the same side of the market, and positively affect the chances of those on the opposite side in a frictional market. In the simplest case with homogeneous agents, Hosios (1990) shows that random search with *ex post* wage bargaining yields inefficient outcomes in the labor market unless the vacancy-elasticity of the matching function equals the firm bargaining power. Workers and employers do not internalize the externalities they generate when bargaining over the surplus in a bilateral monopoly situation.

In contrast, under directed search, applicants apply more to jobs with higher announced wages(Moen 1997) or target the submarket where employers open positions with specific requirements and announce optimally designed take-it-or-leave-it wage schedules (Menzio and Shi 2010; Menzio, Telyukova, and Visschers 2016). In most models, directed search behavior implies constrained efficiency of the labor market allocation.[1] Intuitively, agents internalize congestion externalities by realizing the trade-off between the wage and the likelihood of being hired. Thus, labor market regulations may be welfare-improving under random search, but not under directed search.

[1]An exception is the multiple applications model of Galenianos and Kircher (2009).

The directed search constrained efficiency allocation often carries over to more complex models. For instance, under directed search Moen and Rosén (2004) show that poaching activity does not distort training decisions. In contrast, Acemoglu (1997) finds that training subsidies increase welfare because poaching induces suboptimal training investment under random search. With respect to other policies such as minimum wages and unemployment insurance, several papers show welfare-improving effects under search frictions (Acemoglu and Shimer 2000; Acemoglu 2001; Flinn 2006).

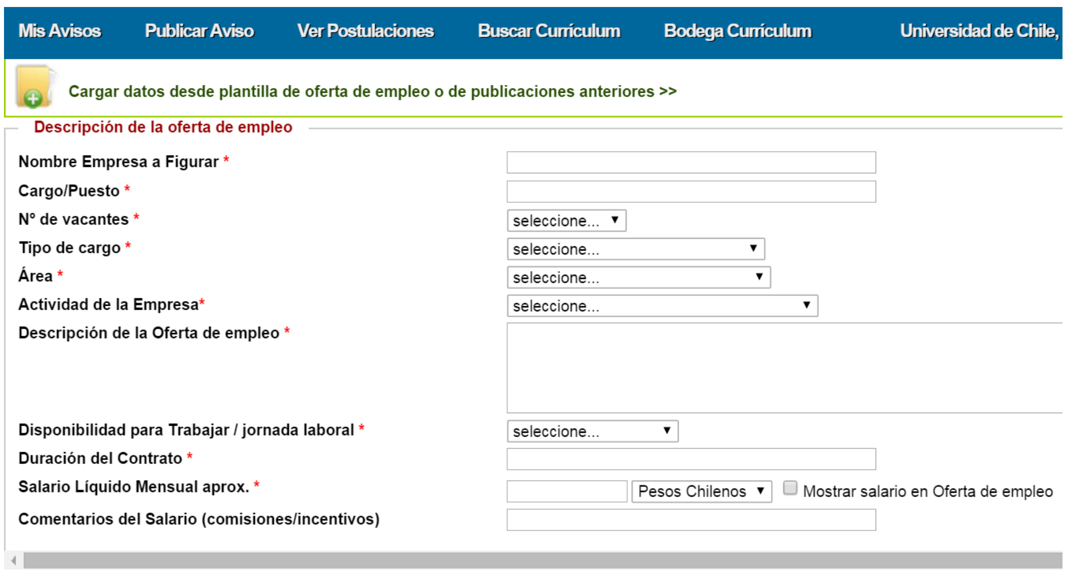
Hence, empirical evidence on the prevailing type of job search behavior should shape policy recommendations. However, finding solid evidence for random or directed search is difficult for at least two reasons. In an ideal experiment for homogeneous jobs, we would clone job ads except for an exogenously modified offered wage and compare application responses. Then, we would estimate the average causal impact of wages in applications received, as in Belot, Kircher, and Muller (2015). Potential problems of this approach are aggregate effects of the intervention and suspicious jobseekers detecting identical ads with different wages. Instead, to test for directed search behavior, we use proprietary data from the Chilean job board `www.trabajando.com`, described in Section 2. The data merge the information of applicants, firms, applications, and job ads in a context of heterogeneous workers and positions.

A second challenge is that most employers do not explicitly post wages, and if they do, the advertised positions are clearly different from those in which wages are not revealed. Surmounting this sample selection issue is important to provide convincing evidence of directed search because job ads with hidden wages are predominant. Such ads account for 86.6% of all job ads in `www.trabajando.com`, 75.2% in `www.monster.com` (Brenčič 2012), 80% in `www.careerbuilder.com` (Marinescu and Wolthoff 2015), and 83% in `www.zhaopin.com`, a Chinese online job board (Kuhn and Shen 2013). In contrast, we investigate the behavior of applicants facing offered wages *even if employers choose not to show them in the job ad*. This is due to the job ad form for prospective employers having a mandatory field of "approximated net monthly wage"[2] (*Salario líquido mensual aproximado* in Spanish) as shown in Figure 1. Next to it, there is a box to make this wage visible to applicants, an option selected for only 13.4% of ads in our sample. In Section 2.5, we show that offered wages are a reliable measure of wages actually paid to hired workers, even if the employer chose

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

to hide them from applicants. To the best of our knowledge, this is a unique feature among databases of this sort that allows us to circumvent a large sample selection problem when estimating the responsiveness of applications to wages.

Figure 1: Standard job ad form



Note: Accessed on May 5th, 2015.

Section 3 shows our results for directed search and wage posting. First, using negative binomial models for count data allowing for under- or over-dispersion (Cameron and Trivedi 2013) and fixed-effects linear regressions, in Section 3.1, we find evidence of directed search in the sense that the number of applications increases in the offered wage, *even if hidden*. This impact is significantly larger for ads in which the wage offer is observable for applicants. Notably, applicants react to hidden wages, probably because they infer them through information in the job ad. Consequently, we interchangeably refer to them as hidden or *implicit* wages. The evidence suggests that directed search prevails for job seekers in the online job board, even if wages are not explicit. We thus interpret implicit wage job ads as noisy signals that attract skilled applicants, perhaps indicating potential *ex post* bargaining, as in the Michelacci and Suarez (2006) model. In addition, we also show that job ads posting low explicit wages receive significantly fewer applications, controlling for job ad features and firm characteristics.

Third, as endogenous segmentation arises in directed search models with heterogeneity on at least one side of the market (e.g. Shi 2002; Menzio, Telyukova, and Visschers 2016), we slice the data in several ways to show that similar workers tend to apply for the same jobs and their qualifications closely meet employers' requirements in Section 3.2. We also show that wages attract applications also within submarkets defined in various ways in Section 3.3. Therefore, the observed behavior of applicants is inconsistent with random search within submarkets, a hypothesis competing with directed search.

Fourth, we show evidence on wage posting behavior, a decision interlinked with applications in Section 3.4. We find that firms are more likely to post a wage explicitly for low-skill jobs. This evidence, on top of the negative impact of explicit wage posting in the number of applicants in Section 3.1, suggests that employers post explicit wages to receive fewer applications. In this way, they avoid large screening costs, especially for simple jobs in which differentiation across suitable candidates barely matters. Posting explicit wages is a strategic decision correlated with factors also affecting offered wages. Hence, studying directed search behavior only through explicitly posted wages leads to biased evidence. In fact, given the empirical estimates obtained in Sections 3.1 and 3.4, we conclude that there is an upward bias in the sensitivity of applications to wages when neglecting the endogenous decision of posting explicit wages.

Section 4 compares our results to those in the literature. While there is some evidence on application positively responding to higher wages in other papers, we are the first showing this effect for employers not posting explicit wages. While the literature showing (often weak) correlations between worker and firm effects in matched employer-employee databases might shed light on the segmentation hypothesis, the same evidence is consistent with random search and selective hiring. Instead, we document jobseekers targeting ads with requirements that fit their characteristics, regardless of the final hiring decision. We also show that our results about wage posting behavior are somewhat consistent with previous work.

Finally, Section 5 summarizes and concludes that applicants noticeably react to information posted (or hidden) in job ads, and employers strategically configure ads to attract or to hinder targeted groups of workers.

2 Data description

Our data covers all job ads posted, all job seekers and all job applications between January 1st, 2008 and June 4th, 2014 for the Chilean job board `www.trabajando.com`. This job board operates several websites, generating multiple simultaneous appearances of job ads, or repetitions of previously posted ads. There are three main databases: the first one has applications and personal data on the applicants; the second one contains employer information, and the third one gathers information on job ads.

Applicants register for free in the website and fill a form to provide demographic information, educational record, previous worker experience, etc. Employers fill the form in Figure 1 and pay[3] USD 116 for a 60-day term posting, as of December 2014. While `www.trabajando.com` keeps records of hidden wages, employers may provide nonsensical information. We keep 6,131,626 applications during the mentioned period, after removing nearly two million cases with unreliable wage information. We discuss data cleaning details in the online appendix (OA) in Section A.1.

Jobseekers can filter job ads by job title keywords, region, posting date, occupation, job ad type, and full/part time arrangement. They can also filter jobs by monthly wage offer level in ranges as narrow as CLP 100,000 (USD 163) for wages below CLP 1,000,000. For wages between CLP 1,000,000 and 3,500,000, jobseekers could filter in ranges of CLP 500,000 at most. Our own user experience in the website and private communications with managers of the job board show that ads with hidden wage are often listed when filtering by wage offer level. However, we have no information regarding the filters jobseekers actually use to find postings. Since users are not required to login for seeing job offers, `www.trabajando.com` does not register these behaviors.

2.1 Applicants

Individuals are identified in the database by unique combinations of years of experience, date of birth, date of entry of the resume, sex, nationality, and profession. Only nine duplicated cases are dropped.

We are considering only people ranging from 18 to 69 years old with less than 20 years of experience (longer experiences are suspected to be typing errors). We also discard individuals reporting monthly net wages higher than 5 million pesos in their previous work (9,745 USD per month[4], which is well above the 99th percentile according to CASEN 2011, a Chilean household survey akin to the March CPS). We also exclude individuals with monthly wage expectations over 5 million pesos, and those who omit an expected figure in the ap-

[3] The price was CLP 59,900 + 19% of value added tax. Current terms are located at `http://www1.trabajando.cl/empresas/noticia.cfm?noticiaid=3877`. The cost in dollars is computed using the December 2014 average CLP/USD spot exchange rate.

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

plication form (as econometricians, we observe this expectation even if applicants choose to hide it from employers). Excluding these cases, we get 463,495 applicants. Descriptive statistics are in Tables 1 and 2. For more details, see our online appendix (OA) in Section A.1.

The sample is young (30 years old on average) and mostly single. More than 60% of the applicants are in the Metropolitan Region of Santiago. The sample shows a high educational level, so they are likely paid above the legal minimum wage (approximately 377 USD per month). About 42% of the sample has some kind of college education, and 27% of applicants have a technical tertiary degree. We estimate the years of schooling according to the highest educational level achieved (8 years primary, 4 years of high school, 5 years of college, or 4 years for technical tertiary degrees). The average schooling is 15 years, being similar for males and females. 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 sample, most individuals have few years of work experience. On average, individuals possess 6.5 years of experience, with males slightly more experienced. The years of inactivity is estimated as inactivity = age – schooling – experience – 6, which assumes that school starts at age six.[5] Computed inactive time is similar for males and females. A large proportion of the sample are self-reported as unemployed (47.74%), who are more likely to be females. The rest of applicants are on-the-job searchers.

The gender gap in wages paid in the previous job is nearly 44%. A similar difference is obtained in wages expected by the applicants. Applicants expect to be better off from a job change: expected wages for the next job are 3.9% higher than their last or current job. Applicants' wage expectations tend to be private: less than half of the sample chooses to display their wage expectations to be observed by employers.

2.2 Employers

Our sample has 6,386 different firms. In the first two panels of Table 3, we classify firms according to standard industry classifications (CIIU) and their self-reported interval of number of employees. A sizable set of firms have less than 50 employees, but this figure is affected by *recruiting firms* that offer their services to contact and select potential applicants for their clients. We consider a recruiting firm as one posting a number of vacancies exceeding half

[5]This number may be an overestimation because completing a college degree often takes more time than the theoretical years for completing coursework in the Chilean educational system.

Table 1: Applicant 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: Applicant 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

of the upper limit of its reported interval of employees in a given month.[6] Larger firms post more ads and vacancies per month, but do not receive more applicants per ad or vacancy posted. Focusing on industry, we show that a majority of firms are in retail, communications, services, or manufacturing. The posting frequency of ads and vacancies substantially varies across industries, with the highest values in primary sectors (agriculture, fishing, and mining) and the lowest in construction and services. However, job seekers apply more for industries that post less ads or vacancies, such as household services, personal services, and public administration.

The last two panels of Table 3 classify firms according to the level of average offered wages (explicit or not) and the proportion of their ads posting wages explicitly. Most firms post ads that offer between CLP 300,000 - 1,000,000 (580 - 1937 USD) and very few of them post ads offering very low or very high wages. The monthly number of ads varies little with the average wage offered, but firms offering medium-low wages post ads with more vacancies. The number of applicants each firm receives per vacancy is clearly increasing in the average wage offered by the firm. The data also shows that most firms never post an explicit wage (labeled as 0%), and that a small but noticeable group always post explicitly (labeled as 100%). A remaining part of the sample mix the two strategies. Firms mixing explicit and implicit wage posting post more ads and vacancies on average. However, firms that stick to pure explicit or implicit strategies receive many more applicants than their mixing counterparts.

2.3 Job Ads

Job ads have requirements for applicants, a number of open positions (vacancies), and an estimated offered wage, potentially hidden by the employer. Descriptive statistics for job ads are shown in Tables 4, 5, and A2 (OA). Our sample excludes job with (i) an estimated offered monthly wage below CLP 100,000 and over CLP 5,000,000 (USD 194-9,745 approximately); (ii) missing or unreliable information for offered wages (explicit or hidden); and (iii) a requirement of experience over 20 years, or a missing experience request. After

[6]For instance, if a firm in the range of 11-50 employees posts more than 25 vacancies, we classify it as a recruiting one.The intervals are 1-10, 11-50, 51-150, 151-300, 301-500, 501-1000, 1001-5000, +5000 employees. Dealing with this concern was motivated by informal conversations with managers of `www.trabajando.com` who claim these firms exist and are frequent users (clients) of their job search engine. Even though our definition is admittedly *adhoc* and it is not immune to potential misclassification, our results are barely changed by this issue, as we show below.

Table 3: Firm characteristics

	Monthly Ads	Montly Vacs	Monthly Apps	Vacs/Ad	Apps/Ad	Apps/Vac
Size (# employees)						
1-10 (N=1522)	1.5	7.5	20.3	3.6	21.4	16.5
11-50 (N=1751)	1.3	5.3	18.6	3.3	19.2	14.7
51-300 (N=583)	1.5	8.6	15.1	3.8	15.4	11.7
301-1000 (N=600)	3.2	15.6	13.0	3.6	13.1	9.9
>1000 (N=248)	2.2	9.3	18.5	3.2	18.2	14.2
NA (N=191)	1.9	8.6	21.6	3.8	21.4	14.4
Industry						
Agriculture (N=271)	5.3	32.5	16.2	2.0	17.5	16.1
Fishing (N=34)	5.8	29.3	11.4	1.9	12.5	12.2
Mining (N=231)	2.4	7.0	11.4	2.3	11.1	8.7
Manufacturing (N=981)	1.7	7.7	13.1	3.0	13.1	10.9
Elect, water, gas (N=151)	1.9	6.1	14.5	2.6	14.3	12.2
Construction (N=261)	1.0	2.1	20.7	2.1	20.7	17.1
Commerce (N=1120)	1.3	5.9	20.2	4.1	21.0	15.2
Rest. & Hotel (N=221)	1.3	6.7	33.9	4.4	34.1	16.0
Transportation (N=164)	1.4	5.0	22.0	3.3	21.4	16.1
Communication (N=589)	1.2	9.7	13.0	5.1	13.7	9.0
Financial Serv. (N=219)	1.6	6.0	18.7	4.1	19.7	13.0
Business Serv. (N=533)	1.0	4.3	21.5	4.0	23.1	17.7
Household Serv. (N=134)	0.9	1.3	32.1	1.5	35.0	29.8
Personal Serv. (N=629)	1.1	4.0	26.2	3.4	26.1	20.1
Public Admin. (N=71)	1.7	12.0	35.0	5.3	32.9	27.9
Other (N=777)	2.5	11.3	11.8	3.7	11.5	9.4
Avg. offered wage						
TCLP 100-150 (N=54)	1.2	4.5	15.7	4.5	16.6	9.9
TCLP 150-300 (N=685)	1.8	16.6	20.9	8.8	21.6	9.1
TCLP 300-600 (N=2630)	1.8	10.2	15.5	3.6	15.8	11.8
TCLP 600-1,000 (N=1937)	1.5	4.0	17.0	2.2	17.9	14.7
TCLP 1,000-1,500 (N=757)	1.9	4.8	21.2	2.4	21.1	17.9
TCLP 1,500-2,500 (N=268)	1.2	3.4	33.2	2.7	33.1	28.7
TCLP >2,500 (N=55)	1.1	2.2	58.8	2.0	56.5	53.8
% Explicit wage ads						
0% explicit (N=4311)	1.2	4.0	22.3	3.4	22.7	17.4
$(0\%, 10\%]$ explicit (N=437)	5.5	22.1	1.8	2.6	1.1	0.7
$(10\%, 50\%]$ explicit (N=721)	3.0	20.8	3.1	4.0	3.9	2.4
$(50\%, 100\%)$ explicit (N=366)	1.8	16.4	7.8	3.9	10.5	7.4
100% explicit (N=551)	1.0	5.5	27.7	4.8	27.0	19.5
Whole sample (Avg)	1.7	8.0	18.3	3.6	18.8	14.2
Whole sample (Sd)	(23.31)	(11.56)	(40.27)	(26.85)	(43.36)	(39.15)
Observations	6386	6386	6386	6386	6386	6386

Note: Wages in thousands of Chilean pesos (TCLP).

cleaning, 184,920 job ads remained in our sample, some of them with missing fields.

In the online labor market data, only 13.4% of job ads post wages explicitly. In Table 4 we see that most job ads require little labor experience, which is even more noticeable for jobs with explicit wages. The mean and standard deviation of explicit wages is 40% lower than of implicit ones. Job ads with explicit wages tend to require no specific profession or occupation, low experience, and high-school education. In other words, jobs with explicit wages are aimed to low skilled workers.

Explicit-wage ads concentrate in retail, communications, and services, as shown in Table 5. Implicit-wage ads receive substantially more applicants on average than explicit-wage ones. The average number of applications per ad is 34.8, with a large dispersion. Employers seem to exert relatively less effort to advertise explicit-wage jobs since nearly 80% of job ads appear only once among the different websites powered and maintained by `www.trabajando.com`. Moreover, fixed-term contracts and non-full-time jobs are slightly more frequent among ads posting explicit wages. Table A2 in the OA, Section A.2, provides additional statistics about job ads.

2.4 Job Ad Titles

The job title itself may convey relevant information on the set of tasks that a worker would undertake once hired, the hierarchy in the organization, relevant qualifications, etc. Marinescu and Wolthoff (2015) use job titles from `www.careerbuilder.com` data to assess their predictive power on the 20% of job ads that post an explicit wage in their sample. In the same fashion, we use job titles (in Spanish) of ads posted in `www.trabajando.com`.

Our approach to extract information from 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 denoted as *Other*. For the whole sample of job ads, the first word was catalogued as *Other* only in the 7.04% of ad titles. 17.22%, 27.33% and 12.68% of job ads were categorized into the *Other* group for the second, third, and fourth words, respectively.

Since most words in Spanish are not gender neutral, we consider male and female words

Table 4: Job Ads Characteristics (I)

	Explicit wage	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
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)
Observations	24867	160053	184920

Note: Fixed-term ads announce explicit time frame for the job. Undefined-term jobs post no finishing date. These are legal distinctions in the Chilean labor law.

Table 5: Job Ads Characteristics (II)

	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
Applications per ad (%)			
0	14.44	14.94	14.87
1 - 2	10.91	6.62	7.20
3 - 5	12.16	7.96	8.53
6 - 10	13.83	10.66	11.09
11 - 20	16.23	15.36	15.48
21 - 30	9.15	10.36	10.20
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	0.08	0.15	0.14
Applications per ad (Avg/S.D.)	25.3	36.3	34.8
	(49.68)	(64.52)	(62.84)
Applications per vacancy (Avg/S.D.)	15.8	27.9	26.2
	(34.05)	(54.16)	(52.07)
Ad 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
Ad appearances (Avg/S.D.)	3.31	3.12	3.15
	(10.49)	(12.48)	(12.24)
Observations	24867	160053	184920

as the same. This entails some loss of information since the employer could succinctly define a desired gender for the applicant, a feature employed in the literature (Kuhn and Shen 2013). In Figures A1 and A2 in the Section A.3 of the OA, 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 ad titles are used as dummy controls in the estimations in the models specified in Tables 7 and 11 in the main text, and A3 - A6, A8 - A11 in the OA.

2.5 Reliability of Implicit Wages

Are employers reliably reporting offered wages when they are choosing not to show them to applicants? The first reason for employers caring about reporting is that the job board allows jobseekers to filter by wage ranges, even for implicit wages. Therefore, posting nonsensical information is potentially detrimental for the employer. On top of this, in this section, we try to assess how reliable implicit wages are assuming that explicit wages are truthfully reported. We proceed as follows:

First, we estimate a predictive equation for log wages for explicit-wage and implicit-wage job ads, separately. The baseline explanatory variables are job ad title word, regional, and time binary variables. In augmented models, we incorporate additional regressors in steps, such as experience, education, and major requirements in job ads. The first two columns of Table 6 reports the R^2 statistics obtained from regressions of log wages for explicit-wage job ads. Implicit-wage job ads results are in the third and fourth columns. In the upper panel, we report that observed characteristics explain 62.2% of the variance of explicit log wages and 57.7% for implicit log wages. As we incorporate more variables, the explained share of variance increases to 72.3% and 67.8% for explicit and implicit log wages, respectively.

Second, we use the explicit-wage equation to predict wages for implicit-wage job ads in the lower panel of Table 6. We compute a squared correlation coefficient (cross-equation R^2) between the actual implicit wages and their corresponding predictions coming from the explicit-wage equation. This is a measure of goodness-of-fit of the out-of-sample prediction.

Third, we compare the R^2 of the implicit-wage equation with the cross-equation R^2 for the same implicit wages. The former, the standard R^2, is a natural upper limit for the explanatory power that another equation could achieve for implicit wages. Indeed, the ratio between the two in the more complete model is 0.626/0.678 = 92.3%. This exercise shows that implicit wages are very well-predicted by an equation constructed only from explicit-wage job ads, as hypothesized to some extent by Marinescu and Wolthoff (2015). This is suggestive evidence that leads us to conclude that hidden wages are generally truthfully declared because employers posting a job ad of a fixed set of characteristics post substantially similar wages regardless of the explicitness of the wage.

Table 6: Predictive power of job ad features on log wages

		Explicit wage		Implicit wage	
		R^2	N	R^2	N
Regression	title, region, time	0.622	24867	0.577	160053
	+ exper	0.668	24867	0.625	160053
	+ educ	0.711	24867	0.670	160053
	+ major	0.723	24867	0.678	160053
Cross	title, region, time			0.502	160053
Prediction	+ exper			0.563	160053
	+ educ			0.620	160053
	+ major			0.626	160053

3 Empirical Results

In this section, we test several relevant predictions. First, job ads posting higher wages or benefits attract more applicants (Moen 1997). Second, job ads offer wages or benefits to attract specific groups of workers, who optimally choose to apply to them, i.e. there is endogenous segmentation in heterogeneous labor markets (Menzio and Shi 2010; Menzio, Telyukova, and Visschers 2016). Third, we test if directed search prevails within labor market segments in order to rule out random search within segments. Finally, given the distinctive behavior of workers towards explicit- and implicit-wage job ads, we examine the major factors behind employer wage posting, an issue tightly related to directed search.

In the literature, typically random or directed search are assumed in contexts of *ex ante* homogeneous jobs. We extend this rationale to a multidimensional setting, considering jobs as bundles of attributes that may attract or deter applications. If directed search prevails, applicants should react to characteristics of job ads, especially to explicit or implicit wages. Considering the wealth of information available in an online job board, an extreme version of random search in which no job ad features impact application decisions is hardly tenable.

3.1 Do applications increase in wages?

In a setting of homogeneous jobs, as in Moen (1997), we ideally want to test if workers apply more to high-wage jobs which are otherwise identical. To isolate the true effect of increasing wages on a particular job ad, we control for a large set of variables related to wages including education, experience, major, job titles, and even firm fixed effects. Since we observe all offered wages, we circumvent the sample selection issue of hidden offered wages so prevalent in online job boards.

We use a count model since the dependent variable takes non-negative integer values. A Poisson model imposes that the conditional expectation of the dependent variables equals the conditional variance. Thus, we opt for a Negative Binomial (NB) model that relaxes this constraint, allowing for either under- or over-dispersion (Cameron and Trivedi 2013). In Table 7 we also allow for firm-level unobserved heterogeneity arbitrarily correlated with observables by using a linear model and firm-fixed effects. These estimates allow us to disentangle the role of wages as drivers of applications from other job features. We also circumvent the potential selection bias by estimating our equations using data on hidden or implicit wages, We only present a subset of estimates here. Full results are in Tables A3 and A4 in the OA, Section A.4.

The first three columns of Table 7 show the NB estimates (β), the estimated standard errors, and the average marginal elasticity ($\eta = \partial\mathbb{E}[\log A|X]/\partial \log z$) of the number of applications, A, with respect to a variable z if considered continuous (offered log wage, ad appearances, number of vacancies, etc), or the expected log point change of the dependent variable ($\eta = \mathbb{E}[\log y|X, z = 1] - \mathbb{E}[\log y|X, z = 0]$), if z is binary (explicit wage, educational status, etc.) Figure 2 depicts the conditional expectations of the number of applications implied by the NB model as a function of offered log wages, number of vacancies in the ad, and the level of required experience. We also plot referential lines showing quantiles of the latter variables.

Job ads with an explicitly posted wage receive significantly fewer applications. The point estimate suggests a mean marginal effect of 13.2% less applications when a job ad is explicit. The first panel of Figure 2 shows that the effect is stronger for lower wages and much smaller at the 75th percentile. For higher wages, the pattern is reversed.

The offered wage has both a statistically and economically important effect: increasing log wage by 1% increases the number of applicants by 0.1% if wages are implicit. Although the explicit wage effect (0.224) is larger than the implicit one (0.076), both kinds of wages have a highly significant positive effect on applicant behavior. The combination of these findings is clear in Figure 2 showing that the conditional expectation of applications of explicit and implicit wages cross each other.

How do we interpret the explicit-implicit wage-elasticity gap? Because higher implicit wages attract more applications in spite of being hidden, our results could be interpreted as applicants inferring wages from the text, requirements of the job ad, and potentially the job ad filter in the website. The evidence is consistent with a signal extraction process over the text of the job ad, coupled with directed search. The milder yet sizable response of applications to implicit wages is coherent with the job ad conveying noisy information regarding the wage. However, the evidence is also compatible with higher reporting error in implicit offered wages. A mixture of both explanations is also possible.

In line with these interpretations, the exercise in Table 6 shows that key words in the job title and other information regarding education, experience, and other requirements explain a sizable share of the variance, although lower than found in other online job boards (Marinescu and Wolthoff 2015). In addition, our prediction of implicit wages using an explicit-wage "pricing" equation entails a notable accuracy loss. This is consistent with either noisy-signal posting as well as larger measurement error in implicit-wage job ads.

Theoretical models explaining explicit wage posting link hidden wages with *ex post* bargaining (Ellingsen and Rosén 2003; Michelacci and Suarez 2006). Directed search and committed take-it-or-leave-it offers (i.e. competitive search) are also key ingredients in many theoretical models for delivering efficient competitive equilibrium in labor markets. However, we observe that higher implicit wages attract more applicants, something we should not expect if there is random search and *ex post* bargaining. Thus, directed search is empirically relevant even in cases where we may expect *ex post* wage bargaining.

How do we explain that low explicit-wage jobs attract fewer applicants? It may be challenging to rationalize that rare low implicit wage job ads receive more applications than do their abundant low explicit wage counterparts, as depicted in Figure 2. While we do not pretend to give a definitive answer, we consider as the most likely explanation that explicit or implicit wage-posting is a way to induce self-selection of applicants to obtain a smaller pool of candidates who better fit the profile the employer wants. At the infancy of online job boards, Autor (2001) stated that "*excess applications* appears to be the norm for online job postings". Online marketplaces such as oDesk (now `www.upwork.com`) or Amazon Mechanical Turk, and even the academic job market for junior economists, suffer from congestion problems typically considered by scholars in market design (Roth and Sotomayor 1992; Niederle and Roth 2009). Due to low marginal costs of application, job seekers may apply for positions that they are not well suited for and generate potentially large screening costs for employers.

The rationales behind strategies for reducing applicants may differ by worker type. For jobs requiring low skills, employers would like to discourage too many applications because any worker may be a close substitute for another. A small pool of candidates is often enough. For complex jobs, a strategy rendering fewer but fitted applications is reasonable because sending an application on a job board is cheap, but screening one is quite costly. Previous research documents that employers devote considerable resources to recruiting activities (Barron, Bishop, and Dunkelberg 1985; Oyer and Schaefer 2011; Muehlemann and Pfeifer 2016).

Moreover, employers may want to avoid receiving too many applicants because the quality of hirings may decrease, as in some theoretical models (Seabright and Sen 2014). In line with this conjecture, Chandler, Horton, and Johari (2015) report an experiment using the oDesk platform, in which they randomly impose questions for workers to apply for jobs, raising their application costs. Treated job ads received fewer but more qualified applicants, so that the overall number of matches remains invariant.

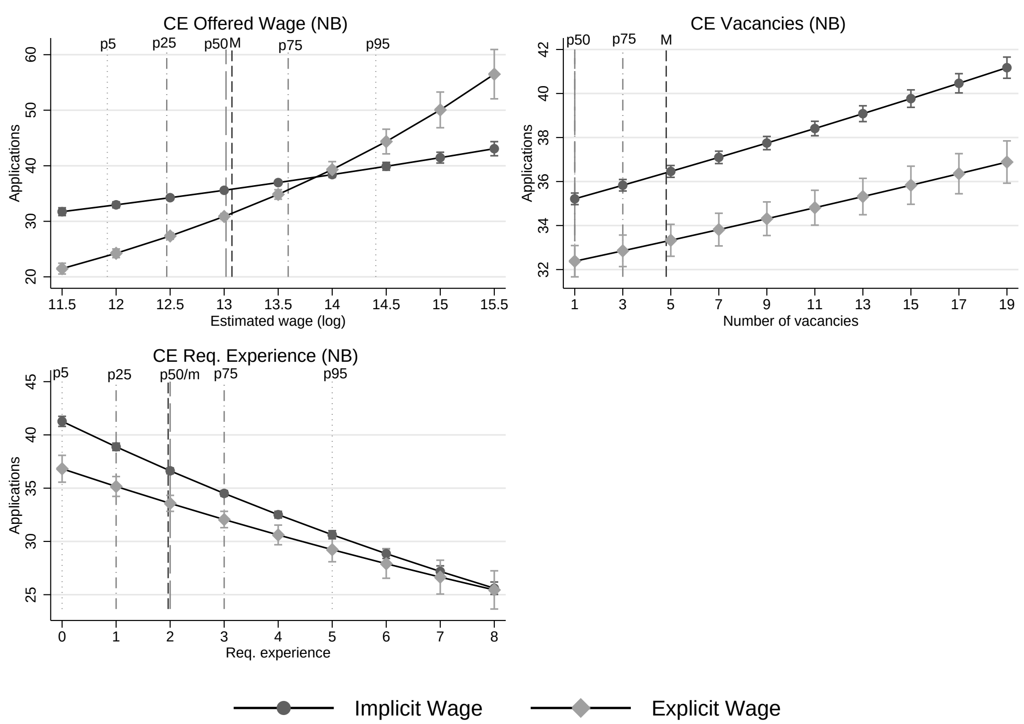
How do we interpret findings on vacancies, ad appearances, and other ad traits? The number of vacancies mentioned in the job ad marginally increases the number of applications received, but the magnitude of the effect suggests important decreasing returns to scale in the recruiting technology. The elasticity implied in the NB model is significantly lower than one. We interpret this finding as evidence of simultaneous search, that is, the existence of a selection process of applicants (van Ours and Ridder 1992; Villena-Roldan 2012). When engaged in sequential search, employers use a reservation productivity optimal strategy that implies that vacancies and applicants are proportional. Instead, under non-sequential or simultaneous search, the impact of more available vacancies increases applications less than proportionally, as noticed in 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 by a particular posting, probably due to 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 pool of applicants. The higher the educational level requested, the higher the number of applications received. Since college workers are a majority of the applicants in the job board, it is likely that they apply to job ads requiring college degrees, as we show in the next Section 3.2.

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. Commission and temporary replacement jobs receive fewer applications than full-time, while part-time and internships receive significantly more. There are also a wealth of results concerning computer knowledge, industries, and specific occupations posted in job ads, but these presented in the OA, Section A.4. In addition, the NB model shows over-dispersion, i.e. the conditional variance surpasses the conditional expectation of applications.

Figure 2: Conditional expectations of applications by explicitness of wage (Table 7, NB Model)



Note: Effects computed from model *without* controlling for recruiting firms. Vertical bars surrounding circles indicate 95% confidence intervals. Vertical lines labeled p5, p25, p50, p75, p95 stand for the corresponding wage distribution percentiles. The vertical line labeled M denotes the mean of the wage distribution.

Are these results robust? In the second column of Table 7 we show the estimates of a linear regression (OLS) in which the dependent variable is $log(1+$ number applications). This is done mostly for comparison with a well-known estimation method, even though the

Table 7: Models explaining the number of received applications

	Negative Binomial			OLS			OLS, Firm FE		
	β	SE	η	β	SE	η	β	SE	η
Explicit wage	-2.312***	0.187	-0.132	-1.818***	0.176	-0.148	-2.184***	0.175	-0.038
Ad appearances	-0.033***	0.001	-0.103	-0.009***	0.000	-0.028	-0.008***	0.000	-0.025
Number of vacancies	0.009***	0.000	0.040	0.005***	0.000	0.021	0.005***	0.000	0.023
Req. experience	-0.060***	0.002	-0.115	-0.047***	0.002	-0.089	-0.047***	0.002	-0.092
log wage	0.076***	0.006	0.099	0.085***	0.006	0.102	0.060***	0.006	0.082
Explicit $\times$ Num. of vac.	-0.001***	0.001		-0.001	0.000		-0.001	0.000	
Explicit $\times$ Req. experience	0.013**	0.006		0.014**	0.006		-0.001	0.006	
Explicit $\times$ log wage	0.165***	0.015		0.126***	0.014		0.164***	0.014	
Days ad available	0.004***	0.000		0.003***	0.000		0.002***	0.000	
log wage - Implicit			0.076			0.085			0.060
log wage - Explicit			0.224			0.209			0.226
Highest educ									
Primary (1-8 years)	-0.326***	0.028	-0.326	-0.220***	0.026	-0.220	-0.297***	0.027	-0.297
Tech. High School	-0.010	0.011	-0.010	0.049***	0.010	0.049	0.019*	0.010	0.019
Tech. Tertiary Educ.	0.068***	0.011	0.068	0.136***	0.011	0.136	0.083***	0.011	0.083
College	0.180***	0.013	0.180	0.202***	0.012	0.202	0.159***	0.013	0.159
Graduate	-0.103***	0.039	-0.103	-0.083**	0.037	-0.083	-0.022	0.036	-0.022
Professional Area									
Commerce and Management	0.047***	0.010	0.047	0.069***	0.009	0.069	0.039***	0.009	0.039
Agropecuary	0.556***	0.043	0.556	0.529***	0.040	0.529	0.474***	0.040	0.474
Art and Architecture	0.312***	0.030	0.312	0.233***	0.029	0.233	0.239***	0.029	0.239
Natural Sciences	-0.165***	0.033	-0.165	-0.113***	0.031	-0.113	-0.174***	0.031	-0.174
Social Sciences	0.104***	0.023	0.104	0.053**	0.023	0.053	0.003	0.022	0.003
Law	0.320***	0.060	0.320	0.352***	0.058	0.352	0.395***	0.057	0.395
Education	-0.016	0.036	-0.016	-0.021	0.033	-0.021	-0.069**	0.033	-0.069
Humanities	-0.271***	0.053	-0.271	-0.317***	0.053	-0.317	-0.268***	0.055	-0.268
Health	-0.423***	0.031	-0.423	-0.429***	0.027	-0.429	-0.441***	0.027	-0.441
Non-declared	-0.231***	0.009	-0.231	-0.185***	0.008	-0.185	-0.185***	0.009	-0.185
Other	0.493***	0.062	0.493	0.271***	0.054	0.271	0.222***	0.057	0.222
Legal contract type									
Fixed-term	-0.211***	0.012	-0.211	-0.195***	0.011	-0.195	-0.113***	0.011	-0.113
Undefined term	0.034***	0.010	0.034	0.096***	0.009	0.096	0.074***	0.010	0.074
Availability									
Commission-earner	-0.519***	0.034	-0.519	-0.524***	0.033	-0.524	-0.299***	0.034	-0.299
Half time	0.026	0.021	0.026	-0.013	0.020	-0.013	-0.017	0.020	-0.017
Part-time	0.259***	0.021	0.259	0.123***	0.019	0.123	0.128***	0.019	0.128
Shift-work	0.007	0.011	0.007	-0.033***	0.010	-0.033	-0.055***	0.010	-0.055
Internship	0.448***	0.030	0.448	0.271***	0.025	0.271	0.361***	0.027	0.361
Replacement	-0.262***	0.038	-0.262	-0.154***	0.035	-0.154	-0.253***	0.033	-0.253
Observations	184,920			184,920			184,920		
Estimated avg. applications	35.45			2.59			2.59		
pseudo - R^2	0.089								
R^2				0.542			0.611		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.. Selected coefficients of models *without* controlling for recruiting firms. Tables A3 and A4 in the OA, Section A.4, show full specifications. Omitted or reference groups: *Highest educ:* Science-humanity high-school; *Contract law* Other. *Availabilty:* Full-time. *Computer knowledge level:* None. In all 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.

discrete nature of the dependent variable is not considered. While estimates of β cannot be directly compared between NB and OLS, the η coefficients can. Results are virtually unchanged.

A potential setback for our NB and OLS results is that workers often have idiosyncratic preferences for different firms. Hence, applicants could direct their search to a particular firm if they can figure out the employer's identity. Sometimes this information is conveyed explicitly in the ads. For example, workers may have preferences for particular firms due to potential colleagues, known fringe benefits, status, location, organizational climate, and other features which are unobservable by 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 a linear regression with firm fixed-effects in the third column of Table 7.[7]

We see no important differences between estimates of η effects in the three models of Table 7. These findings suggest that either (i) variables which are observable for us contain enough information for applicants to direct their job searches, so that firm identities are mostly redundant data; or (ii) applicants cannot generally recognize which firm they are applying to, because most job ads present generic descriptions without mentioning specific firms.

For the sake of completeness, in the OA (Section A.4, Tables A5 and A6), we also provide estimates for a model including job ads posted by recruiting firms. Evidence shows that recruiting firms received fewer applicants, and that the rest of conclusions remain unaltered.

Finally, we take into account the potential effect of the search filter of `www.trabajando.com`. As explained before in Section 2, jobseekers could filter implicit-wage ads in brackets of CLP 100,000 for wages below CLP 1,000,000, and brackets of CLP 500,000 for wages above that level. Therefore, jobseekers using this filter to target ads offering more than CLP 1,000,000 face much more uncertainty about the actual wage offer. Thus, we define a filter binary variable for wages above CLP 1,000,000 and include it in NB, OLS, and OLS-FE models, as well as interactions of filter with log wage, explicit dummy, and explicit $\times$ log wage. Hence, we capture application responses to the discontinuity in the quality of infor-

[7]Estimating a maximum likelihood (ML) negative binomial model including firm fixed effects would be theoretically unappealing and numerically challenging. There is no general procedure for estimating nonlinear models conditional on fixed effects. The straightforward extension of including a large set of dummy variables in a nonlinear model generates an unconditional fixed effect model with poor statistical properties (Wooldridge 2010).

mation. In the Figure A6, Section A.4 of the OA, we depict the conditional expectations of applications received once we introduce the aforementioned regressors. Other than moderately widening the confidence intervals, our results do not change significantly. Thus, implicit-wage ads still attract applications when the wage uncertainty is significantly higher. This is consistent with jobseekers inferring implicit wages from contextual information of the ad.

3.2 Are workers applying to the "right" jobs (submarkets, segments)?

In directed search models with heterogeneity, applicants direct their search effort to a particular submarket where employers are posting offers to specifically attract them (Shi 2002; Menzio, Telyukova, and Visschers 2016). Thus, the directed search mechanism generates endogenous segmentation of the labor market. We assess the relevance of this prediction in two complementary ways.

First, we ask if job ad requirements or characteristics, such as experience and schooling, are correlated with the corresponding average attributes of the received applications. In the upper-left panel of Figure 3, we fit a Local Polynomial Regression (LPR) between the required experience in the job ad and the average experience of the applicants to such job ad. To assess the strength of the relation, we compute a 99% horizontal confidence interval for the LPR showing that the average pool of candidates applying to jobs of a given level of required experience shows little variance. We interpret this as evidence of workers directing their applications to job ads requiring the experience level they possess.

A similar segmentation phenomenon appears when we look at applications to job ads according their required educational level. On the vertical axis of the upper-right panel of Figure 3, we have ordered levels of educational requirements (Primary (P), Scientific-Humanistic High School (HS), Technical High School (T1), Technical Tertiary (T2), College (C), Graduate(G)), and conventionally attach values 1 to P, 2 to HS, and so on.[8] Then, we fit a LPR correlating the education requirement for a job and the average imputed schooling years[9] of the applicants to such job ad. For job ads requiring high school (HS or T1), there is no clear relation between years of schooling and requirements. 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 in educational level across job ads requiring these

[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 college education) or technical.

[9]Described in Section 2.1.

low levels of education. Therefore, the educational requirement does not segment the market in this particular subset of applicants (nearly 30% in Table 2). For higher levels of schooling requirements, workers tend to apply for jobs that nearly match their own educational attainment. To understand the upper portion of the panel, note that we impute 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.

The three remaining panels of Figure 3 show LPR models between log wages (implicit, explicit, and both) and the average log expected wage of individuals applying for those jobs. We observe a clear positive correlation. 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 horizontal 99% confidence interval has a similar width for different levels, showing a constant degree of variation in average log expected wages of applicants around the log offered wage of the employer. We interpret this as evidence of directed search because applicants tend to apply for jobs that intend to pay them relatively closely to what they expect. This constitutes evidence of a precise signal extraction because the applicants accurately interpret features of the job ad, and make applications based on this information.

In the case of explicit wages, the picture shows a 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 less variance of average expected log wages across job ads. We interpret this as employers posting more precise signals of wages when choosing to be explicit. However, explicit wage posting for high-wage jobs seem to attract small pools of applicants, enlarging confidence intervals.

Table 8 portrays a matrix of the major educational areas of applicants. On the vertical axis, there are educational majors required by job ads, while the horizontal axis lists the educational major possessed by applicants. At each entry, the table displays the share of applicants with a particular educational major who apply for jobs requiring a specific educational major. Since the main diagonal of the matrix shows high percentages, applicants tend to apply more for jobs explicitly matching their own major. In jobs requiring law, health, and social sciences majors, more than 60% of the applicants have the exact kind of major required by the employer. There is some dispersion across applicant majors for every spe-

Figure 3: Correlations between job ad requirements and average applicant characteristics

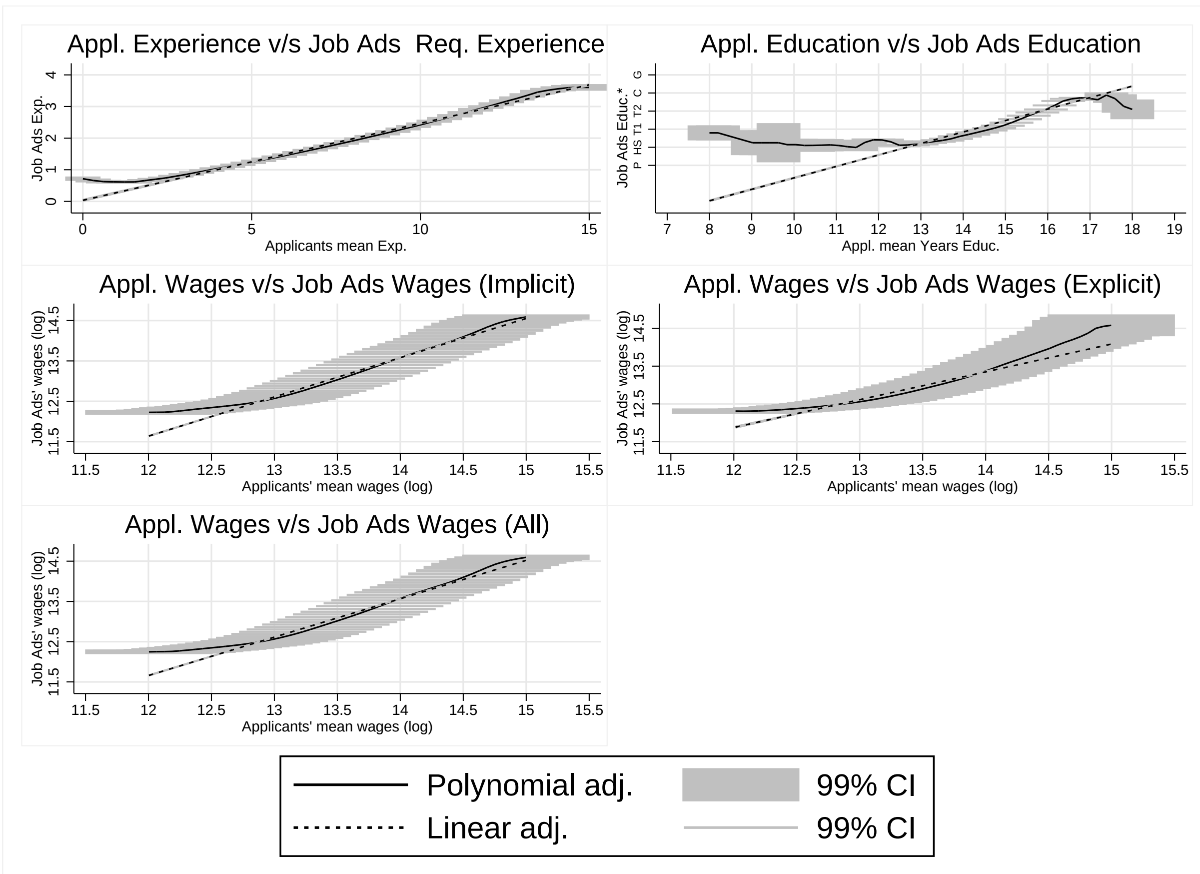


Table 8: Educational area of applicants vs educational area required by job ads

Job Ads Requirements		Applicants Mean Distribution											
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(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 9: Educational level of applicants vs educational level required by job ads

Job Ads Req.		Applicants Mean Distribution					
		(1)	(2)	(3)	(4)	(5)	(6)
	(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**

cific requirement, but in all cases the mode is applying for a job with the same requirement that the applicant possesses. A similar pattern is shown by Table 9 regarding education level. Jobseekers modal decision is to apply to jobs requiring the same education level they have. The only exception is that many jobseekers with graduate level apply for jobs that only require undergraduate level. This could be explained by the scarcity of jobs requiring graduate education level.

Jobseekers apply for job ads receiving applications coming from individuals similar to them. Applicants nearly meet employer requirements in terms of wage expectations, experience, and major. This is particularly important since it constitutes a more stringent test for directed search behavior. The sole fact that applications react positively to higher wages *ceteris paribus* can be interpreted as a positively sloped labor supply at the job ad level, as Dal Bó, Finan, and Rossi (2013) suggest, for instance. We show that workers leave job opportunities on the table when they are not a good fit, an empirical implication of directed search beyond the positive association between wages and applications.

We show that the correlation between requirements and applicant features is noticeable but not perfect. Moreover, higher implicit wages tend to attract more applicants, and job ads with specific requirements tend to attract workers with characteristics that meet them. As a consequence, both directed search and *ex post* bargaining may be at work. Hence, a theoretical linkage between signal posting attracting specific workers and *ex post* bargaining would be fruitful. Along these lines, Menzio (2007) provides a cheap-talk model of job ads that actually guides job seekers towards employers paying wages that are correlated with their announcements posted without commitment. Cheremukhin, Restrepo-Echavarria, and Tutino (2015) develop a model that sees job seeker behavior as costly information processing, generating an equilibrium that is in between random and directed search, allowing for *ex post* bargaining as a wage-setting mechanism. Stacey (2015) builds a theoretical setting in which both sides of the market can strategically post ask or bid prices to induce directed search, but there is a potential *ex post* bargaining that can be triggered in equilibrium.

3.3 Random Search in Segments?

To some extent, in this Section we want to assess the right scope for directed search. In a market with highly heterogeneous ads and applicants, we may consider an alternative interpretation of Section 3.2 in which jobseekers randomly search within segments of the market. If this is the case, applicant behaviors may be confounded with directed search if job ads receive more applications in high-wage segments of the labor market, either because of a larger supply of applicants or relatively lower application costs. It is also possible that the analysis of Section 3.1 estimates average responses, neglecting heterogeneity across submarkets.

Thus, we want to test if wages drive applications even into segments or submarkets. In doing so, we allow for heterogeneous directed search behaviors across submarkets. Finer segmentation would allow us to improve on the conceptual accuracy of the test, but at the expense of reducing the sample size and power of testing.

In Table 10 we report NB regressions for *a priori* defined subsamples to estimate potentially heterogeneous reactions of applicants to wages across segments. We divide job ads in professional area requirements defined by Commerce, Technology, and Non-Declared. Simultaneously we also classify our sample by educational requirements considering Regular High School, Technical High School, Technical Tertiary Education, and College. These twelve segments defined by the crossover of these categories cover 90.5% of the sample of job ads. As in Section 3.1, β is the model parameter, and η the average elasticity or differential response.

We find a lower but positive sensitivity of the number of applications to wages in highly-educated segments. This mainly occurs in the Technology and Commerce areas, and less for the other professional areas. For example, while a 1% increment of offered wages raises applications 0.283% in the segment regular High School & Commerce, it only increases applications 0.075% in the segment College & Commerce. Moreover, we observe a lower effect of explicit wages in high-education levels, and a higher reaction to explicit wages changes for low-educated segments. On the other hand, we observe a higher negative effect of experience requirements over applications for high-educated levels, especially in Commerce.

Applicant responses are heterogeneous across segments. Low-educated workers are more sensitive to offered wages, and the high-educated ones to experience requirements. A rationale for these findings is that unskilled workers apply to simple jobs in which the most important attribute is the wage offer. Instead, jobseekers with high education or experience can access to higher wages by fulfilling the ad requirements.

We also approach the segmentation question in more agnostic way by relying in an unsupervised machine learning technique, the k-means classification algorithm (Everitt et al. 2011, see for instance). This technique defines k segments of job ads based on a predefined number of observable characteristics such as quarter, educational level required, experience required, and occupation dummies, among others. The procedure begins by randomly grouping all observations into k sets. The first step is to compute the centroid of each group as the vector of means of each observable characteristic. The second step assigns each observation (job ad) to the nearest group centroid. Once the assignment is completed, we check if one or more observations changed groups. If they did, we go back to the first step. Otherwise, we stop.

Figure 4 shows the sorted estimated coefficients of linear models for all segments defined by the k-means algorithm, with a chosen $k = 50$. In these models, the dependent variable is the log of the number of applications by ad, and the explanatory variables are required educational level, industry, career, firm size, contractual terms, computer skills, remuneration schemes, location, word-title dummies, firm fixed effects, and quarterly fixed effects. Shaded areas indicate 95% confidence intervals. The horizontal red lines show the estimates for the whole sample, comparable to OLS estimation in Table 7. The Figures also report the mean, 5th, and 95th percentile of the estimates. In the OA, Section A.5, Table A7, we present a

Table 10: Negative binomial models for number of applications received by occupation/education segments

	Commerce		Technology		Non-declared	
	β	η	β	η	β	η
Science-humanity High						
Explicit wage	-3.029	-0.216	3.294	0.361	-3.018***	-0.185
log wage	0.236**	0.286	0.330*	0.280	0.143***	0.194
Explicit wage × log wage	0.223		-0.243		0.230***	
Ad appear.	-0.070***	-0.138	-0.189***	-0.255	-0.025***	-0.104
Number of vac.	0.011***	0.048	0.011**	0.064	0.007***	0.080
Req. exper.	-0.027	-0.013	-0.101*	-0.116	-0.037***	-0.036
Explicit wage × Number of vac.	-0.012***		-0.007		-0.003***	
Explicit wage × Req. exper.	0.086		0.120		0.008	
Obs.	*1483*		*555*		*36939*	
Tech. High School						
Explicit wage	-5.420***	-0.200	-3.188*	-0.282	-5.157***	-0.054
log wage	0.118***	0.202	0.119**	0.153	0.138***	0.206
Explicit wage × log wage	0.415***		0.236*		0.411***	
Ad appear.	-0.074***	-0.114	-0.029***	-0.051	-0.079***	-0.148
Number of vac.	0.004	0.012	0.036***	0.095	0.008***	0.034
Req. exper.	-0.029***	-0.063	-0.078***	-0.139	-0.011	-0.028
Explicit wage × Number of vac.	0.002		-0.034***		-0.008***	
Explicit wage × Req. exper.	-0.040		-0.004		-0.044	
Obs.	*7725*		*4237*		*14234*	
Tech. Tertiary Educ.						
Explicit wage	-2.691***	-0.170	-1.718**	-0.110	-3.973***	-0.115
log wage	0.159***	0.187	-0.004	0.008	0.070***	0.099
Explicit wage × log wage	0.193***		0.119**		0.289***	
Ad appear.	-0.042***	-0.089	-0.107***	-0.221	-0.027***	-0.337
Number of vac.	0.015***	0.038	0.020***	0.038	0.003**	0.018
Req. exper.	-0.036***	-0.084	-0.056***	-0.111	-0.024***	-0.040
Explicit wage × Number of vac.	0.021***		-0.021***		0.014***	
Explicit wage × Req. exper.	-0.018		0.039**		0.021	
Obs.	*19905*		*13314*		*14684*	
College						
Explicit wage	-3.063***	-0.119	-2.589***	-0.077	-2.710**	-0.006
log wage	0.055***	0.075	-0.037***	-0.027	-0.018	-0.004
Explicit wage × log wage	0.220***		0.186***		0.197**	
Ad appear.	-0.093***	-0.135	-0.087***	-0.143	-0.136***	-0.296
Number of vac.	0.028***	0.045	0.048***	0.071	0.023***	0.041
Req. exper.	-0.048***	-0.137	-0.087***	-0.245	-0.067***	-0.174
Explicit wage × Number of vac.	-0.004		0.000		-0.025***	
Explicit wage × Req. exper.	-0.007		-0.020		0.027	
Obs.	*12189*		*32401*		*9602*	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.. In all the equations, we control for firm size dummies, industry dummies, quarter dummies to capture seasonality, first four words job title dummies, contract law dummies, required availability dummies, computer knowledge requirements, and the number of days the vacancy was open. We do not control for recruiting firm.

general characterization in terms of observable variables of the 50 clusters generated by the algorithm.

The left panel shows how the coefficient associated with log wage varies across the $k = 50$ segments. Nearly 2/3 of point estimates are negative, and a majority of those could not be statistically distinguished from zero with 95% of confidence. Indeed, roughly 3/4 of coefficients are not distinguished from the coefficient estimated for the whole sample. The center panel displays the estimates for the explicit wage binary variable. A large set of point estimates are not statistically different from the whole-sample negative coefficient. Finally, the right panel shows estimated coefficients associated with the differential effect of directed search for explicit-wage job ads. The lion's share is positive and statistically undistinguishable from the whole-sample estimate. If random search within segments prevailed, we would not see application responsiveness to wages and wage-explicitness in segments. In fact, we see that the coefficients estimated across different segments are not significantly distinct from those estimated for the whole sample. Hence, the evidence points to prevailing directed search behavior within labor market segments, as in the whole job board.

In the literature, there are several methods to determine the "best" number of clusters, k. Since the right choice of k is highly dependent on many tuning choices such as variables defining clusters, distance metric, and selection method, we simply verify that our conclusions remain intact if (1) we consider a different number of segments ($k = 25, 50$, and 100) and (2) we define segments based on larger sets of job ad characteristics. We present these results in the OA, Section A.5.

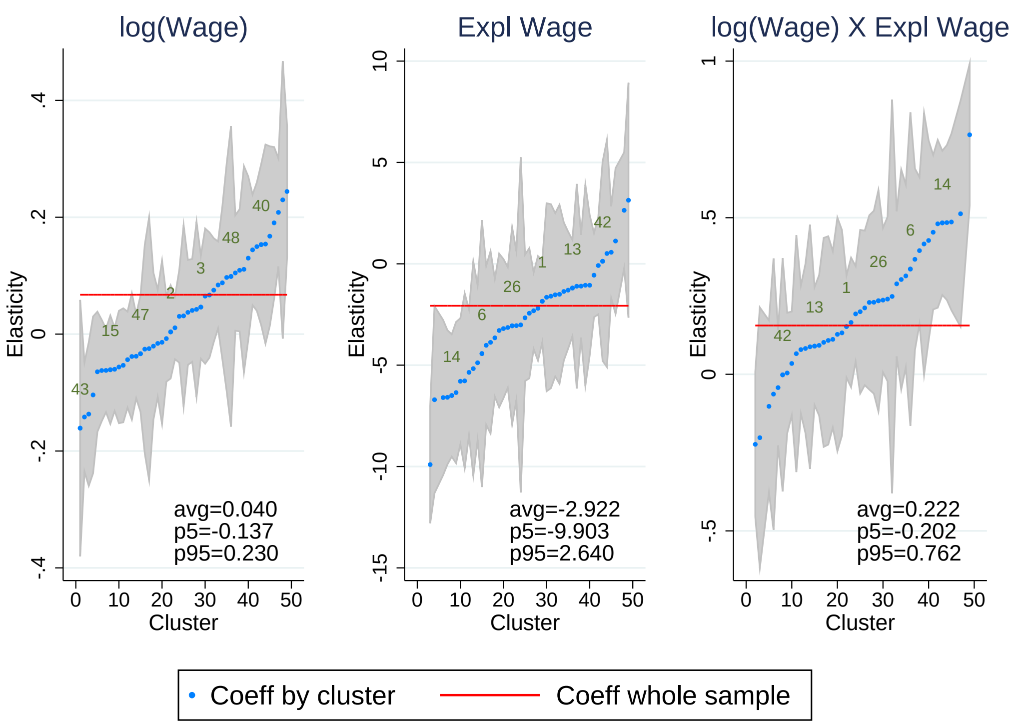
3.4 Why do employers show or hide wages?

The previous sections shows that applicants react differently to explicit wages. Employers are likely to know that showing or hiding wages matters and make strategic decisions to induce certain applicant behaviors. Consequently, we investigate the determinants behind explicit wage posting.

We estimate probit and linear probability models to examine the impact of job ad characteristics such as the 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.

Table 11 shows selected estimates of the probit results in its first panel. As in the models of Table 7, the coefficients β represent actual model coefficients. The coefficients η are

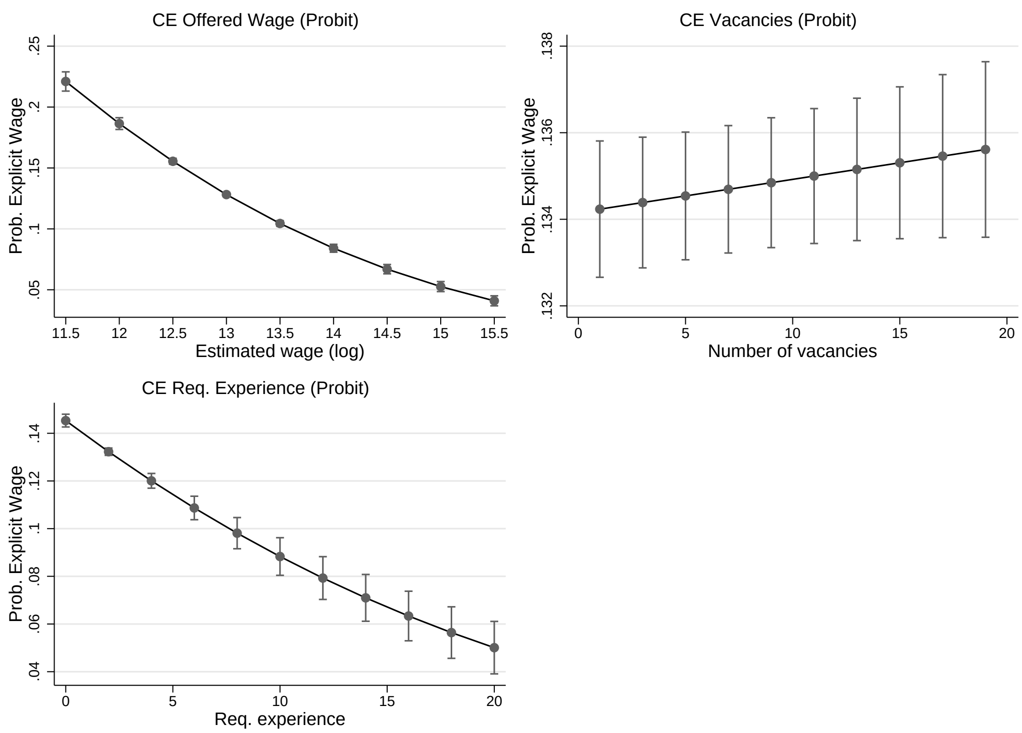
Figure 4: Distribution of estimated coefficients by cluster (k=50)



Note: Blue dots represent estimated coefficients of linear models by segment (cluster). Plotted coefficients come from linear models computed with observations in each segment. Shaded areas are 95% confidence intervals. Variables used to define clusters are quarter, educational level required, experience required, and occupation dummies. In the models, the dependent variable is the log of the number of received applications by ad, and the explanatory variables are required educational level, industry, career, firm size, contractual terms, computer skills, remuneration schemes, location, word-title dummies, firm fixed effects, and quarterly fixed effects. Numbers displayed on top of blue dots label the corresponding segments. A characterization of the clusters is in the OA, SectionA.5, Table A7. Horizontal red lines show the estimated value of the coefficient for the whole sample. Segment assignment of ads is the one with the highest Caliński and Harabasz (1974) statistic among 15 stochastic realizations of the k-means algorithm.

the average marginal effects for (quasi) continuous regressors such as log wage or number of vacancies, that is $\eta = \frac{\partial \text{Prob}(Y|X)}{\partial z}$. If z is a binary variable, such as educational level or occupation, η is the probability change due to a switch of a binary variable, i.e. $\eta = \text{Prob}(Y|X, z = 1) - \text{Prob}(Y|X, z = 0)$. Most of the estimated coefficients are portrayed in Tables A8 and A9. We consider all job ads in the sample, even those suspected to be posted by recruiting firms. In Tables A10 and A11 in the OA, Section A.6, we show the results including a binary variable for recruiting firm. Nevertheless, results barely change.

Figure 5: Conditional probability of explicit wage posting (Table 11, probit)



Note: Effects computed from model *without* controlling for recruiting firms. Vertical bars indicate 95% Confidence Intervals.

An increase of one log point of offered wage decreases the probability of explicit wage posting by 5.2%. These results remain virtually unchanged if we do not include the recruiting firms control. In Figure 5, we plot the average conditional probability of posting an explicit wage. We show that 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 nearly 3%.

Table 11: Models for probability of explicit wage posting

	Probit			OLS			OLS, Firm FE		
	β	SE	η	β	SE	η	β	SE	η
Number of vac.	0.000	0.000	0.000	0.000***	0.000	0.001	0.000	0.000	0.000
Req. exper.	-0.034***	0.003	-0.010	-0.005***	0.001	-0.010	-0.005***	0.001	-0.009
log wage	-0.268***	0.010	-0.051	-0.043***	0.002	-0.043	-0.028***	0.002	-0.028
Highest educ									
Primary (1-8 years)	0.211***	0.034	0.052	0.066***	0.008	0.066	0.022***	0.008	0.022
Tech. High School	-0.108***	0.015	-0.023	-0.032***	0.003	-0.032	-0.022***	0.003	-0.022
Tech. Tertiary Educ.	-0.257***	0.016	-0.052	-0.066***	0.003	-0.066	-0.041***	0.003	-0.041
College	-0.328***	0.019	-0.064	-0.074***	0.004	-0.074	-0.048***	0.004	-0.048
Graduate	-0.276***	0.075	-0.055	-0.069***	0.011	-0.069	-0.043***	0.011	-0.043
Professional Area									
Commerce and Manag.	0.139***	0.015	0.026	0.022***	0.003	0.022	0.017***	0.003	0.017
Agropecuary	0.015	0.076	0.003	0.008	0.012	0.008	0.021*	0.012	0.021
Art and Architecture	0.221***	0.049	0.044	0.031***	0.009	0.031	0.009	0.009	0.009
Natural Sciences	0.066	0.053	0.012	0.011	0.010	0.011	0.011	0.009	0.011
Social Sciences	0.003	0.039	0.001	-0.006	0.007	-0.006	-0.006	0.006	-0.006
Law	0.141	0.097	0.027	0.023	0.018	0.023	0.020	0.017	0.020
Education	0.080	0.053	0.015	0.016	0.010	0.016	-0.019**	0.010	-0.019
Humanities	0.620***	0.074	0.145	0.165***	0.016	0.165	0.080***	0.016	0.080
Health	0.142***	0.046	0.027	0.026***	0.008	0.026	0.030***	0.008	0.030
Non-declared	0.058***	0.015	0.011	0.008***	0.003	0.008	0.005**	0.003	0.005
Other	0.386***	0.074	0.082	0.090***	0.016	0.090	0.011	0.017	0.011
Legal contract type									
Fixed-term	0.346***	0.016	0.066	0.071***	0.003	0.071	0.032***	0.003	0.032
Undefined term	0.161***	0.015	0.028	0.030***	0.003	0.030	0.026***	0.003	0.026
Availability									
Commission	-0.264***	0.059	-0.043	-0.053***	0.010	-0.053	-0.058***	0.010	-0.058
Half time	0.129***	0.029	0.026	0.034***	0.006	0.034	0.006	0.006	0.006
Part-time	-0.114***	0.030	-0.020	-0.021***	0.006	-0.021	-0.019***	0.006	-0.019
Shift-work	0.072***	0.015	0.014	0.021***	0.003	0.021	0.021***	0.003	0.021
Internship	0.033	0.034	0.006	0.018**	0.008	0.018	0.010	0.008	0.010
Replacement	0.085*	0.050	0.017	0.012	0.011	0.012	-0.004	0.010	-0.004
Observations	183997			184920			184920		
Avg. Probability	0.135			0.134			0.134		
pseudo - R^2	0.131								
R^2				0.113			0.316		
Adj. R^2				0.109			0.289		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.Selected coefficients of models *without* controlling for recruiting firms. Omitted groups: *Highest educ:* Science-humanity high-school; *Contract law* Other. *Availability:* Full-time. *Computer knowledge level:* None. In all the equations, we control for profession/occupation dummies, firm size dummies, industry dummies, quarter dummies to capture seasonality, first four words job title dummies, and the number of days the vacancy was open.

In Table 11, 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 explicit wage posting by 0.6% on average. In Figure 5, we show that ads that do not ask for any experience have a 14% of probability of having an explicit wage, while positions with experience requirements over 20 years have a probability close to 6%. Since job complexity is associated with the level of experience required, firms decide to post a specific wage offer when trying to hire skills that are relatively abundant in the market.

We might expect that the larger number of vacancies increases the probability of an explicit wage because massive hirings tend to be frequent in low skilled, standardized jobs, as found by Brenčič (2012). In our case, the number of vacancies offered in the job ad does not show a significant impact on the probability of announcing the wage, probably because the job quality is adequately captured by other covariates.

The probability of announcing an explicit wage is 3.5% higher for recruiting firms. This is potential evidence for a standardized procedure of recruiting, or a lower marginal cost of interviewing, given the specialization of these firms. We confirm that job ads with explicit wages tend to target unskilled workers because the probability of explicit wage posting decreases in the required education level. The evidence also shows that undefined term jobs, often thought of as more stable positions, are less likely to post explicit wages compared to those with fixed terms. This suggests that lower-quality jobs are the ones showing explicit wages.

Results in Table 11 also show that professions/occupations related to the humanities are much more likely to announce an explicit wage. Job ads not requesting a specific profession/occupation or those associated with retailing are also more likely to announce explicit wages. In contrast, professions in technology areas show the opposite pattern. There are also important differences across the industry of the employer posting the job ad. In agriculture, transportation, and public administration explicit wage ads prevail. Hall and Krueger (2012) also show that job ads in the public administration sector exhibit a larger likelihood of explicit wage posting.

What conclusions would we reach if we did not observe implicit or hidden wages when estimating models in the previous section, as often occurs in other studies of job search on the internet? Because explicit-wage ads typically target low productivity workers, directed search evidence solely based on explicit wages as in Dal Bó, Finan, and Rossi (2013) and Marinescu and Wolthoff (2015) is likely to overestimate the average effect of wages on applications. Indeed, job ad characteristics affecting the response of applications to explicit wages may be simultaneously determining the probability of explicit wage posting. Therefore, inferring the true effect of wages on applications is subject to a sample selection problem. Let A be the applications received by a job ad, X be the corresponding set of job ad traits, including wage W. The binary variable D takes value 1 if the wage is explicitly posted, and 0 otherwise. We show in the OA, Section A.7 that only if condition

$$\frac{\partial \mathbb{E}[\log A|X,D=0]}{\partial \log W} - \frac{\partial \mathbb{E}[\log A|X,D=1]}{\partial \log W} = \\ -\frac{\partial P(D=1|X)}{\partial \log W}\left(\frac{\mathbb{E}[\log A|X,D=1]-\mathbb{E}[\log A|X,D=0]}{1-P(D=1|X)}\right) \tag{1}$$

holds we could obtain the true response of applications to wages just by estimating the effect with explicit wage job ads. A wage increase not only affects the number of applicants received, but also the probability that the employer makes the wage offer explicit. Application-wage elasticities must have a very specific relation to other estimated magnitudes in order to uncover unbiased estimates for all job ads solely based on those with explicit wages. Using the NB model in Table 7, we compute the left-hand side of (1) to be 0.148 (implicit-explicit elasticity-wage gap). Using the marginal probability response to log wage of -0.051 from the probit model in Table 11 and the expected implicit-explicit log wage gap in Table 7 of -0.132, we obtain a small and negative right-hand side value in (1) of -0.007. Therefore, the observed explicit-implicit sensitivity to wages is not compensated by the expected log wage gap, considering how wages affect the probability of posting an explicit wage.

Our facts are consistent with the Michelacci and Suarez (2006) model. Under certain parameterizations, their model allows for a separating equilibrium in which high-productivity workers apply for good jobs with hidden wages and low-productivity workers go for bad jobs with explicit wages. Intuitively, for high-quality jobs hiding wages is a strategic choice of employers to signal *ex post* bargaining when match-specific requirements are important. Hence, if job quality is imperfectly observed, an employer choosing an implicit wage may reveal some information, or attract applicants with specific knowledge of the job or the economic sector. The targeted group could guess wages and other job characteristics more accurately. In contrast, an explicit wage could reveal that a job does not require a match specific skill or information, so that the job quality is perceived as low.

We also include in Table 11 OLS linear probability estimates for the sake of comparison. Moreover, in the third column we also include firm fixed effects to account for all firm idiosyncratic factors that may influence the wage explicitness decision, such as corporate culture, or specific managerial standards. However, neither OLS or OLS-FE change results in a meaningful way. We also show these linear models controlling for recruiting firms in the OA, Section A.6, Tables A10 and A11. The results remain intact in any case.

4 Literature review and some discussion

Besides our results, few other papers find some sort of directed search evidence. In an early paper, using the Employment Opportunity Pilot Project (EOPP) data, Holzer, Katz, and Krueger (1991) show that vacancies for which minimum wage regulation are binding have longer job queues. Employers cannot fully offset the extra cost imposed by the regulation by cutting fringe benefits or raising hiring standards, and therefore those jobs provide extra rents that attract more applicants.

Dal Bó, Finan, and Rossi (2013) focus on the responses of applicants to government sector job ads in Mexico. They find that higher wages attract more and better qualified applicants according to detailed registered screening assessments. Applicant search in their sample is also driven by job characteristics such as location and municipality features. The facts are thus consistent with the premises of directed search. They find that applicants apply more for high-wage jobs and selectively apply for positions that presumably better satisfy their requirements.

Marinescu and Wolthoff (2015) use online job ads by `www.careerbuilder.com` and explain job ad posted wages mainly through job titles, as we do in our results. They provide sound evidence of directed search job ads with explicitly posted wages, which comprise nearly 20% of their sample, but they cannot claim anything about the larger share of job ads with hidden wages. As we showed in Section3.4, they probably overestimate the sensitivity of applicants to wages.

Belot, Kircher, and Muller (2015) setup a field experiment by altering original posted wages of real job ads. Their results support the directed search hypothesis, since high-wage jobs receive 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.

Braun et al. (2016) show a different setup to test for directed search. They use NLSY data to estimate duration models and show that search effort is higher in high-wage markets compared to medium-wage markets. Finally, directed search behavior is also tested in product markets, as in Lewis (2011), who shows that internet seekers for used cars react significantly to posted information regarding automobile quality.

To the best of our knowledge, only Dal Bó, Finan, and Rossi (2013) provide some evidence interpretable as segmentation. Papers showing sorting between productivity types of firms and worker such as Abowd, Kramarz, and Margolis (1999) might mistakenly be taken as job search segmentation. However, the sorting between firm and worker fixed effects –statistically weak in general– is not informative about the correlation between job requirements and workers qualifications, given the large heterogeneity of jobs within firms.[10] Indeed, fixed effects do not identify idiosyncratic productivities because mismatched agents (over- or under-qualified) compensate their partners for their opportunity cost (Eeckhout and Kircher 2011). Moreover, it is critical to distinguish between two non-excluding reasons for positive assortative matching. Good workers may apply for good jobs as directed search models imply, but workers may also simultaneously and randomly apply for jobs and be screened and selected later, as in non-sequential random search models (Moen 1999; Villena-Roldan 2012). Thus, positive assortative matching may not be caused by the segmentation predicted in directed search models.

In line with our findings, Brenčič (2012) shows that explicit wage posting is standard in job ads requiring low qualifications and those that need to be filled fast, which is consistent with strategic disclosure of wage offers. The evidence suggests that firms face a trade-off when announcing a wage: it reduces search costs, but decreases the quality of applicants.

Due to the theoretical link between directed search and committed explicit wage posting in most models (i.e. competitive search), some authors investigate wage-posting versus wage-bargaining behavior. Gartner and Holzner (2015) find that a job with *ex post* bargaining reduces the number of suitable applicants, especially skilled ones. If *ex post* wage-bargaining is akin to implicit wages, their results seem inconsistent with ours, perhaps explained by our more educated sample. Brenzel, Gartner, and Schnabel (2014) report that 70% of labor matches in the German labor market involved take-it-or-leave-it offers, but more skilled workers are often involved in bargaining. In a similar vein, Hall and Krueger (2012) find that one-third of respondents said they had negotiated their last wage, particularly skilled workers. In addition, nearly one-third of workers were largely certain of the wage paid before applying. However, the latter may not be related to explicit wage-posting or directed search: it may just reflect an anticipation of the bargaining result.

All in all, the evidence suggests that implicit wage posting is frequently used to target skilled workers and that *ex post* bargaining and directed search may coexist.

[10] Banfi, Choi, and Villena-Roldán (2017) using `www.trabajando.com` data provide evidence of positive assortative matching at the worker-job level.

5 Conclusions

Our evidence shows that directed search is a prevalent behavior in the online labor market studied. Thanks to the remarkable availability of offered wages for virtually all job ads in the job board we studied, we can circumvent the large selection bias arising in other databases, which typically can analyze no more than 25% of their job ads.

Applicants react to information provided by employers such as offered wages or educational requirements, as predicted by standard directed search models. We show that workers apply more for jobs offering higher wages even if employers choose to hide them, after controlling for a detailed set of job characteristics, including requirements over education level, major, experience, job title binary variables, and even firm fixed effects. Nevertheless, applicants are more sensitive to changes in wages when they are explicit and less when they are hidden. Explicit-wage job ads provide a low-noise signal to applicants, driving their search behavior more decisively. In turn, the evidence suggests that applicants infer hidden wages from job ads, so we refer to them as implicit wages.

A second more stringent testable prediction of directed search behavior is that workers apply for job ads targeting them in a specific submarket. We slice the data in several ways to show that there is a notable alignment between job ad requirements and worker characteristics in terms of offered/expected wage, educational level, occupation, and experience. These results notably hold for implicit wages, too.

Evidence suggests that employers use explicit/implicit wage posting strategies to reduce the pool of applicants and increase their quality or suitability. Low marginal application costs potentially spurs too many applications, imposing a large screening burden on the employers' side. By making explicit wage offers for simple jobs, employers dissuade too many applications when differentiation among candidates is rarely a concern and take-it-or-leave-it offers prevail. On the other side of the wage distribution, differentiation across candidates matters and employers often prefer implicit wages, perhaps as a way to signal they are open for bargaining, in line with the theory of Michelacci and Suarez (2006). Consistent with this view, we also show that employers tend to post explicit wages in job ads with low educational and experience requirements.

Beyond labor market efficiency implications, a practical lesson is that there is a large scope for strategic communication and job ad design for firms in order to attract the kind and number of applicants they desire. This is important since hiring involves a costly selection process among heterogeneously productive workers, especially for job positions for skilled workers (Oyer and Schaefer 2011; Muehlemann and Pfeifer 2016).

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Table A1: Deleting Process Summary

Dataset	**Original Data**	**Final Data**	**Losses**
Applications	8,285,727	6,131,626	26%
Job Ads	252,42	184,92	26.74%
Firms	6,78	6,386	5.81%
Appicants	502,183	463,495	7.7%

Appendix A Not intended for publication

A.1 Detailed data cleaning process

The original application database has 8,285,727 observations, and the sample of analysis ended up with the 74% of the raw data. The procedure consists of two steps

- Wage cleaning process:

  1. We treat an observation as a missing if the wage attached to a job ad is non-informative because it is equal to zero, lower than CLP$12,345, or it is a suspicious number implying unreasonably low monthly rates (CLP 123,456; CLP 123,123, and CLP 111,111). This procedure discards 18.46% of the job ads.
  2. Wage values below to CLP 30,000 were multiplied by 10 because they were most likely originated as a typo. These modifications affected the 0.16% of the raw dataset.

- Deleting process. We drop:

  1. Observations with estimated wages below CLP 100,000 and above CLP 5,000,000 for implicit and explicit wages, 3.74% of the data.
  2. Ads with experience requirements over 20 years, 0.03% of the data.
  3. Applicants with expected and last job wages below CLP 100,000 or above CLP 5,000,000, 0.76% of the data.
  4. Applicants with more than five years of inactivity, 3.12% of the data.
  5. Applicants younger than 18 or older than 69 years, 0.1% of the data.

Table A1 summarizes the deleted data to create the sample of analysis.

A.2 Additional data description

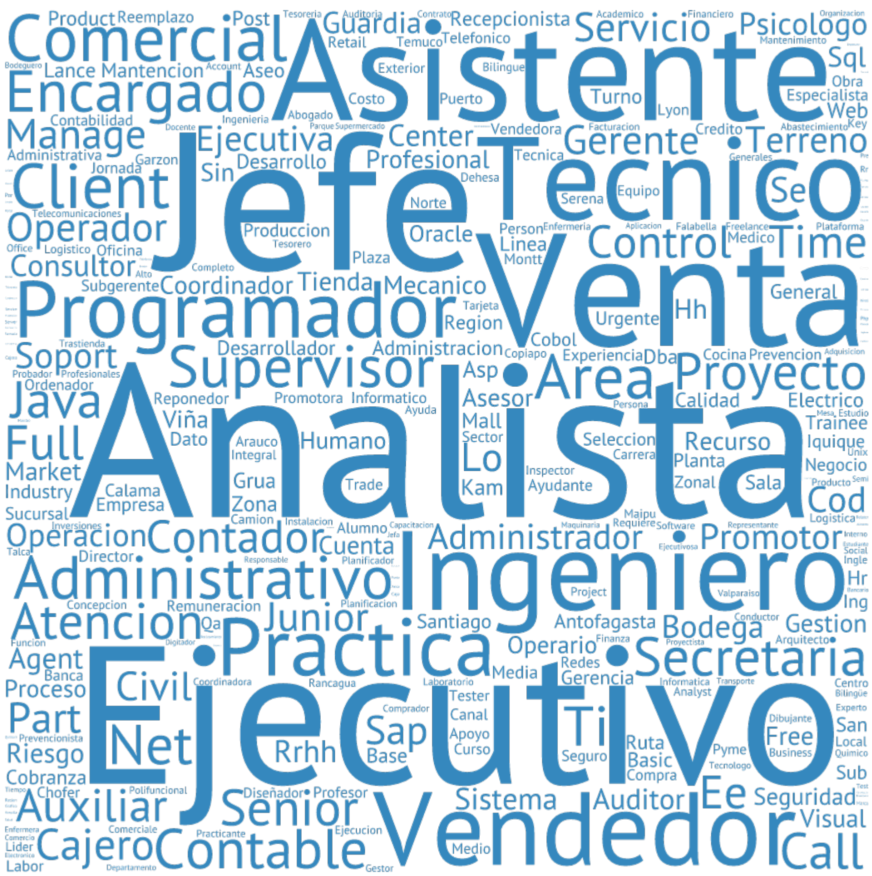
Table A2: Job Ads Characteristics (III)

	Explicit Wage Posting	Implicit Wage	All
Vacancies per ad (%)			
1	45.88	61.82	59.68
2	13.54	11.29	11.59
3 - 5	14.46	12.17	12.48
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)
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
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
Job arrangement (%)			
Comission-earner	0.35	0.70	0.65
Full-time	75.57	85.74	84.37
Part-time	4.97	3.82	3.97
Shift work	15.31	7.89	8.89
Internship	3.16	1.35	1.60
Replacement	0.65	0.50	0.52
Ads from Recruiting Firms* (%)	45.72	36.15	37.44
Observations	24867	160053	184920

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

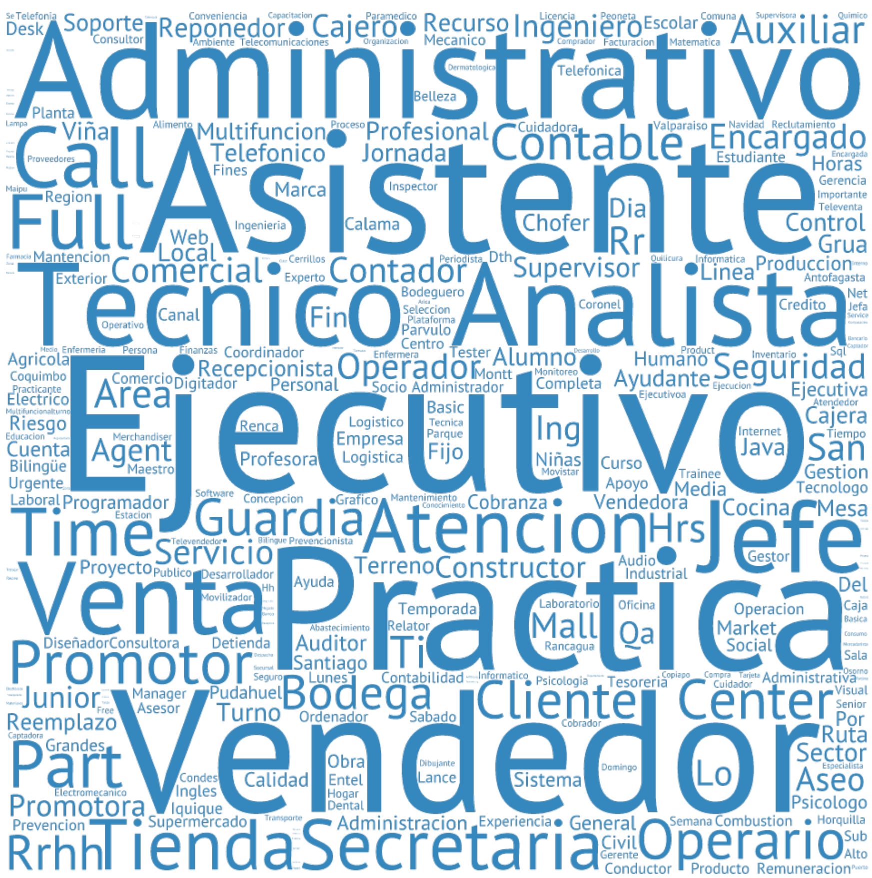
A.3 Word cloud for job titles

Figure A1: Job Ad Titles with Implicit Wages



Note: Generated in www.tagul.com

Figure A2: Job Ad Titles with Explicit Wages



Note: Generated in www.tagul.com

A.4 Additional estimates for received applications, Section 3.1

Table A3: Models explaining the number of received applications, Part I

	Negative Binomial			OLS			OLS, Firm FE		
	β	SE	η	β	SE	η	β	SE	η
Explicit wage	-2.312***	0.187	-0.132	-1.818***	0.176	-0.148	-2.184***	0.175	-0.038
Ad appearances	-0.033***	0.001	-0.103	-0.009***	0.000	-0.028	-0.008***	0.000	-0.025
Number of vacancies	0.009***	0.000	0.040	0.005***	0.000	0.021	0.005***	0.000	0.023
Req. experience	-0.060***	0.002	-0.115	-0.047***	0.002	-0.089	-0.047***	0.002	-0.092
log wage	0.076***	0.006	0.099	0.085***	0.006	0.102	0.060***	0.006	0.082
Explicit × Num. of vac.	-0.001***	0.001		-0.001	0.000		-0.001	0.000	
Explicit × Req. experience	0.013**	0.006		0.014**	0.006		-0.001	0.006	
Explicit × log wage	0.165***	0.015		0.126***	0.014		0.164***	0.014	
Days ad available	0.004***	0.000		0.003***	0.000		0.002***	0.000	
log wage - Implicit			0.076			0.085			0.060
log wage - Explicit			0.224			0.209			0.226
Highest educ									
Primary (1-8 years)	-0.326***	0.028	-0.326	-0.220***	0.026	-0.220	-0.297***	0.027	-0.297
Tech. High School	-0.010	0.011	-0.010	0.049***	0.010	0.049	0.019*	0.010	0.019
Tech. Tertiary Educ.	0.068***	0.011	0.068	0.136***	0.011	0.136	0.083***	0.011	0.083
College	0.180***	0.013	0.180	0.202***	0.012	0.202	0.159***	0.013	0.159
Graduate	-0.103***	0.039	-0.103	-0.083**	0.037	-0.083	-0.022	0.036	-0.022
Professional Area									
Commerce and Management	0.047***	0.010	0.047	0.069***	0.009	0.069	0.039***	0.009	0.039
Agropecuary	0.556***	0.043	0.556	0.529***	0.040	0.529	0.474***	0.040	0.474
Art and Architecture	0.312***	0.030	0.312	0.233***	0.029	0.233	0.239***	0.029	0.239
Natural Sciences	-0.165***	0.033	-0.165	-0.113***	0.031	-0.113	-0.174***	0.031	-0.174
Social Sciences	0.104***	0.023	0.104	0.053**	0.023	0.053	0.003	0.022	0.003
Law	0.320***	0.060	0.320	0.352***	0.058	0.352	0.395***	0.057	0.395
Education	-0.016	0.036	-0.016	-0.021	0.033	-0.021	-0.069**	0.033	-0.069
Humanities	-0.271***	0.053	-0.271	-0.317***	0.053	-0.317	-0.268***	0.055	-0.268
Health	-0.423***	0.031	-0.423	-0.429***	0.027	-0.429	-0.441***	0.027	-0.441
Non-declared	-0.231***	0.009	-0.231	-0.185***	0.008	-0.185	-0.185***	0.009	-0.185
Other	0.493***	0.062	0.493	0.271***	0.054	0.271	0.222***	0.057	0.222
Observations	184,920			184,920			184,920		
Estimated avg. applications	35.45			2.59			2.59		

Note: Table A4 continues the estimated results

Table A4: Models explaining number of received applications, Part II

	Negative Binomial			OLS			OLS, Firm fixed effect		
	β	SE	η	β	SE	η	β	SE	η
Industry									
Agriculture	0.174***	0.026	0.174	0.268***	0.026	0.268	0.145***	0.030	0.145
Fisheries	-0.262***	0.053	-0.262	-0.097*	0.052	-0.097	-0.166**	0.079	-0.166
Mining	0.355***	0.021	0.355	0.343***	0.020	0.343	0.167***	0.028	0.167
Manufacturing	0.005	0.011	0.005	0.017	0.011	0.017	-0.045***	0.013	-0.045
Electricity, water, and gas	0.056***	0.018	0.056	0.059***	0.018	0.059	0.066***	0.023	0.066
Construction	0.024	0.018	0.024	0.043**	0.018	0.043	-0.003	0.022	-0.003
Restaurants and Hotels	0.100***	0.022	0.100	0.019	0.022	0.019	-0.060*	0.031	-0.060
Transportation	0.057***	0.015	0.057	0.013	0.015	0.013	-0.090***	0.019	-0.090
Communication	-0.231***	0.012	-0.231	-0.265***	0.011	-0.265	-0.114***	0.014	-0.114
Financial Serv.	0.106***	0.013	0.106	0.067***	0.013	0.067	0.018	0.015	0.018
Business Serv.	-0.028**	0.012	-0.028	-0.067***	0.012	-0.067	-0.114***	0.014	-0.114
Household Serv.	-0.002	0.026	-0.002	0.022	0.027	0.022	0.006	0.030	0.006
Personal Serv.	0.112***	0.010	0.112	0.100***	0.010	0.100	-0.022*	0.013	-0.022
Public Admin.	-0.171***	0.024	-0.171	-0.213***	0.024	-0.213	-0.137***	0.038	-0.137
Others	0.012	0.013	0.012	-0.017	0.013	-0.017	-0.019	0.014	-0.019
Legal contract type									
Fixed-term	-0.211***	0.012	-0.211	-0.195***	0.011	-0.195	-0.113***	0.011	-0.113
Undefined term	0.034***	0.010	0.034	0.096***	0.009	0.096	0.074***	0.010	0.074
Availability									
Comission-earner	-0.519***	0.034	-0.519	-0.524***	0.033	-0.524	-0.299***	0.034	-0.299
Half time	0.026	0.021	0.026	-0.013	0.020	-0.013	-0.017	0.020	-0.017
Part-time	0.259***	0.021	0.259	0.123***	0.019	0.123	0.128***	0.019	0.128
Shift-work	0.007	0.011	0.007	-0.033***	0.010	-0.033	-0.055***	0.010	-0.055
Internship	0.448***	0.030	0.448	0.271***	0.025	0.271	0.361***	0.027	0.361
Replacement	-0.262***	0.038	-0.262	-0.154***	0.035	-0.154	-0.253***	0.033	-0.253
Computer knowledge level									
Low level	0.021	0.018	0.021	0.145***	0.016	0.145	0.077***	0.016	0.077
Expert level	-0.243***	0.024	-0.243	-0.202***	0.022	-0.202	-0.238***	0.022	-0.238
Professional level	-0.184***	0.014	-0.184	-0.050***	0.013	-0.050	-0.061***	0.013	-0.061
Technical level	-0.032*	0.017	-0.032	0.058***	0.015	0.058	0.008	0.016	0.008
User level	0.087***	0.007	0.087	0.115***	0.007	0.115	0.043***	0.007	0.043
Advanced User level	0.070***	0.008	0.070	0.122***	0.008	0.122	0.077***	0.008	0.077
Constant	-5.192***	0.184		-1.832***	0.163		-1.316***	0.159	
log(α)	0.087***	0.003							
Observations	184,920			184,920			184,920		
Estimated avg. applications	35.45			2.59			2.59		
pseudo - R^2	0.089								
R^2				0.542			0.611		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.. All estimates of Table 7 in the main text, a model not distinguishing recruiting firms. Omitted or reference groups: *Highest educ:* Science-humanity high-school; *Contract law* Other. *Availabilty:* Full-time. *Computer knowledge level:* None. In all 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.

Table A5: Models explaining number of received applications (controlling for recruiting firms), Part I

	Negative Binomial			**OLS**			**OLS, Firm FE**		
	β	SE	η	β	SE	η	β	SE	η
Explicit wage	-2.030***	0.189	-0.121	-1.666***	0.179	-0.141	-2.268***	0.179	-0.037
Ad appearances	-0.030***	0.001	-0.100	-0.008***	0.000	-0.025	-0.008***	0.000	-0.026
Number of vacancies	0.008***	0.000	0.039	0.005***	0.000	0.023	0.005***	0.000	0.022
Req. experience	-0.057***	0.002	-0.110	-0.045***	0.002	-0.088	-0.047***	0.002	-0.093
log wage	0.079***	0.006	0.100	0.093***	0.006	0.109	0.055***	0.006	0.078
Explicit × Num. of vac.	-0.001	0.001		-0.001	0.000		-0.000	0.000	
Explicit × Req. experience	0.009	0.006		0.008	0.006		0.001	0.006	
Explicit × log wage	0.145***	0.015		0.116***	0.014		0.171***	0.014	
Days ad available	0.003***	0.000		0.003***	0.000		0.002***	0.000	
Recruiting firm (=1)	-0.270***	0.008	-0.270	-0.284***	0.007	-0.284	0.000	.	0.000
log wage - Implicit			0.079			0.093			0.055
log wage - Explicit			0.224			0.209			0.226
Highest educ									
Primary (1-8 years)	-0.333***	0.028	-0.333	-0.256***	0.026	-0.256	-0.287***	0.028	-0.287
Tech. High School	-0.009	0.011	-0.009	0.048***	0.011	0.048	0.020*	0.011	0.020
Tech. Tertiary Educ.	0.056***	0.012	0.056	0.130***	0.011	0.130	0.086***	0.011	0.086
College	0.169***	0.014	0.169	0.196***	0.013	0.196	0.160***	0.013	0.160
Graduate	-0.136***	0.039	-0.136	-0.100***	0.038	-0.100	-0.030	0.037	-0.030
Professional Area									
Commerce and Management	0.031***	0.010	0.031	0.057***	0.009	0.057	0.034***	0.009	0.034
Agropecuary	0.515***	0.044	0.515	0.537***	0.042	0.537	0.494***	0.043	0.494
Art and Architecture	0.288***	0.031	0.288	0.198***	0.030	0.198	0.224***	0.030	0.224
Natural Sciences	-0.164***	0.034	-0.164	-0.115***	0.032	-0.115	-0.183***	0.032	-0.183
Social Sciences	0.093***	0.023	0.093	0.039	0.024	0.039	-0.005	0.023	-0.005
Law	0.296***	0.061	0.296	0.335***	0.059	0.335	0.380***	0.059	0.380
Education	0.030	0.038	0.030	0.046	0.035	0.046	-0.038	0.035	-0.038
Humanities	-0.423***	0.055	-0.423	-0.433***	0.054	-0.433	-0.311***	0.058	-0.311
Health	-0.466***	0.031	-0.466	-0.445***	0.028	-0.445	-0.454***	0.028	-0.454
Non-declared	-0.238***	0.010	-0.238	-0.174***	0.009	-0.174	-0.190***	0.009	-0.190
Other	0.469***	0.065	0.469	0.269***	0.056	0.269	0.286***	0.061	0.286
Observations	170,365			170,365			170,365		
Estimated avg. applications	34.87			2.59			2.59		

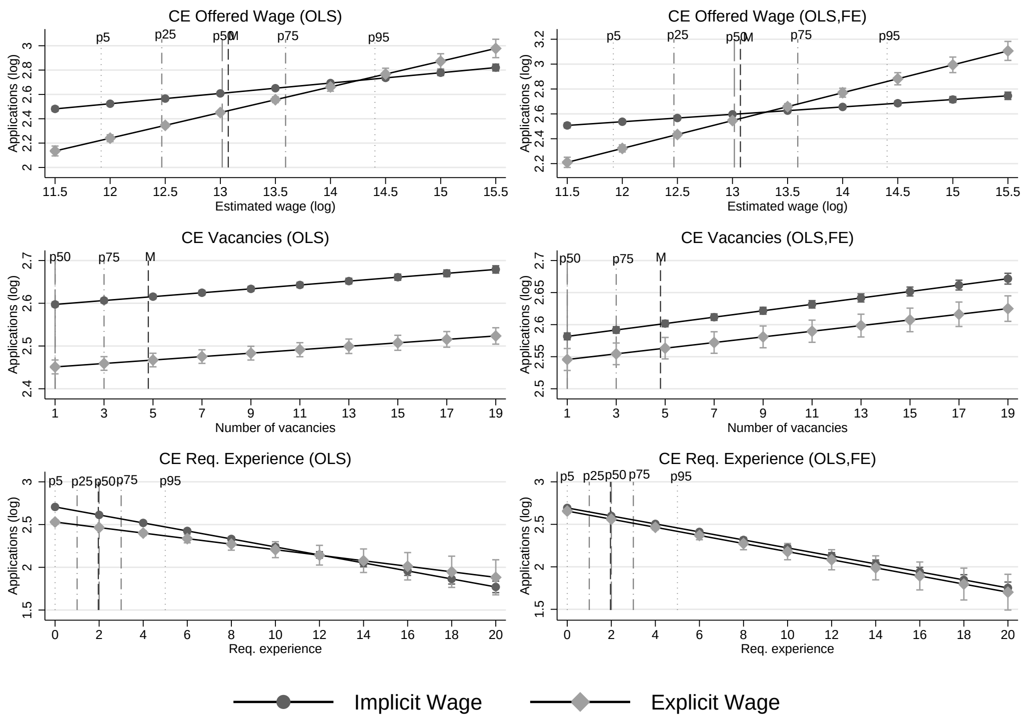
Note: Table A6 continues the estimated results

Table A6: Models explaining number of received applications (controlling for recruiting firms), Part II

	Negative Binomial			**OLS**			**OLS, Firm FE**		
	β	SE	η	β	SE	η	β	SE	η
Industry									
Agriculture	0.183***	0.027	0.183	0.263***	0.027	0.263	0.161***	0.032	0.161
Fisheries	-0.278***	0.054	-0.278	-0.110**	0.054	-0.110	-0.259***	0.085	-0.259
Mining	0.290***	0.021	0.290	0.298***	0.021	0.298	0.151***	0.029	0.151
Manufacturing	-0.027**	0.011	-0.027	-0.007	0.011	-0.007	-0.048***	0.013	-0.048
Electricity, water, and gas	0.042**	0.018	0.042	0.049***	0.018	0.049	0.074***	0.024	0.074
Construction	-0.016	0.018	-0.016	0.008	0.018	0.008	-0.010	0.023	-0.010
Restaurants and Hotels	0.066***	0.023	0.066	-0.001	0.022	-0.001	-0.051	0.032	-0.051
Transportation	0.054***	0.016	0.054	0.019	0.016	0.019	-0.104***	0.020	-0.104
Communication	-0.214***	0.012	-0.214	-0.256***	0.012	-0.256	-0.120***	0.015	-0.120
Financial Serv.	0.114***	0.013	0.114	0.078***	0.013	0.078	0.016	0.016	0.016
Business Serv.	-0.017	0.012	-0.017	-0.050***	0.012	-0.050	-0.120***	0.015	-0.120
Household Serv.	-0.041	0.026	-0.041	-0.013	0.027	-0.013	-0.004	0.031	-0.004
Personal Serv.	0.077***	0.011	0.077	0.070***	0.010	0.070	-0.033**	0.014	-0.033
Public Admin.	-0.266***	0.025	-0.266	-0.284***	0.025	-0.284	-0.161***	0.042	-0.161
Others	-0.008	0.014	-0.008	-0.037***	0.013	-0.037	-0.017	0.015	-0.017
Legal contract type									
Fixed-term	-0.208***	0.012	-0.208	-0.191***	0.011	-0.191	-0.113***	0.012	-0.113
Undefined term	0.016	0.011	0.016	0.066***	0.010	0.066	0.065***	0.010	0.065
Availability									
Commission-earner	-0.567***	0.034	-0.567	-0.571***	0.033	-0.571	-0.314***	0.035	-0.314
Half time	0.061***	0.022	0.061	0.011	0.021	0.011	-0.020	0.021	-0.020
Part-time	0.217***	0.021	0.217	0.091***	0.020	0.091	0.097***	0.020	0.097
Shift-work	0.000	0.011	0.000	-0.027**	0.011	-0.027	-0.046***	0.011	-0.046
Internship	0.437***	0.031	0.437	0.283***	0.026	0.283	0.358***	0.029	0.358
Replacement	-0.241***	0.040	-0.241	-0.142***	0.037	-0.142	-0.242***	0.036	-0.242
Computer knowledge level									
Low level	-0.019	0.019	-0.019	0.094***	0.016	0.094	0.071***	0.016	0.071
Expert level	-0.325***	0.024	-0.325	-0.270***	0.023	-0.270	-0.239***	0.023	-0.239
Professional level	-0.238***	0.014	-0.238	-0.086***	0.013	-0.086	-0.069***	0.014	-0.069
Technical level	-0.092***	0.017	-0.092	0.013	0.016	0.013	-0.008	0.016	-0.008
User level	0.045***	0.007	0.045	0.071***	0.007	0.071	0.041***	0.008	0.041
Advanced User level	0.041***	0.009	0.041	0.092***	0.008	0.092	0.076***	0.009	0.076
Constant	-4.842***	0.189		-1.581***	0.167		-1.261***	0.164	
$\log(\alpha)$	0.057***	0.004							
Observations	170,365			170,365			170,365		
Estimated avg. applications	34.87			2.59			2.59		
pseudo - R^2	0.090								
R^2				0.545			0.606		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.. All estimates, considering a recruiting form dummy as defined in Section 2.2. Omitted or reference groups: *Highest educ:* Science-humanity high-school; *Contract law* Other. *Availabilty:* Full-time. *Computer knowledge level:* None. In all 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.

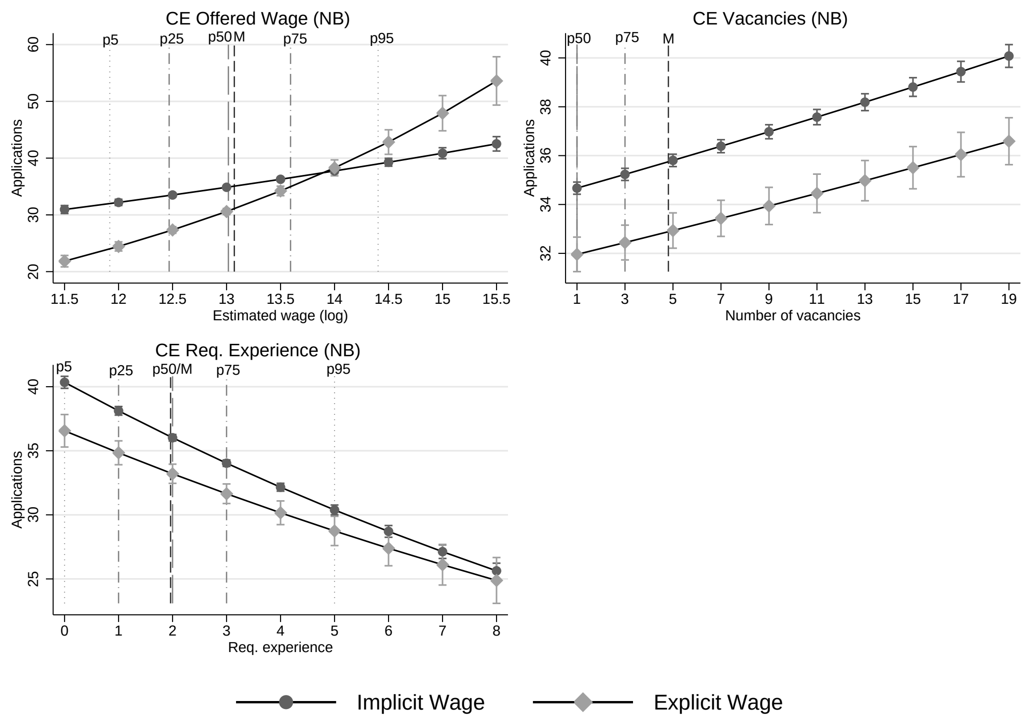
Figure A3: Conditional expectations of applications by explicitness of wage (Tables A3 and A4, OLS and OLS Firm FE)



Note: Model without controlling for recruiting firms. Vertical bars indicate 95% Confidence Intervals.

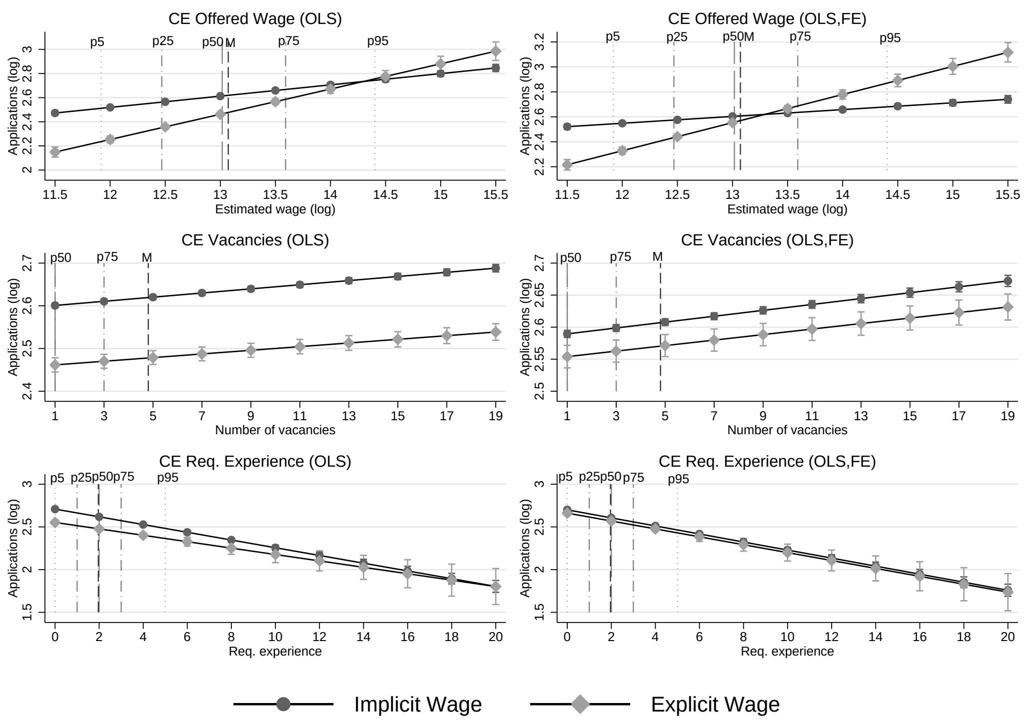
A.5 Additional information for testing random search in segmented markets, Section 3.3

Figure A4: Conditional expectations of applications by explicitness of wage (Tables A5 and A6, NB Model)



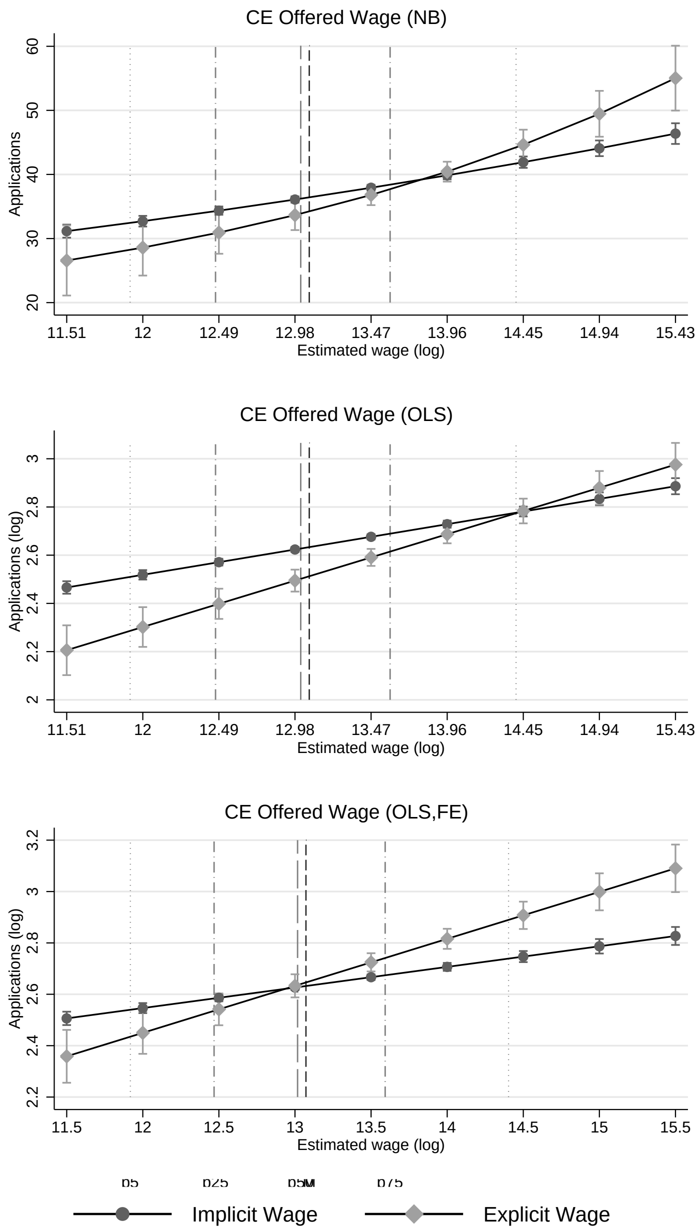
Note: Model controlling for recruiting firms. Vertical bars indicate 95% Confidence Intervals.

Figure A5: Conditional expectations of applications by explicitness of wage (Tables A5 and A6, OLS and OLS Firm FE)



Note: Model controlling for recruiting firms. Vertical bars indicate 95% Confidence Intervals.

Figure A6: Conditional expectations of applications by explicitness of wage including internet filter dummy



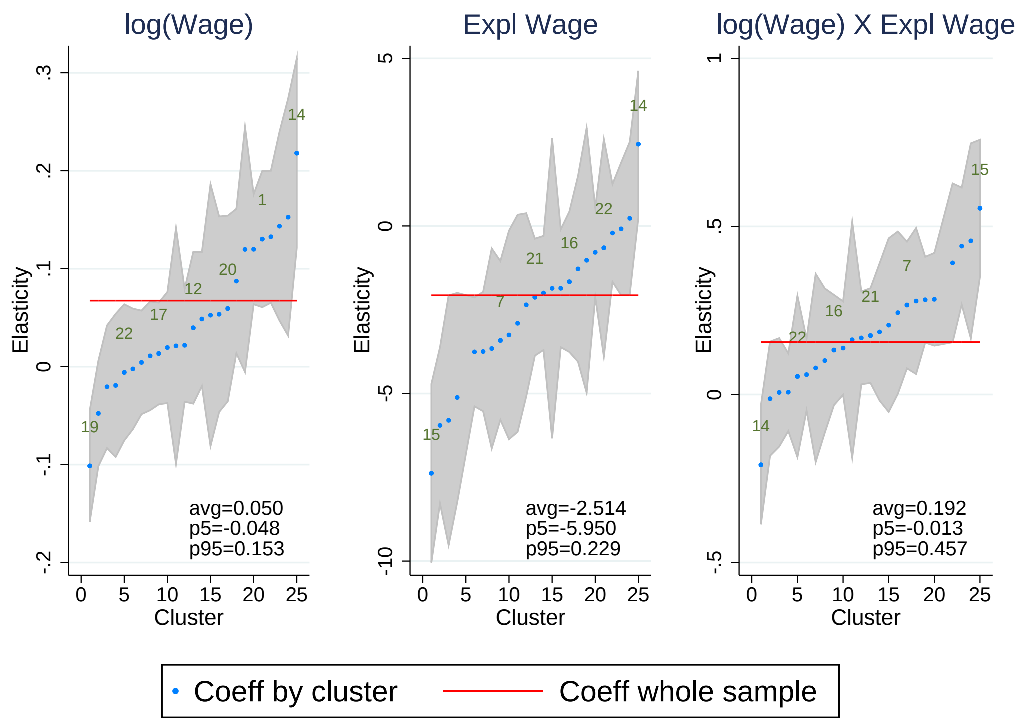
Note: Model including interactions of wage-filtering with log wage, explicit-wage dummy, and log wage $\times$ explicit-wage dummy. Vertical bars indicate 95% Confidence Intervals.

Table A7: Description of clusters used in estimating coefficients for Figure 4

Cluster	Obs	Avg # applic	Avg wage offer	Avg expl wage	Avg req exper	Mode trim	Mode req educ	Mode occup
1	5316	7.9	311358	0.20	1.03	2008q3 (29%)	High school SH (46%)	Non-declared (73%)
2	7011	24.1	359419	0.18	1.06	2011q1 (26%)	High school SH (62%)	Non-declared (90%)
3	4917	43.1	718041	0.10	3.00	2012q2 (13%)	Tertiary tech (90%)	Commerce/Manag (56%)
4	3531	38.7	328953	0.18	1.20	2014q1 (69%)	High school SH (86%)	Non-declared (96%)
5	5688	5.3	419147	0.08	0.03	2008q2 (29%)	Tertiary tech (52%)	Non-declared (89%)
6	2711	33.2	637009	0.07	3.00	2011q4 (19%)	Tertiary tech (100%)	Commerce/Manag (46%)
7	6391	39.7	347537	0.20	1.02	2014q1 (15%)	High school TP (100%)	Non-declared (50%)
8	2187	23.5	369624	0.17	0.00	2008q3 (19%)	College (47%)	Commerce/Manag (68%)
9	2504	19.7	955595	0.09	4.84	2008q1 (18%)	College (48%)	Non-declared (99%)
10	3341	10.5	710286	0.07	3.00	2008q2 (35%)	Tertiary tech (49%)	Non-declared (81%)
11	2871	33.0	1558202	0.04	5.59	2011q4 (26%)	College (91%)	Technology (58%)
12	5433	44.7	432542	0.20	1.00	2014q1 (11%)	Tertiary tech (100%)	Commerce/Manag (79%)
13	3642	24.0	597972	0.09	0.47	2008q3 (24%)	College (86%)	Technology (92%)
14	4857	35.9	621008	0.13	1.67	2012q3 (14%)	Tertiary tech (100%)	Technology (100%)
15	3826	15.8	441713	0.11	2.01	2008q2 (19%)	Tertiary tech (28%)	Non-declared (98%)
16	3473	32.7	994518	0.07	3.00	2011q2 (27%)	College (77%)	Technology (38%)
17	2827	29.2	350450	0.22	1.05	2011q1 (24%)	High school TP (100%)	Non-declared (58%)
18	3737	30.6	651543	0.13	2.54	2010q4 (30%)	College (39%)	Non-declared (93%)
19	6250	30.1	282616	0.28	0.00	2012q1 (15%)	High school SH (71%)	Non-declared (98%)
20	2486	43.4	338069	0.19	0.00	2013q4 (13%)	Tertiary tech (52%)	Commerce/Manag (84%)
21	3716	28.8	576238	0.11	2.00	2011q3 (24%)	Tertiary tech (100%)	Commerce/Manag (36%)
22	4973	65.7	771323	0.11	1.00	2013q1 (12%)	College (100%)	Technology (49%)
23	3733	27.7	955089	0.06	3.00	2008q3 (15%)	College (81%)	Technology (76%)
24	1542	35.9	415184	0.20	0.00	2011q4 (35%)	College (55%)	Technology (61%)
25	1239	32.3	762935	0.08	5.18	2011q3 (30%)	Tertiary tech (97%)	Commerce/Manag (38%)
26	5897	56.0	1207470	0.05	3.00	2012q2 (12%)	College (93%)	Technology (60%)
27	1266	23.6	497755	0.13	1.11	2011q4 (11%)	Tertiary tech (100%)	Technology (99%)
28	3954	28.7	623262	0.13	2.00	2011q1 (30%)	College (46%)	Non-declared (62%)
29	3301	37.1	433114	0.18	2.06	2012q2 (16%)	High school TP (100%)	Non-declared (44%)
30	1677	28.3	846620	0.13	4.98	2008q3 (14%)	Tertiary tech (47%)	Commerce/Manag (98%)
31	4474	61.2	1783839	0.03	5.62	2012q2 (13%)	College (92%)	Technology (100%)
32	2721	40.8	337799	0.16	1.04	2009q3 (28%)	High school SH (37%)	Non-declared (69%)
33	5541	44.8	583995	0.14	2.20	2012q2 (14%)	Tertiary tech (97%)	Commerce/Manag (73%)
34	826	60.3	1372855	0.04	5.44	2013q3 (15%)	College (86%)	Soc Science (35%)
35	1282	34.6	957295	0.04	4.76	2012q2 (11%)	Tertiary tech (100%)	Technology (88%)
36	6504	62.6	996123	0.06	2.00	2012q2 (13%)	College (99%)	Technology (56%)
37	2127	45.9	829229	0.11	3.74	2010q2 (21%)	College (69%)	Commerce/Manag (98%)
38	2372	26.0	499110	0.13	2.00	2008q3 (20%)	Tertiary tech (49%)	Commerce/Manag (96%)
39	3185	54.2	1139636	0.07	5.07	2013q2 (13%)	College (50%)	Commerce/Manag (100%)
40	6680	34.7	312788	0.23	1.16	2013q1 (29%)	High school SH (89%)	Non-declared (95%)
41	997	37.2	856451	0.09	5.03	2012q1 (15%)	Tertiary tech (28%)	Non-declared (97%)
42	3037	20.9	755791	0.05	2.00	2008q2 (21%)	College (68%)	Technology (88%)
43	1163	35.9	855633	0.13	2.96	2011q4 (31%)	College (92%)	Commerce/Manag (100%)
44	7453	23.1	285541	0.19	1.14	2012q1 (30%)	High school SH (91%)	Non-declared (95%)
45	3824	30.9	1444238	0.04	5.52	2010q4 (13%)	College (89%)	Technology (90%)
46	4628	43.8	947422	0.07	1.66	2011q3 (18%)	College (97%)	Technology (100%)
47	4585	33.0	357539	0.18	1.03	2010q4 (40%)	High school SH (43%)	Non-declared (79%)
48	1075	32.2	512411	0.14	3.00	2014q1 (20%)	High school SH (49%)	Non-declared (96%)
49	4864	23.5	260924	0.26	0.00	2011q4 (21%)	High school SH (72%)	Non-declared (98%)
50	3285	57.4	479504	0.13	0.00	2013q3 (12%)	College (69%)	Technology (74%)

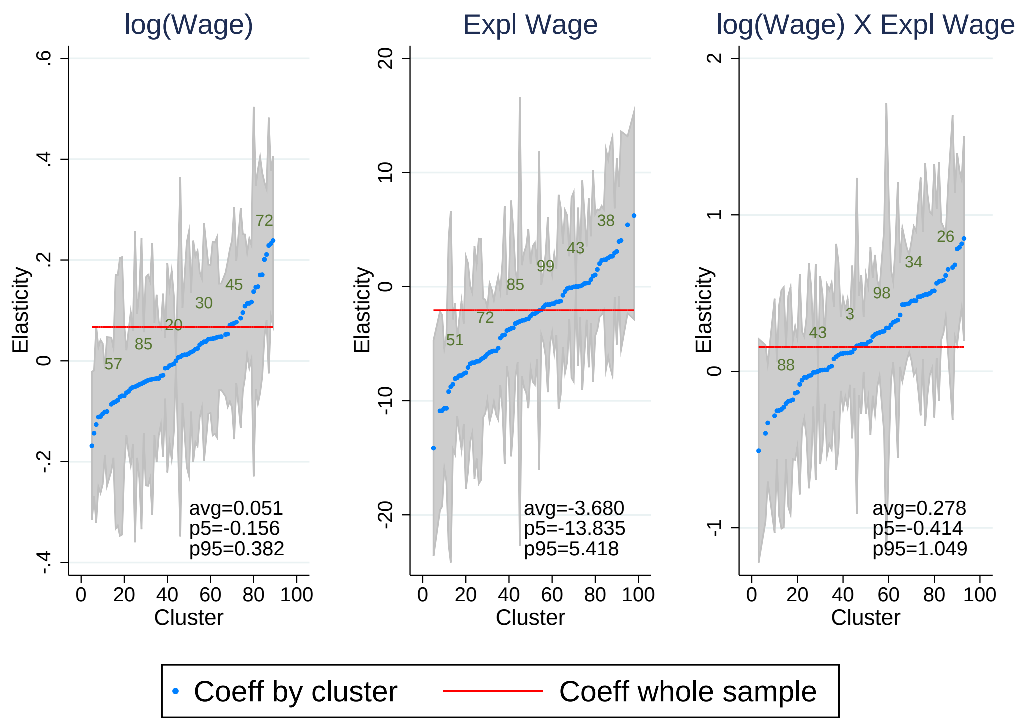
Note: These 50 clusters are defined by the highest Caliński and Harabasz (1974) statistic among 15 computations of k-means method.

Figure A7: Distribution of estimated coefficients by cluster (*k*=25)



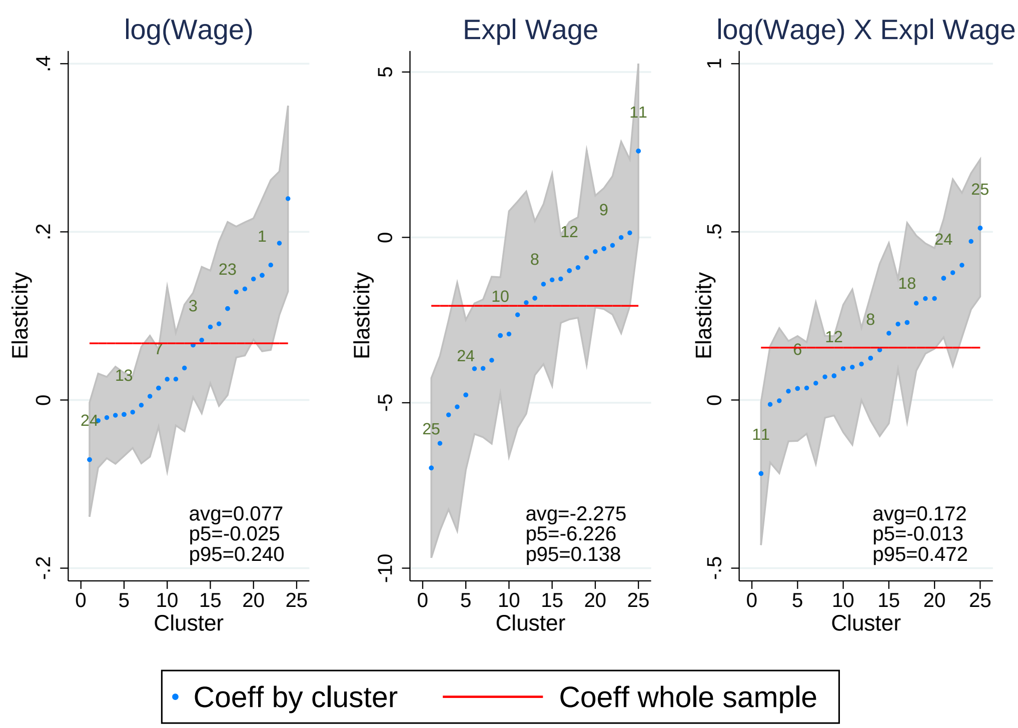
Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński and Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are quarter, educational level required, experience required, and occupation dummies. Plotted coefficients come from linear models computed with observations in each segment. In the models, the dependent variables is the log of received application by ad plus one, and the explanatory variables are required educational level, industry, career, firm size, contractual terms, computer skills, remuneration schemes, location, word-title dummies, firm fixed effects, and quarterly fixed effects.

Figure A8: Distribution of estimated coefficients by cluster (k=100)



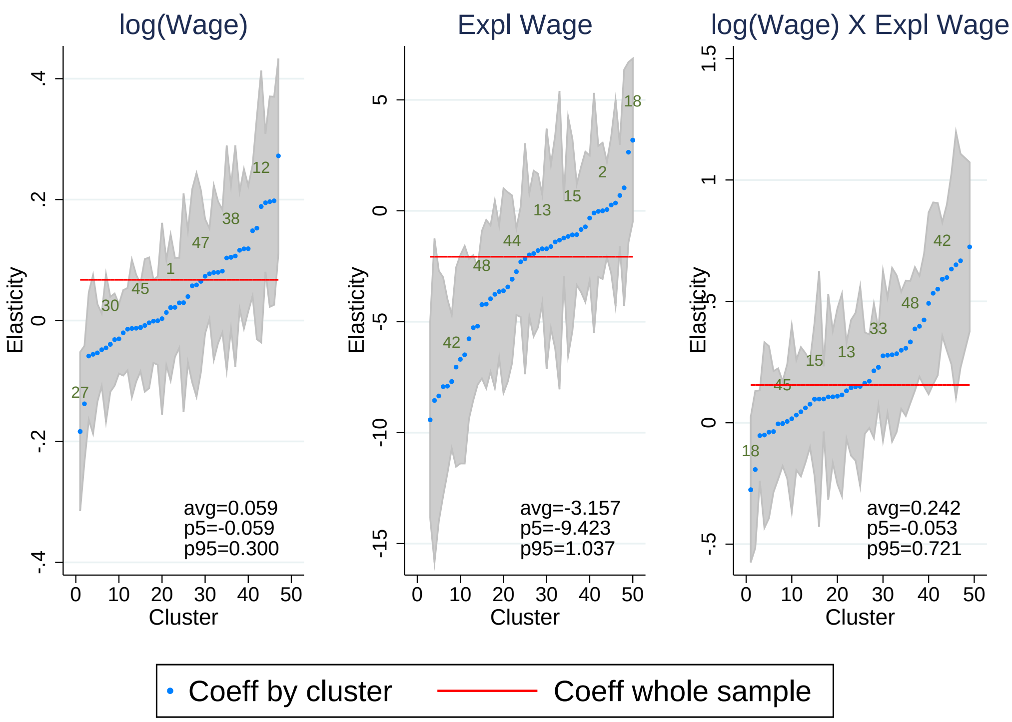
Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński and Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are quarter, educational level required, experience required, and occupation dummies. Plotted coefficients come from linear models computed with observations in each segment. In the models, the dependent variables is the log of received application by ad plus one, and the explanatory variables are required educational level, industry, career, firm size, contractual terms, computer skills, remuneration schemes, location, word-title dummies, firm fixed effects, and quarterly fixed effects.

Figure A9: Distribution of estimated coefficients by cluster (k=25)



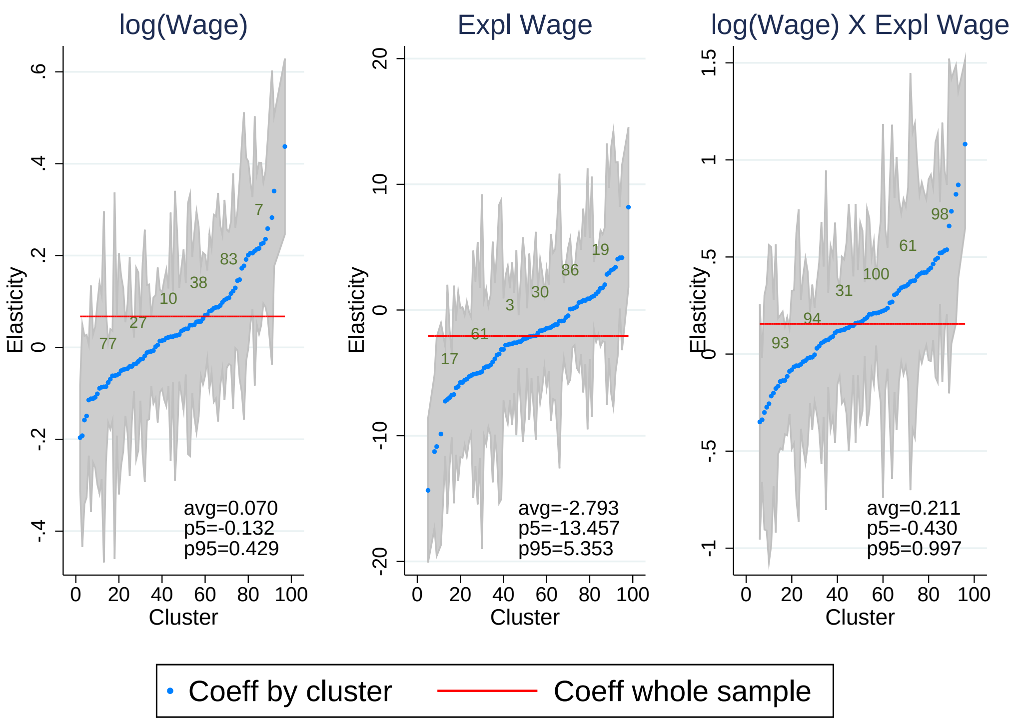
Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński and Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are quarter, educational level required, experience required, occupation, industry, and firm size dummies.. Plotted coefficients come from linear models computed with observations in each segment. In the models, the dependent variables is the log of received application by ad plus one, and the explanatory variables are required educational level, industry, career, firm size, contractual terms, computer skills, remuneration schemes, location, word-title dummies, firm fixed effects, and quarterly fixed effects.

Figure A10: Distribution of estimated coefficients by cluster (k=50)



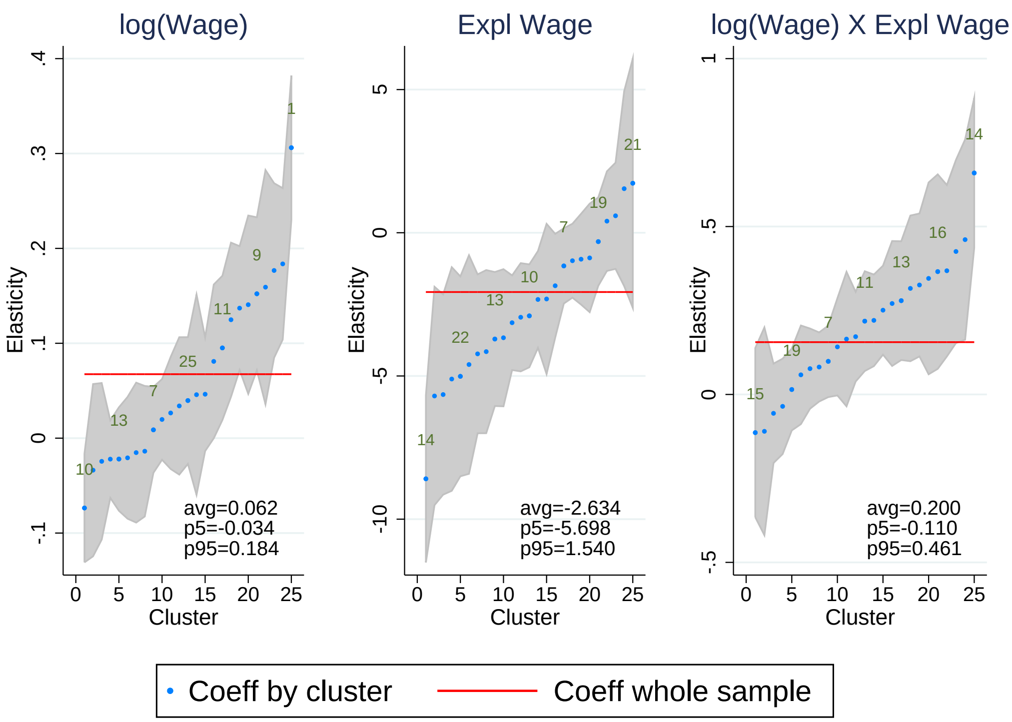
Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński and Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are quarter, educational level required, experience required, occupation, industry, and firm size dummies.. Plotted coefficients come from linear models computed with observations in each segment. In the models, the dependent variables is the log of received application by ad plus one, and the explanatory variables are required educational level, industry, career, firm size, contractual terms, computer skills, remuneration schemes, location, word-title dummies, firm fixed effects, and quarterly fixed effects.

Figure A11: Distribution of estimated coefficients by cluster (k=100)



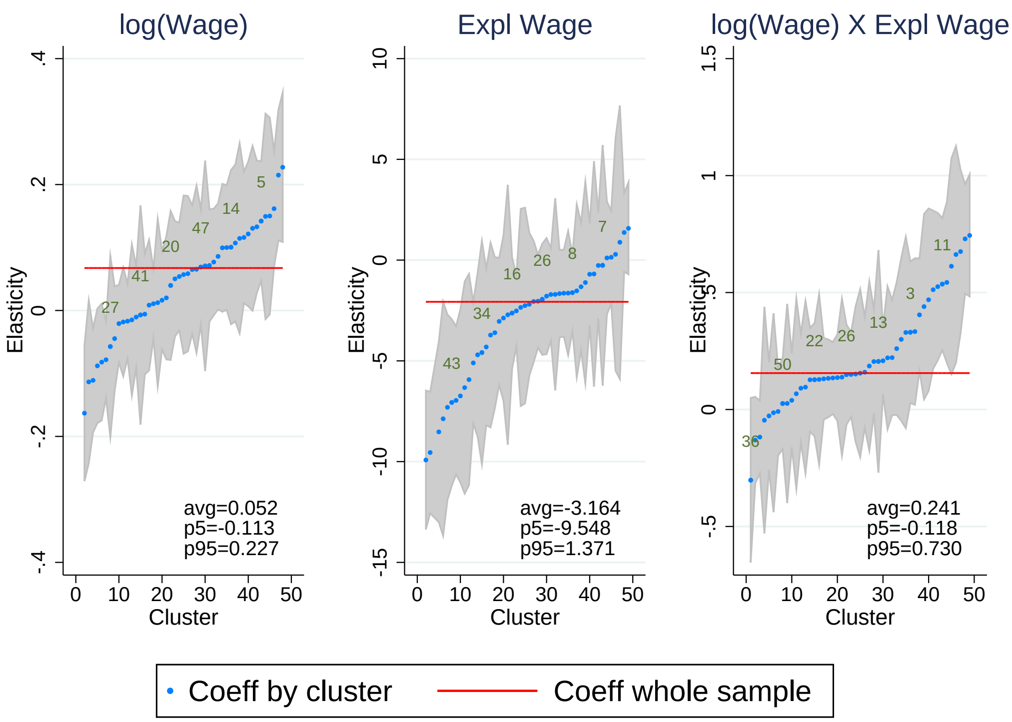
Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński and Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are quarter, educational level required, experience required, occupation, industry, and firm size dummies.. Plotted coefficients come from linear models computed with observations in each segment. In the models, the dependent variables is the log of received application by ad plus one, and the explanatory variables are required educational level, industry, career, firm size, contractual terms, computer skills, remuneration schemes, location, word-title dummies, firm fixed effects, and quarterly fixed effects.

Figure A12: Distribution of estimated coefficients by cluster (*k*=25)



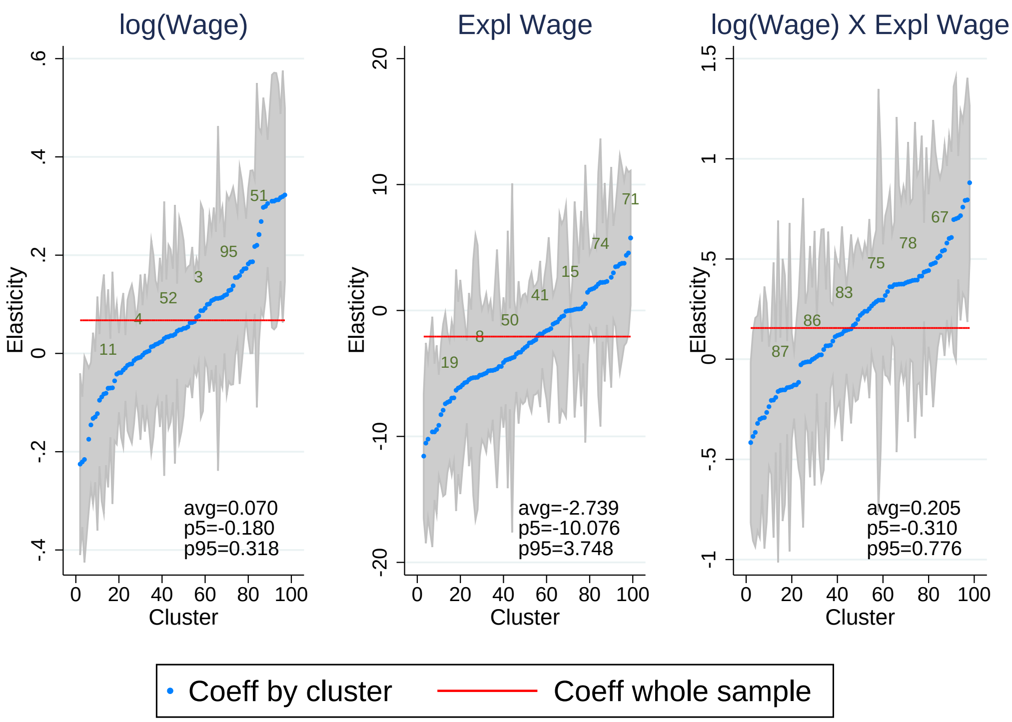
Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński and Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are quarter, educational level required, experience required, occupation, industry, firm size, and location dummies.. Plotted coefficients come from linear models computed with observations in each segment. In the models, the dependent variables is the log of received application by ad plus one, and the explanatory variables are required educational level, industry, career, firm size, contractual terms, computer skills, remuneration schemes, location, word-title dummies, firm fixed effects, and quarterly fixed effects.

Figure A13: Distribution of estimated coefficients by cluster (k=50)



Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński and Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are quarter, educational level required, experience required, occupation, industry, firm size, and location dummies.. Plotted coefficients come from linear models computed with observations in each segment. In the models, the dependent variables is the log of received application by ad plus one, and the explanatory variables are required educational level, industry, career, firm size, contractual terms, computer skills, remuneration schemes, location, word-title dummies, firm fixed effects, and quarterly fixed effects.

Figure A14: Distribution of estimated coefficients by cluster (k=100)



Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński and Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are quarter, educational level required, experience required, occupation, industry, firm size, and location dummies.. Plotted coefficients come from linear models computed with observations in each segment. In the models, the dependent variables is the log of received application by ad plus one, and the explanatory variables are required educational level, industry, career, firm size, contractual terms, computer skills, remuneration schemes, location, word-title dummies, firm fixed effects, and quarterly fixed effects.

A.6 Additional estimates for explicit wage posting, Section 3.4

Table A8: Models for the probability of explicit wage posting, not considering recruiting firms (Part I)

	Probit			OLS			OLS, Firm FE		
	β	SE	η	β	SE	η	β	SE	η
Number of vac.	0.000	0.000	0.000	0.000***	0.000	0.001	0.000	0.000	0.000
Req. exper.	-0.034***	0.003	-0.010	-0.005***	0.001	-0.010	-0.005***	0.001	-0.009
log wage	-0.268***	0.010	-0.051	-0.043***	0.002	-0.043	-0.028***	0.002	-0.028
Highest educ									
Primary (1-8 years)	0.211***	0.034	0.052	0.066***	0.008	0.066	0.022***	0.008	0.022
Tech. High School	-0.108***	0.015	-0.023	-0.032***	0.003	-0.032	-0.022***	0.003	-0.022
Tech. Tertiary Educ.	-0.257***	0.016	-0.052	-0.066***	0.003	-0.066	-0.041***	0.003	-0.041
College	-0.328***	0.019	-0.064	-0.074***	0.004	-0.074	-0.048***	0.004	-0.048
Graduate	-0.276***	0.075	-0.055	-0.069***	0.011	-0.069	-0.043***	0.011	-0.043
Professional Area									
Commerce and Manag.	0.139***	0.015	0.026	0.022***	0.003	0.022	0.017***	0.003	0.017
Agropecuary	0.015	0.076	0.003	0.008	0.012	0.008	0.021*	0.012	0.021
Art and Architecture	0.221***	0.049	0.044	0.031***	0.009	0.031	0.009	0.009	0.009
Natural Sciences	0.066	0.053	0.012	0.011	0.010	0.011	0.011	0.009	0.011
Social Sciences	0.003	0.039	0.001	-0.006	0.007	-0.006	-0.006	0.006	-0.006
Law	0.141	0.097	0.027	0.023	0.018	0.023	0.020	0.017	0.020
Education	0.080	0.053	0.015	0.016	0.010	0.016	-0.019**	0.010	-0.019
Humanities	0.620***	0.074	0.145	0.165***	0.016	0.165	0.080***	0.016	0.080
Health	0.142***	0.046	0.027	0.026***	0.008	0.026	0.030***	0.008	0.030
Non-declared	0.058***	0.015	0.011	0.008***	0.003	0.008	0.005**	0.003	0.005
Other	0.386***	0.074	0.082	0.090***	0.016	0.090	0.011	0.017	0.011
Computer knowledge level									
Low level	0.062***	0.023	0.011	0.014***	0.005	0.014	0.028***	0.005	0.028
Expert level	0.270***	0.037	0.055	0.040***	0.007	0.040	0.011*	0.006	0.011
Professional level	0.068***	0.023	0.013	0.013***	0.004	0.013	-0.020***	0.004	-0.020
Technical level	0.179***	0.024	0.035	0.035***	0.005	0.035	0.009**	0.005	0.009
User level	0.051***	0.011	0.009	0.010***	0.002	0.010	0.011***	0.002	0.011
Advanced User level	0.105***	0.014	0.020	0.018***	0.002	0.018	0.008***	0.002	0.008
Constant	2.246***	0.291		0.687***	0.050		0.429***	0.046	
Legal contract type									
Fixed-term	0.346***	0.016	0.066	0.071***	0.003	0.071	0.032***	0.003	0.032
Undefined term	0.161***	0.015	0.028	0.030***	0.003	0.030	0.026***	0.003	0.026
Observations	183997			184920			184920		

Note: Table A9 continues the estimated results

Table A9: Models for the probability of explicit wage posting, not considering recruiting firms (Part I)

	Probit			OLS			OLS, Firm FE		
	β	SE	η	β	SE	η	β	SE	η
Industry									
Agriculture	0.121***	0.043	0.022	0.022***	0.008	0.022	0.012	0.009	0.012
Fisheries	-0.963***	0.176	-0.094	-0.075***	0.016	-0.075	0.001	0.023	0.001
Mining	-0.147***	0.041	-0.023	-0.011*	0.006	-0.011	0.010	0.008	0.010
Manufacturing	0.056***	0.017	0.010	0.012***	0.003	0.012	0.024***	0.004	0.024
Electricity, water, and gas	0.131***	0.030	0.024	0.034***	0.005	0.034	0.021***	0.007	0.021
Construction	-0.053*	0.032	-0.009	-0.006	0.005	-0.006	0.005	0.007	0.005
Restaurants and Hotels	-0.040	0.034	-0.007	-0.011*	0.007	-0.011	-0.005	0.009	-0.005
Transportation	0.424***	0.022	0.089	0.104***	0.005	0.104	0.099***	0.006	0.099
Communication	0.182***	0.018	0.034	0.037***	0.003	0.037	-0.001	0.004	-0.001
Financial Serv.	-0.026	0.021	-0.004	0.000	0.004	0.000	0.018***	0.004	0.018
Business Serv.	0.221***	0.018	0.042	0.048***	0.004	0.048	0.032***	0.004	0.032
Household Serv.	-0.027	0.047	-0.005	-0.001	0.008	-0.001	0.012	0.009	0.012
Personal Serv.	0.112***	0.016	0.020	0.025***	0.003	0.025	0.040***	0.004	0.040
Public Admin.	0.421***	0.035	0.088	0.093***	0.007	0.093	0.060***	0.011	0.060
Others	0.150***	0.020	0.028	0.032***	0.004	0.032	0.033***	0.004	0.033
Availability									
Commission	-0.264***	0.059	-0.043	-0.053***	0.010	-0.053	-0.058***	0.010	-0.058
Half time	0.129***	0.029	0.026	0.034***	0.006	0.034	0.006	0.006	0.006
Part-time	-0.114***	0.030	-0.020	-0.021***	0.006	-0.021	-0.019***	0.006	-0.019
Shift-work	0.072***	0.015	0.014	0.021***	0.003	0.021	0.021***	0.003	0.021
Internship	0.033	0.034	0.006	0.018**	0.008	0.018	0.010	0.008	0.010
Replacement	0.085*	0.050	0.017	0.012	0.011	0.012	-0.004	0.010	-0.004
Observations	183997			184920			184920		
Avg. Probability	0.135			0.134			0.134		
pseudo - R^2	0.131								
R^2				0.113			0.316		
Adj. R^2				0.109			0.289		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.. Estimated coefficients of models *without* controlling for recruiting firms. Omitted groups: *Highest educ:* Science-humanity high-school; *Contract law* Other. *Availabilty:* Full-time. *Computer knowledge level:* None. In all the equations, we control for profession/occupation dummies, firm size dummies, industry dummies, quarter dummies to capture seasonality, first four words job title dummies, and the number of days the vacancy was open.

Table A10: Models for the probability of explicit wage posting, controlling for recruiting firms (Part I)

	Probit			OLS			OLS, Firm FE		
	β	SE	η	β	SE	η	β	SE	η
Number of vac.	0.000	0.000	0.000	0.000**	0.000	0.001	0.000*	0.000	0.000
Req. experience	-0.036***	0.004	-0.011	-0.005***	0.001	-0.010	-0.005***	0.001	-0.009
log wage	-0.276***	0.010	-0.053	-0.046***	0.002	-0.046	-0.029***	0.002	-0.029
Recr. firm	0.098***	0.011	0.019	0.026***	0.002	0.026	0.000	.	0.000
Highest educ									
Primary (1-8 years)	0.216***	0.035	0.054	0.069***	0.008	0.069	0.024***	0.008	0.024
Tech. High School	-0.093***	0.015	-0.020	-0.029***	0.003	-0.029	-0.022***	0.003	-0.022
Tech. Tertiary Educ.	-0.250***	0.016	-0.051	-0.066***	0.003	-0.066	-0.043***	0.003	-0.043
College	-0.319***	0.020	-0.063	-0.073***	0.004	-0.073	-0.049***	0.004	-0.049
Graduate	-0.246***	0.076	-0.050	-0.066***	0.012	-0.066	-0.044***	0.011	-0.044
Professional Area									
Commerce and Manag.	0.130***	0.016	0.025	0.021***	0.003	0.021	0.015***	0.003	0.015
Agropecuary	0.052	0.079	0.010	0.013	0.013	0.013	0.020	0.013	0.020
Art and Architecture	0.182***	0.051	0.036	0.027***	0.009	0.027	0.009	0.009	0.009
Natural Sciences	0.064	0.055	0.012	0.012	0.010	0.012	0.011	0.010	0.011
Social Sciences	-0.010	0.041	-0.002	-0.008	0.007	-0.008	-0.006	0.007	-0.006
Law	0.145	0.099	0.028	0.022	0.019	0.022	0.019	0.017	0.019
Education	0.111**	0.056	0.021	0.023**	0.011	0.023	-0.013	0.010	-0.013
Humanities	0.666***	0.077	0.161	0.182***	0.017	0.182	0.096***	0.017	0.096
Health	0.148***	0.047	0.029	0.028***	0.009	0.028	0.033***	0.008	0.033
Non-declared	0.053***	0.015	0.010	0.007**	0.003	0.007	0.005*	0.003	0.005
Other	0.417***	0.077	0.091	0.100***	0.018	0.100	0.009	0.018	0.009
Legal contract type									
Fixed-term	0.338***	0.017	0.065	0.071***	0.003	0.071	0.032***	0.003	0.032
Undefined term	0.162***	0.016	0.029	0.031***	0.003	0.031	0.026***	0.003	0.026
Observations	169487			170365			170365		

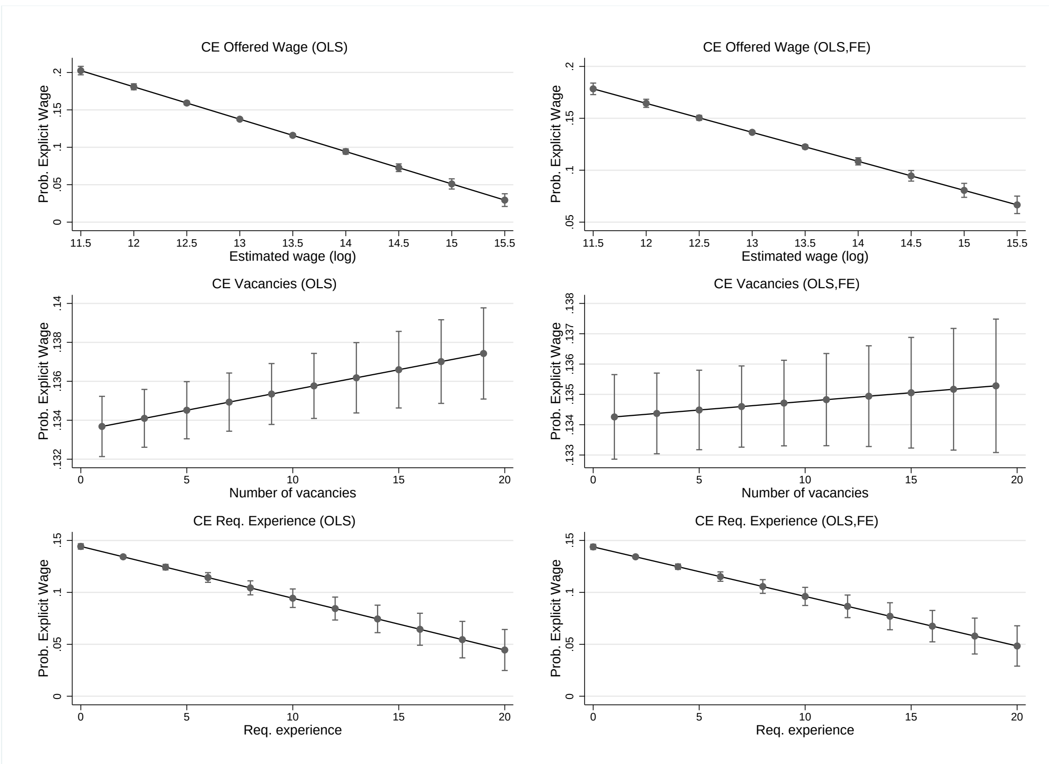
Note: Table A11 continues the estimated results

Table A11: Models for the probability of explicit wage posting, controlling for recruiting firms (Part II)

	Probit			OLS			OLS, Firm FE		
	β	SE	η	β	SE	η	β	SE	η
Industry									
Agriculture	0.110**	0.045	0.020	0.022***	0.008	0.022	0.014	0.009	0.014
Fisheries	-0.983***	0.177	-0.100	-0.083***	0.017	-0.083	-0.007	0.025	-0.007
Mining	-0.174***	0.043	-0.028	-0.013**	0.007	-0.013	0.006	0.009	0.006
Manufacturing	0.048***	0.018	0.009	0.011***	0.003	0.011	0.024***	0.004	0.024
Electricity, water, and gas	0.091***	0.031	0.017	0.028***	0.006	0.028	0.018***	0.007	0.018
Construction	-0.057*	0.032	-0.010	-0.005	0.006	-0.005	0.008	0.007	0.008
Restaurants and Hotels	-0.059*	0.035	-0.010	-0.014**	0.007	-0.014	-0.004	0.009	-0.004
Transportation	0.413***	0.023	0.088	0.104***	0.005	0.104	0.105***	0.006	0.105
Communication	0.149***	0.019	0.028	0.031***	0.004	0.031	-0.001	0.004	-0.001
Financial Serv.	-0.047**	0.021	-0.008	-0.003	0.004	-0.003	0.019***	0.005	0.019
Business Serv.	0.192***	0.019	0.037	0.044***	0.004	0.044	0.032***	0.004	0.032
Household Serv.	-0.059	0.048	-0.010	-0.004	0.008	-0.004	0.013	0.009	0.013
Personal Serv.	0.107***	0.017	0.020	0.025***	0.003	0.025	0.041***	0.004	0.041
Public Admin.	0.452***	0.036	0.099	0.104***	0.008	0.104	0.071***	0.013	0.071
Others	0.151***	0.021	0.029	0.034***	0.004	0.034	0.034***	0.004	0.034
Availability									
Comission earner	-0.263***	0.061	-0.044	-0.052***	0.010	-0.052	-0.060***	0.011	-0.060
Half time	0.072**	0.031	0.014	0.020***	0.007	0.020	0.005	0.006	0.005
Part-time	-0.126***	0.031	-0.023	-0.023***	0.006	-0.023	-0.015**	0.006	-0.015
Shift-work	0.092***	0.016	0.018	0.027***	0.003	0.027	0.023***	0.003	0.023
Internship	0.066*	0.035	0.013	0.029***	0.008	0.029	0.021**	0.009	0.021
Replacement	0.033	0.054	0.007	0.001	0.012	0.001	-0.012	0.011	-0.012
Computer knowledge level									
Low level	0.094***	0.023	0.018	0.023***	0.005	0.023	0.033***	0.005	0.033
Expert level	0.289***	0.038	0.060	0.046***	0.007	0.046	0.015**	0.007	0.015
Professional level	0.086***	0.024	0.016	0.016***	0.004	0.016	-0.017***	0.004	-0.017
Technical level	0.225***	0.025	0.045	0.044***	0.005	0.044	0.015***	0.005	0.015
User level	0.066***	0.012	0.012	0.014***	0.002	0.014	0.012***	0.002	0.012
Advanced User level	0.119***	0.014	0.023	0.021***	0.003	0.021	0.010***	0.003	0.010
Constant	2.311***	0.297		0.698***	0.052		0.457***	0.048	
Observations	169487			170365			170365		
Avg. Probability	0.139			0.139			0.139		
pseudo - R^2	0.134								
R^2				0.118			0.315		
Adj. R^2				0.114			0.288		

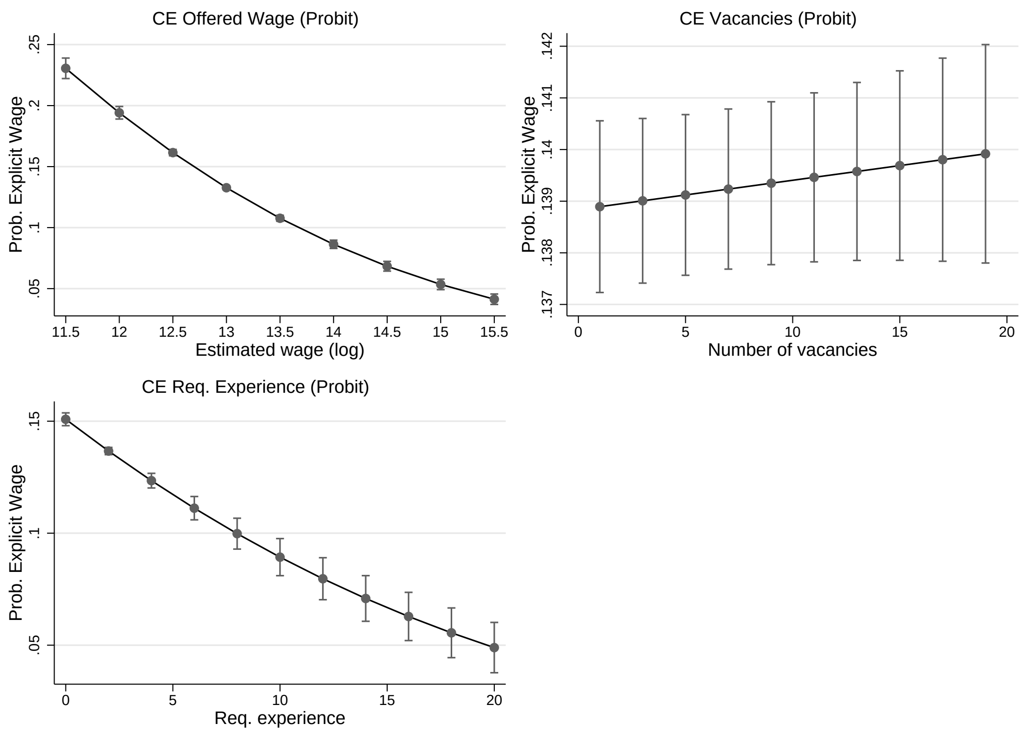
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.. Estimated coefficients of models controlling for recruiting firms. Omitted groups: *Highest educ:* Science-humanity high-school; *Contract law* Other. *Availabilty:* Full-time. *Computer knowledge level:* None. In all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

Figure A15: Conditional probability of explicit wage posting (Tables A8 and A9, OLS and OLS Firm FE)



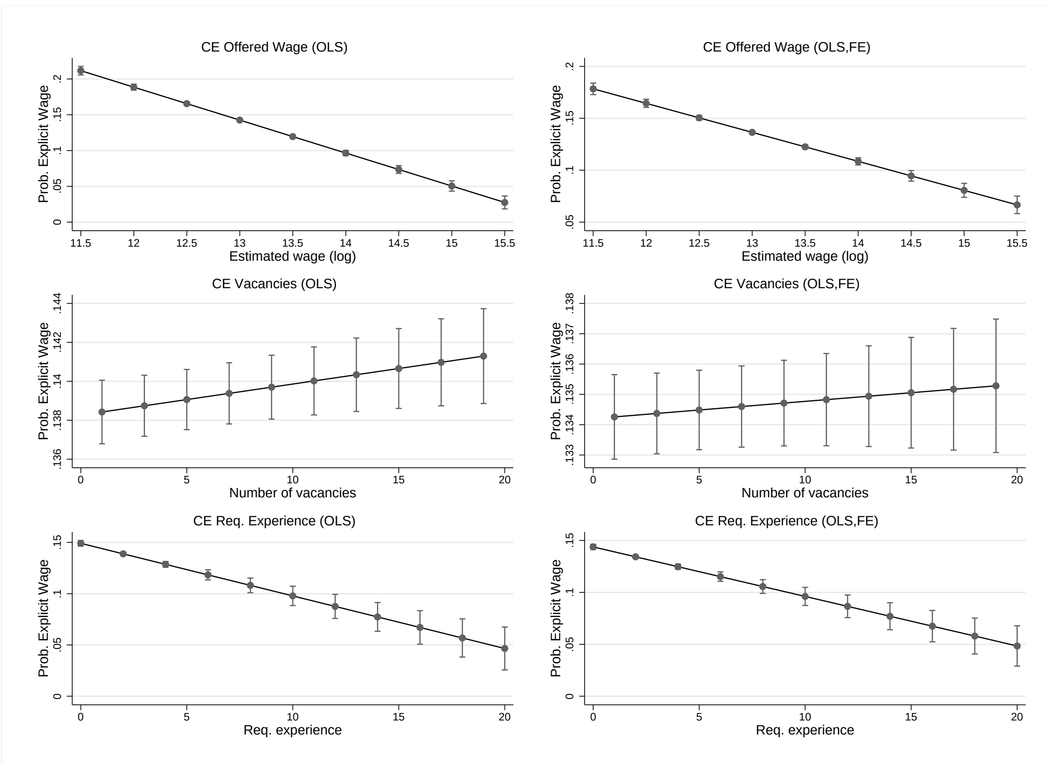
Note: Effects computed *without* controlling for recruiting firms. Vertical bars indicate 95% Confidence Intervals.

Figure A16: Conditional probability of explicit wage posting (Tables A10 and A11, probit)



Note: Effects computed controlling for recruiting firms. Vertical bars indicate 95% Confidence Intervals.

Figure A17: Conditional probability of explicit wage posting (Tables A10 and A11, OLS and OLS Firm FE)



Note: Effects computed controlling for recruiting firms. Vertical bars indicate 95% Confidence Intervals.

A.7 Derivation of condition (1)

Denoting A as the number of applications received by a job ad with characteristics X, we use the law of total expectation to write

$$\mathbb{E}[\log A|X] = \mathbb{E}[\log A|X, D=1]P(D=1|X)) + \mathbb{E}[\log A|X, D=0]P(D=0|X)$$

where D is an indicator for explicit wage posting. Taking derivatives with respect to $\log W$, we show that the expected marginal impact of wages on applications is given by the following formula

$$\begin{aligned}\frac{\partial \mathbb{E}[\log A|X]}{\partial \log W} = \frac{\partial \mathbb{E}[\log A|X, D=1]}{\partial \log W} - P(D=0|X))\left(\frac{\partial \mathbb{E}[\log A|X, D=1]}{\partial \log W} - \frac{\partial \mathbb{E}[\log A|X, D=0]}{\partial \log W}\right) \\ - \frac{\partial P(D=0|X)}{\partial \log W}\left(\mathbb{E}[\log A|X, D=1] - \mathbb{E}[\log A|X, D=0]\right)\end{aligned}$$

From this expression, we learn that the impact of wages on applications is not correctly estimated from explicit wage job ads in general. The marginal expected impact of log wage is the same for the whole population and for the sample of ads with explicit wages only if

$$\begin{aligned}P(D=0|X)\left(\frac{\partial \mathbb{E}[\log A|X, D=1]}{\partial \log W} - \frac{\partial \mathbb{E}[\log A|X, D=0]}{\partial \log W}\right) \\ = -\frac{\partial P(D=0|X)}{\partial \log W}\left(\mathbb{E}[\log A|X, D=1] - \mathbb{E}[\log A|X, D=0]\right).\end{aligned}$$

The result in equation (1) follows after some standard algebraic manipulation.

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