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

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Abstract

Labor markets become more efficient in theory if jobseekers direct their search. Using online job board data, we show that high-wage ads attract more applicants as in directed search models. Due to distinctive data features, we also estimate significant but milder directed search for hidden (or implicit) wages, suggesting that ad texts and requirements tacitly convey wage information. Since explicit-wage ads often target unskilled workers, other estimates in the literature ignoring hidden-wage ads may suffer from selection bias. Moreover, job ad requirements are aligned with their applicants' traits, as predicted in directed search models with heterogeneity.

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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 other Latin American countries. 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, jobseekers have information about specific job offers and apply more to positions 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 & Shi, 2010; Menzio *et al.* , 2016). Since these models predict a unique (sub)market equilibrium wage, an observed cross-sectional positive correlation between wages and applications would be out of equilibrium. Models with multiple applications, a sensible assumption in our online context, can solve this tension because they predict a positive correlation and equilibrium wage dispersion as a consequence of the strategic behavior of applicants and employers (Albrecht *et al.* , 2006; Galenianos & Kircher, 2009; Kircher, 2009). Moreover, unobserved heterogeneity in both sides of the market could also be a reason for coexistence of wage dispersion and directed search behavior. A recent in-depth survey for directed search is Wright *et al.* (2017).

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. For instance, under directed search Moen & 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 & Shimer, 2000; Acemoglu, 2001; Flinn, 2006).

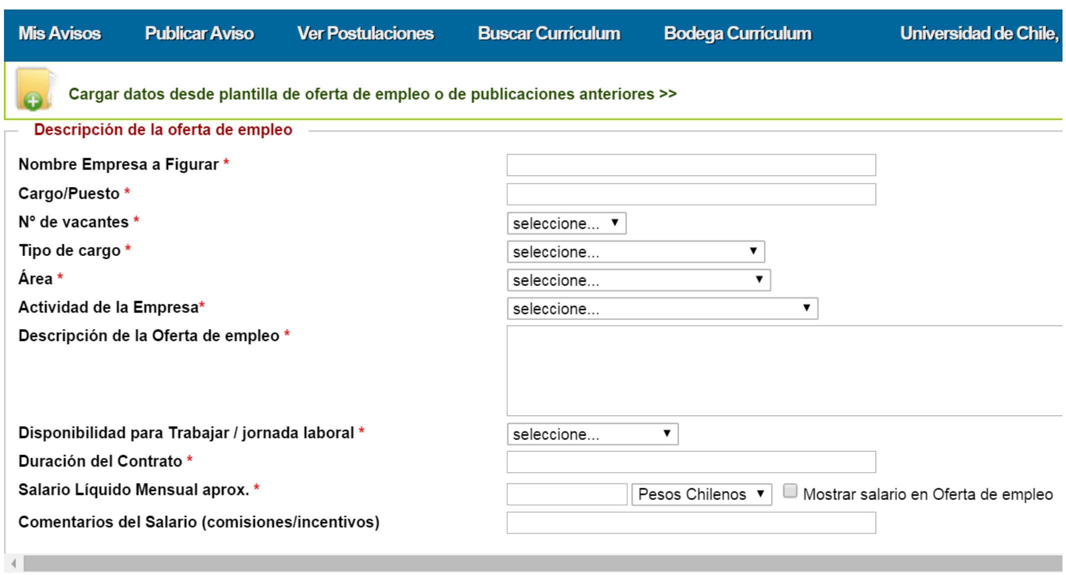
Hence, empirical evidence on the prevailing type of job search behavior should shape policy recommendations. However, finding solid evidence for random or directed search is difficult for at least two reasons. In an ideal experiment for homogeneous jobs, we would clone job ads except for an exogenously modified offered wage and compare application responses. Then, we would estimate the average causal impact of wages in applications received, as in Belot *et al.* (2017). The 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 merges 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 & Wolthoff, 2015), and 83% in `www.zhaopin.com`, a Chinese online job board (Kuhn & Shen, 2013). In contrast, we investigate the behavior

[1] Within the class of multiple application models Kircher (2009) is an example of decentralized constrained efficiency in contrast to Galenianos & Kircher (2009).

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. The prospective employer has to enter a single amount representing a monthly net wage offer. Unlike other websites, entering a wage range is not allowed. However, next to the wage box employers can choose if they want to make the wage visible to applicants. This option is selected for only 13.4% of ads in our sample. In Section 2.5, we show that hidden wages are reliable measures of wages that employers intend to pay. 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



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Cargar datos desde plantilla de oferta de empleo o de publicaciones anteriores >>

Descripción de la oferta de empleo

Nombre Empresa a Figurar *
Cargo/Puesto *
N° de vacantes * seleccione...
Tipo de cargo * seleccione...
Área * seleccione...
Actividad de la Empresa* seleccione...
Descripción de la Oferta de empleo *
Disponibilidad para Trabajar / jornada laboral * seleccione...
Duración del Contrato *
Salario Líquido Mensual aprox. * Pesos Chilenos Mostrar salario en Oferta de empleo
Comentarios del Salario (comisiones/incentivos)

Note: Accessed on May 5th, 2015. Red asterisks indicate that the required field is mandatory.

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 & Trivedi, 2013) 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

[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%).

for ads in which the wage offer is observable for applicants. Applicants react to hidden wages probably because they use search filters by wage bracket that are fine for low wages and coarse for large ones. Even within a bracket, as we show below, applicants may infer wages through information in the job ad. Consequently, we refer to hidden wages as *implicit* interchangeably. 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 & 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.

In the literature few empirical papers show some evidence on application responding positively to higher wages. We believe we are the first showing this effect for employers not posting explicit wages. Holzer *et al.* (1991) show that vacancies for which minimum wage regulation is binding provide extra rents that attract more applicants. Dal Bó *et al.* (2013) find that higher wages attract more and better qualified applicants in a Mexican public sector online job board. Marinescu & 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 evidence of directed search job ads with explicitly posted wages, which comprise nearly 20% of their sample, but they are silent about job ads with hidden wages. Belot *et al.* (2017) set up 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. Braun *et al.* (2016) use NLSY data to estimate duration models and show that search effort is higher in high-wage markets compared to medium-wage markets. Finally, for product markets Lewis (2011) shows that internet seekers for used cars react significantly to posted information regarding automobile quality.

For our second finding, we show that similar workers tend to apply for the same jobs and their qualifications closely meet employers' requirements in Section 3.2, as endogenous segmentation arises in directed search models with heterogeneity on at least one side of the market (e.g. Shi (2002); Menzio *et al.* (2016)), We also show that wages attract applications 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.

In the literature, to the best of our knowledge, only Dal Bó *et al.* (2013) provide some evidence interpretable as segmentation since job characteristics such as location and municipality features drive applicant search. In a similar vein, we document jobseekers targeting ads with requirements that fit their characteristics, regardless of the final hiring decision. Often weak correlations between worker and firm effects found in matched employer-employee databases (e.g. Abowd *et al.* (1999)) might mistakenly be taken as segmentation since good workers match with good jobs as implied by directed search models. However, employers may also select among multiple randomly sent applications as in non-sequential random search models (Moen, 1999; Villena-Roldán, 2012). Hence, these correlations are not necessarily evidence of the segmentation implied by directed search.

Our third empirical fact concerns 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.

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. 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 link between directed search and committed explicit wage posting in most models (i.e. competitive search), some authors investigate the prevalence of wage-posting and wage-bargaining behavior. Brenzel *et al.* (2014) report a sizable share of wage posting, often concentrated in low-skill jobs. Hall & Krueger (2012) report that nearly one-third of workers were largely certain of the wage paid before applying. However, knowing wages is not a concrete indication of directed search since it may just reflect anticipation of a 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.

Finally, Section 4 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 14th, 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 to each job ad 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 out a form to provide demographic information, educational record, previous worker experience, etc. Employers complete 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.[4]

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. Ads with hidden wage are listed in these ranges when filtering by wage offer level. We have no information regarding the filters jobseekers actually use to find postings because users are not required to login to search job offers.

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, gender, nationality, and profession. Only nine duplicated cases are dropped.

[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. The job board also offers preferential rates for big clients.

[4]We discuss data cleaning details in the online appendix (OA) in Section A.1.

We keep individuals between 18 to 69 years old with monthly net wages lower than 5 million pesos in their previous work (9,745 USD per month, using the average nominal exchange rate over 2008Q1 - 2014Q2), 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 net wage expectations over 5 million pesos, and those who omit an expected figure in the application 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.[5]

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 schooling according to the highest educational level achieved (8 years for primary, 12 years for both Scientific-Humanistic or Technical high school, 16 years for technical tertiary degrees, 17 years for university (college) degrees, and 18 years for graduate degrees). The average schooling is 15 years and is 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 potential years of experience, with males slightly more experienced. A large proportion of the sample are self-reported as unemployed (47.74%), who are more likely to be females. The rest of the applicants are on-the-job searchers.

The gender gap in expected wages paid is nearly 44%, similar to the gap of last/current jobs. 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.[6] Applicants' wage expectations tend to be private: less than half of the sample chooses to display their wage expectations to employers.

2.2 Employers

Our sample has 6,386 different firms.[7] 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

[5]For data cleaning details, see our online appendix (OA), Section A.1. For more descriptive details, see our OA, Section A.2, Tables A2 and A3.

[6]Summary statistics of applicant last job wages are reported in the OA, Section A.2, Table A2

[7]We describe firm data in greater detail in the OA, Table A4.

Table 1: Summary of applicant characteristics

	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+	9.55	6.19	7.95
Age (Avg.)	31.25	29.05	30.20
Marital Status (%)			
Married	27.99	19.17	23.79
Single	66.80	74.75	70.59
Other	5.22	6.08	5.63
Wage expectation (%)			
CLP 300.000 $<$	18.18	35.88	26.61
CLP 300.001 - 600.000	30.89	33.29	32.03
CLP 600.001 - 1.000.000	24.76	18.23	21.65
CLP 1.000.000+	23.13	9.86	16.81
No wage or too high	3.17	2.78	2.98
Wage expectation (Avg./S.D.)	838753	559238	705339
	(693009)	(473144)	(614307)
Visible expected wage (%)	48.47	42.77	45.75
Years of experience (%)			
0 - 3	37.08	49.43	42.96
4 - 7	25.38	24.94	25.17
8+	37.54	25.63	31.87
Experience (Avg./S.D.)	7.44	5.38	6.45
	7.21	5.78	6.65
Highest attained educ. level(%)			
Primary/Secondary/Tech. Secondary	29.47	32.78	31.04
Technical Tertiary	27.17	24.80	26.04
College (Tertiary)/Graduate	43.36	42.43	42.92
Estimated Schooling (Avg./S.D.)	15.25	15.10	15.18
	(2.19)	(2.25)	(2.22)
Major study area (%)			
Commerce & Management	13.95	19.50	16.59
Technology	33.23	13.05	23.62
No area	36.46	41.18	38.71
Other	16.36	26.26	21.07
Labor status (%)			
Employed	50.09	38.04	44.35
Unemployed	43.12	52.82	47.74
Inactive	6.79	9.13	7.91
Observations	242733	220762	463495

potential applicants for their clients. We consider a recruiting firm as one posting a number of vacancies exceeding half of the upper limit of its reported interval of employees in a given month.[8] Larger firms post more ads and vacancies per month, but do not receive

[8]For instance, if a firm in the range of 11-50 employees posts more than 25 vacancies, we classify it as a recruiting firm. The intervals are 1-10, 11-50, 51-150, 151-300, 301-500, 501-1000, 1001-5000,

more applicants per ad or vacancy posted. By industry, a majority of firms are in retail, communications, services, or manufacturing. The posting frequency of ads and vacancies varies substantially 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 fewer ads or vacancies, such as household services, personal services, and public administration.

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 Table 2.[9] Our sample excludes jobs with (i) an estimated offered monthly wage below CLP 100,000 or 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 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 2 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. Explicit-wage ads concentrate in retail, communications, and services. 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.

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 & Wolthoff (2015) use job titles from `www.careerbuilder.com` data to assess their

+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 *ad hoc* and it is not immune to potential misclassification, our results are barely changed by this issue, as we show below.

[9]For further details, please see the OA, Section A.2, Tables A5, A6, and A7.

Table 2: Summary of Job Ad Characteristics

	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 - 20	6.16	14.61	13.48
Years of experience (Avg./S.D.)	1.41	2.05	1.96
	(1.40)	(1.80)	(1.76)
Required educ. level (%)			
Primary/Secondary/Tech. Secondary	56.82	34.36	37.38
Technical Tertiary	25.13	28.14	27.74
College (Tertiary)/Graduate	18.05	37.50	34.88
Major study area (%)			
Commerce & Management	23.68	22.24	22.43
Technology	15.78	29.38	27.55
No area	53.45	40.30	42.07
Others	7.09	8.09	7.95
Sectors (%)			
Manufacturing	7.76	8.85	8.71
Electricity/gas/water	4.47	2.37	2.66
Commerce	19.56	19.84	19.80
Transportation	6.81	3.13	3.63
Communication	11.12	9.01	9.30
Financial/Business/Personal Serv.	25.27	25.65	25.60
Others	25.01	31.14	30.31
Offered wage (%)			
CLP 300.000$<$	54.45	31.86	34.89
CLP 300.001 - 600.000	31.52	29.00	29.34
CLP 600.001 - 1.000.000	9.78	22.32	20.63
CLP 1.000.000+	4.24	16.83	15.14
Offered wage (Avg/S.D.)	404887	680704	643614
	(347276)	(587201)	(568778)
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+	13.38	21.43	20.35
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)
Observations	24867	160053	184920

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

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 & 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. Since most words in Spanish are not gender neutral, we consider male and female words 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 & Shen (2013).

The first word 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, it 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. 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 suggests 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 4 and 8 in the main text, and A8 - A11, A13 - A16 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. Hence, posting nonsensical information is potentially detrimental for the employer. Moreover, we assess how reliable implicit wages are by assuming that explicit wages are truthfully reported.

We proceed by estimating a predictive equation for log wages for implicit-wage and explicit-wage job ads, separately. The baseline explanatory variables are job ad title word, regional, and quarter binary variables. In augmented models, we incorporate additional regressors in steps, such as experience, education, and 166 different job areas and computer skill requirements.

The upper panel of Table 3 shows in-sample prediction statistics for regressions by type of wage. The columns report the R^2 (squared correlation coefficient between actual and fitted values), the root-square of the mean squared error ($RMSE$) to measure prediction inaccuracy, and the sample size, N. High R^2 and low $RMSE$ are complementary measures of prediction accuracy both in and out of sample. Observed characteristics such as job title word, region, and quarter dummies explain 57.7% of the variance of implicit log wages and 62.2% for explicit log wages. As we incorporate more variables, the explained share of variance increases to 67.9% and 72.6% for implicit and explicit log wages, respectively. In-sample predictive accuracy is clearly higher for the explicit-wage equation. Additional controls increase R^2 and reduce $RMSE$ in both equations.

The lower panel of Table 3 shows how good the explicit wage equation is at predicting implicit wages and vice versa. For every set of controls, a given type of regression predicts wages of the other kind with remarkable accuracy, particularly in terms of R^2. With all controls, the out-of-sample explicit-wage prediction of hidden wages explains 92.3% (0.627/0.679) of the variance compared to the in-sample implicit-wage prediction. Comparing out-of-sample and in-sample $RMSE$ predictions, the latter is 27.2% larger $(0.560/0.440)$. The counterpart exercise with all controls reveals that the out-of-sample implicit-wage prediction of explicit wages explains 87.6% (0.636/0.726) of the variance relative to the in-sample prediction of explicit wages. The comparable $RMSE$ ratio is 29.8% larger $(0.414/0.319)$

The explicit-wage equation quite accurately predicts hidden wages. In addition, the implicit-wage equation can be used to predict explicit wages as well. These facts illustrate that employers use a similar pricing scheme for all kinds of wages, as hypothesized to some extent by Marinescu & Wolthoff (2015). This evidence shows 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.

3 Empirical Results

In this section, we test several relevant predictions. First, do job ads posting higher wages or benefits attract more applicants Moen (1997). Second, do 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 & Shi (2010); Menzio *et al.* (2016). Third, we test if directed search prevails within labor market segments in

Table 3: Predictive power of job ad features on log wages

In-sample prediction	Implicit predicts implicit			Explicit predicts explicit		
	R^2	*RMSE*	*N*	R^2	*RMSE*	*N*
Title words, region, quarter	0.577	0.505	160053	0.622	0.373	24867
+ req exper (quartic)	0.625	0.475	160053	0.668	0.350	24867
+ req educ & completion	0.671	0.446	160053	0.715	0.324	24867
+ job area & comp skill	0.679	0.440	160053	0.726	0.319	24867

Out-of-sample prediction	Implicit predicts explicit			Explicit predicts implicit		
	R^2	*RMSE*	*N*	R^2	*RMSE*	*N*
Title words, region, quarter	0.522	0.437	24867	0.502	0.632	160053
+ req exper (quartic)	0.576	0.409	24867	0.563	0.589	160053
+ req educ & completion	0.630	0.415	24867	0.621	0.567	160053
+ job area & comp skill	0.636	0.414	24867	0.627	0.560	160053

Note: The first model uses four job ad words described in Section 2.4, regional, and quarter dummies. The second model adds a quartic polynomial in job ad required experience. The third model adds required educational level dummies and completion required level dummies (graduated, certified,ongoing, indifferent, close to graduation) with main and interacted effects. The fourth model includes 166 job area dummies (similar to occupation) and seven categories of computer skills required (none, basic, medium, advanced user, expert, etc). R^2 is the squared correlation between the predicted and actual values of the log wages. *RMSE* is the square-root of the mean squared prediction error. *N* is the sample size used in estimating or predicting the model.

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.[10]

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 effect of increasing wages on a particular job ad, we control for a large set of variables related to wages including education, experience, major, and job title words. Since we observe all offered wages, we circumvent the sample selection issue of hidden offered wages so prevalent in online job boards.

Because the dependent variable takes non-negative integer values, we use a Negative

[10] Due to the nature of our data, we miss some applications to ads posted in early June 2014. However, this is barely a concern because these ads only account for 0.33% of our sample and most applications arrive soon after the posting date, as reported by Banfi *et al.* (2017).

Binomial (NB) model, which is more flexible than Poisson (Cameron & Trivedi, 2013).[11] We circumvent the potential selection bias by estimating our equations using data on hidden or implicit wages. We only present a subset of estimates here.[12]

Table 4 shows the NB estimates (β), the estimated standard errors (SE), 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% fewer 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 marginal impact of wages in number of applications is decreasing since the relation between the number of applications and log wages looks nearly linear. To explain this shape, directed search theory suggests that the probability of being hired declines at increasing rate as more applicants apply.[13] Diminishing marginal utility of consumption (or money) can also help explain this fact.

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 curves of conditional expectation of applications for 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

[11] A standard count data Poisson model imposes equality of conditional variance and mean. In contrast, the NB model relaxes this assumption.

[12] Full results are in Tables A8 and A9 in the OA, Section A.4.

[13] Under the standard assumption of a matching function with constant returns to scale, the job finding probability is a convex function of the number of applicants received.

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 3 shows that key words in the job ad 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 & Wolthoff, 2015). In addition, our prediction of implicit wages using an explicit-wage "pricing" equation entails an 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 & Rosén, 2003; Michelacci & 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. The most likely explanation is 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 on-line 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 & Sotomayor, 1992; Niederle & 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 better suited applications is reasonable because sending a marginal 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 *et al.*, 1985; Oyer & Schaefer, 2011; Muehlemann & 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 & Sen, 2014). In line with this conjecture, Chandler *et al.* (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 & Ridder, 1992; Villena-Roldán, 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 & Russo (2014), 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 because searchers look for job opportunities in many websites simultaneously, or may be aware of previous appearances of the same job ad. For the sake of brevity, we refer the interested reader to the OA, Section A.4, to see further results. In particular, there we show that lower requested experience and higher required educational level increase the number of applications, as expected for a young and highly educated pool of applicants.

Are these results robust? A potential setback for our NB results is that workers often have preferences for firms due to traits that are unobservable by the econometrician such as potential colleagues, fringe benefits, prestige, location, organizational climate, etc. Since these characteristics are often correlated with wages, failing to control for these idiosyncratic factors may generate an omitted variable bias. In other words, we may be erroneously attributing the effect of these unobserved desirable job traits to wages and overestimating the sensitivity of applicants to wages.

To test the robustness of our results, in the OA, Section A.4, besides full NB results,

Table 4: NB Model explaining the number of received applications

	Negative Binomial		
	β	SE	η
Explicit wage	-2.312***	0.187	-0.132
Ad appearances	-0.033***	0.001	-0.103
Number of vacancies	0.009***	0.000	0.040
Req. experience	-0.060***	0.002	-0.115
log wage	0.076***	0.006	0.099
Explicit × Num. of vac.	-0.001***	0.001	
Explicit × Req. experience	0.013**	0.006	
Explicit × log wage	0.165***	0.015	
log wage - Implicit			0.076
log wage - Explicit			0.224
Observations	184,920		
Estimated avg. applications	35.45		
pseudo - R^2	0.089		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.. Selected coefficients of models *without* controlling for recruiting firms. Tables A8 and A9 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.

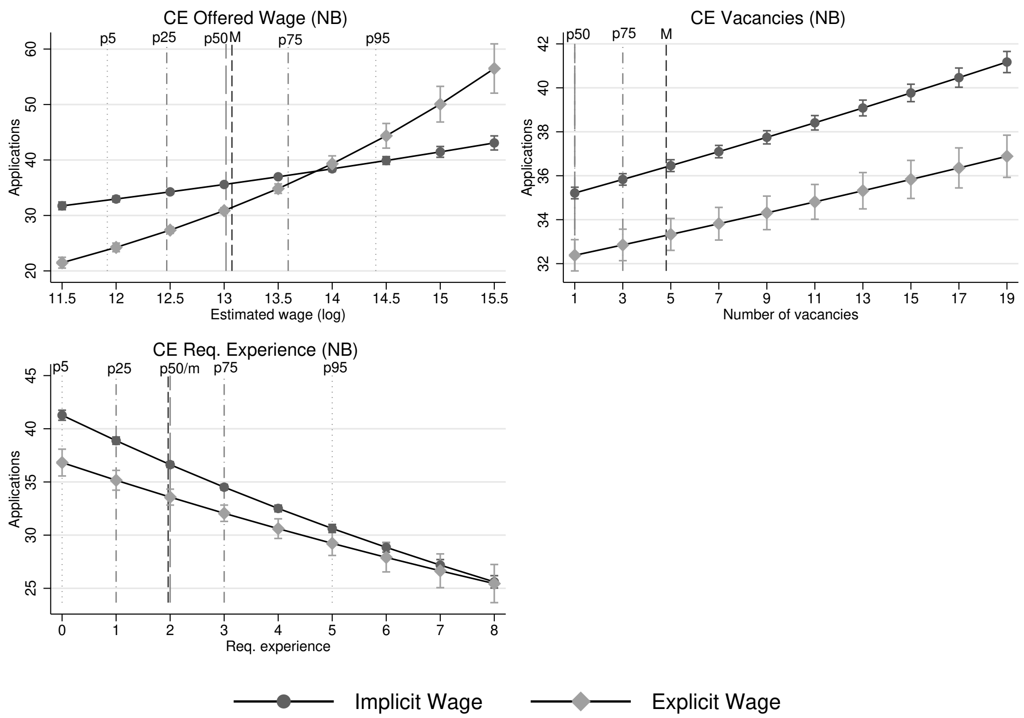
we report linear regression models without (OLS) and with (OLS-FE) firm fixed-effects.[14] Given the different natures of NB and linear models, we can only directly compare estimates the η coefficients reflecting marginal changes or differences in conditional expectations. Results across NB, OLS, and OLS-FE models are very similar. These findings suggest that variables which are observable for us contain enough information for applicants to direct their job searches, so that firm identities are mostly redundant data.

Another potential problem occurs if recruiting firms post ads with generic descriptions without mentioning specific firms. If applicants cannot recognize which firm they are applying to, we may observe different behavior. In the OA (Section A.4, Tables A10 and A11), we report estimates for a model including job ads posted by recruiting firms. Other than recruiting firms receiving fewer applicants, the rest of conclusions remain unaltered.

We finally 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

[14] We use OLS with firm fixed effects since there is no general procedure for estimating nonlinear models conditional on fixed effects (Wooldridge, 2010).

Figure 2: Conditional expectations of applications by explicitness of wage (Table 4, 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.

binary variable for wages above CLP 1,000,000 and include it in the NB, OLS, and OLS-FE models, as well as interactions of the filter with log wage, explicit dummy, and explicit $\times$ log wage. Hence, we capture application responses to the discontinuity in the quality of information. In Figure A6, Section A.4 of the OA, we depict the conditional expectations of applications received once we introduce the aforementioned regressors. Besides 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 *et al.* , 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, 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 linear and a Local Polynomial Regression (LPR) between the average experience of the applicants for a given job and the corresponding ad required experience. To assess the strength of this increasing relation, we compute a 99% confidence interval for the LPR. The figure shows that ads with no required experience (zero) receive applicants with an average of five years of self-declared experience. This is due to the abundance of job ads for unexperienced workers. Moreover, since the experience requirement conveys a minimum bar, more experienced applicants still fit the profile. For jobs requiring less than five years, the LPR shows little variance. Beyond that point, the LPR flattens suggesting that required and actual experience level out in that region. The increasing relation between minimum experience required and average applicant experience is a clear indication of self-selection into the right submarket, in line with directed search models with heterogeneous agents.

There is clear segmentation by educational level. The upper-right panel of Figure 3 fits a LPR correlating the imputed schooling years requirement for job ads and the corresponding average imputed schooling years of applicants. The conversion between education attained and schooling years is explained in Section 2.1. Applicants clearly comply to ad requirements. Nevertheless, the LPR shows that job ads with primary education requirement (eight years) attract applicants with average schooling of more than 12 years. For requirements of technical tertiary education (16 years) or college graduation (17 years), the available pool of applicants meet the specific requirement more closely. Since the overall schooling level of the applicants is high (around 15 years) it is likely that ads with low educational requirements receive overqualified applicants more often on average.

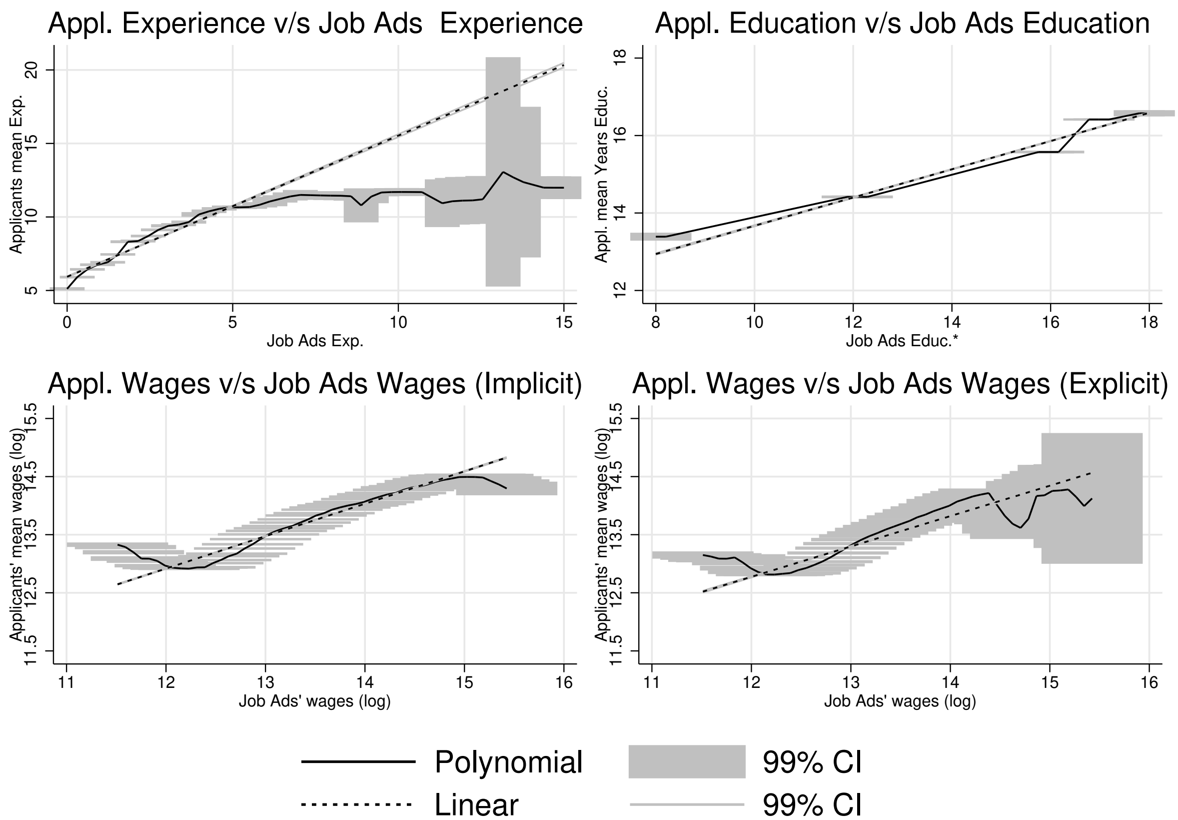
The two remaining panels of Figure 3 show a LPR between log offered wages (implicit and explicit) and the average log expected wage of individuals applying for those jobs. We observe a clear positive correlation. For implicit wages, the polynomial local regression is slightly decreasing at $\exp(12.5) \approx$ CLP 270,000 $\approx$ USD 523 per month, which shows that workers applying for implicit low wage ads have overoptimistic expectations. In the upper portion of the LPR, we observe a sightly decreasing portion, showing the opposite pattern in that region. The 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. In line with the endogenous segmentation implied by directed search behavior, implicit-wage ads attract applicants with similar wage expectations as shown by the modest width of confidence intervals. Moreover, applicant expected wages are closely aligned to hidden ad wages, a pattern consistent with signal extraction from job ads. We advocate this interpretation especially above $\exp(13.8) \approx$ CLP 1,000,000 , a region where the search filter of the website offers much more limited guidance, with wide brackets of CLP $500,000$.

For explicit wages, in the lower-right panel, we observe similar patterns. We observe a notable widening of the confidence intervals due to the relatively small sample size for explicit wages above $\exp(14) \approx$ CLP 1,200,000 while the point estimate of the LPR becomes erratic. Other than this exception, the variability of log average expected wages around any job offer seems very modest for both explicit- and implicit-wage job ads, constituting evidence of self-segmentation as predicted by directed search models with heterogenous agents.

Table 5 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. Given a required specific educational major, the rows of the table show the share of individuals applying to those jobs by jobseeker major. For instance, 9.72% of jobseekers applying to job ads requiring a educational major in Social Sciences (5) have a Commerce & Management major, while a 68.32% of them hold a diploma that meets the requirement. 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. A finer view of educational segmentation is shown by Table 6 in which we distinguish different types of education with equal years of schooling. The modal applicant exactly complies to the major required by the employer. The only exception is that job ads requiring graduate education tend to receive mostly college graduate applicants, probably because of the relative scarcity of this kind of jobseeker in the sample.

Similar jobseekers cluster in applying to similar job ads. Applicants generally meet em-

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



ployer 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 *et al.* (2013) suggest. We show that jobseekers refrain from applying to ads when they are not a good fit, an empirical implication of directed search beyond the positive association between wages and applications.

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

Table 5: Distribution of applicant majors by job ad specific major requirement

		Applicant Educational Major											
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Job Ads Requirements	(1) Commerce and Management	**48.38**	0.53	0.99	0.34	3.52	1.17	0.92	2.16	0.56	18.73	17.85	5.25
	(2) Agropecuary	13.25	**44.96**	0.36	1.06	0.88	0.14	0.22	0.47	2.13	25.29	4.49	6.97
	(3) Art and Architecture	11.92	0.20	**29.17**	0.42	13.38	0.62	1.41	1.26	0.59	27.11	8.09	6.17
	(4) Natural Sciences	7.76	2.95	0.39	**26.30**	0.95	0.20	1.64	0.55	6.80	34.81	13.00	5.66
	(5) Social Sciences	9.72	0.11	2.53	0.13	**68.32**	0.30	1.05	0.98	0.13	4.24	4.41	8.26
	(6) Law	3.85	0.03	0.09	1.24	1.09	**82.11**	0.14	0.48	0.05	2.23	3.78	5.15
	(7) Education	6.70	0.27	1.28	1.41	7.22	0.47	**44.18**	5.03	1.46	5.89	16.98	10.63
	(8) Humanities	12.31	0.24	1.96	0.54	8.70	2.06	7.64	**39.42**	0.75	6.74	14.15	6.22
	(9) Health	3.50	0.74	0.24	1.26	0.83	0.10	1.14	0.27	**70.60**	8.86	11.37	2.84
	(10) Technology	23.38	0.89	0.84	0.55	2.69	0.19	0.25	0.57	0.40	**53.74**	7.41	9.36
	(11) Non-declared	21.84	0.74	1.47	0.79	3.75	1.52	1.58	1.23	1.81	19.34	**44.67**	2.91
	(12) Other	17.86	1.88	3.07	1.26	6.52	1.92	6.68	2.66	2.13	21.53	23.06	**12.13**

Table 6: Distribution of applicant education by job ad education requirement

		Applicant Educational Level					
		(1)	(2)	(3)	(4)	(5)	(6)
Job Ads Req.	(1) Primary (1-8 years)	**1.94**	42.24	26.02	20.76	17.91	0.13
	(2) Science-humanity High School	1.15	**24.13**	24.32	27.22	25.21	0.19
	(3) Tech. High School	0.73	8.49	**26.49**	36.44	28.74	0.31
	(4) Tech. Tertiary Educ.	0.47	2.44	17.20	**37.34**	42.46	0.63
	(5) College	0.25	0.31	6.82	14.94	**76.11**	1.67
	(6) Graduate	0.43	0.26	6.52	6.40	82.45	**4.10**

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 *et al.* (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?

In this section we assess the right scope for directed search. In a market with highly heterogeneous ads and applicants, we may consider two interpretations of Section 3.2: are applicants just attached to a niche and randomly search within it? Or are they actively directing their search using ad information after targeting the right submarket? Thus, we want to test if wages drive applications within segments or submarkets. In doing so, we still allow for directed search behavior across submarkets. Finer segmentation would allow us to test for the scope of directed search, but at the expense of reducing the sample size and power of testing.

In Table 7 we report key parameters of 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 Scientific-Humanities 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.

Across segments, explicit-wage ads consistently receive fewer applications than their implicit-wage counterparts. We also 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 workers in non-declared areas. For example, while a 1% increment of offered wages raises applications 0.286% in the segment regular Science-Humanity High School & Commerce (the log wage elasticity η in the upper-left panel), it only increases applications by 0.075% in the segment College & Commerce (the log wage elasticity η in the lower-left panel). Moreover, we observe a that the positive effect of explicit wages on applications is stronger for low-education segments.

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, while jobseekers with high education or experience can access higher wages by fulfilling the ad requirements.

We also approach segmentation more agnostically by relying on an unsupervised machine learning technique, the k-means classification algorithm (Everitt *et al.* , 2011, for instance). With this technique, we split the sample of ads into $k = 50$ segments. We estimate a linear OLS model to investigate directed search behavior for each segment. For nearly 3/4 of the

Table 7: 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***	
Req. exper.	-0.027	-0.013	-0.101*	-0.116	-0.037***	-0.036
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***	
Req. exper.	-0.029***	-0.063	-0.078***	-0.139	-0.011	-0.028
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***	
Req. exper.	-0.036***	-0.084	-0.056***	-0.111	-0.024***	-0.040
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**	
Req. exper.	-0.048***	-0.137	-0.087***	-0.245	-0.067***	-0.174
Explicit wage × Req. exper.	-0.007		-0.020		0.027	
Obs.	*12189*		*32401*		*9602*	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.In all the specifications, 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.

cases, we cannot reject that the estimate of sensitivity of the number of applicants to wages is the same we obtain for the whole sample at 95% confidence. Nevertheless, 2/3 of the 95% confidence intervals for these parameters contain zero. Considering that each model is estimated with roughly 2% of the whole sample, the evidence regarding directed search within submarkets is naturally weaker than for the whole market. However, it is quite aligned with the findings above for market segments defined by professional area and education. We refer the reader to the OA, Section A.5, to see the results based on *k*-means segmentation in depth.

3.4 Why do employers show or hide wages?

Knowing that applicants react differently to explicit wages, employers may make strategic decisions to induce certain applicant behaviors. Consequently, we investigate the determinants behind explicit wage posting.

We estimate a probit model to examine the impact of job ad characteristics such as the number of vacancies, requested experience, offered wage, educational requirements, etc. In order to control for seasonal effects or trends, we incorporate quarterly binary variables according to the date of the job ad.

Table 8 shows selected estimates from the probit model. As in Table 4, the coefficients β represent actual model coefficients. The coefficients η are 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, η is the probability change due to a switch of the binary variable, i.e. $\eta = \text{Prob}(Y|X, z = 1) - \text{Prob}(Y|X, z = 0)$. Most of the estimated coefficients are shown in the OA, Section A.6, Tables A13 and A14.

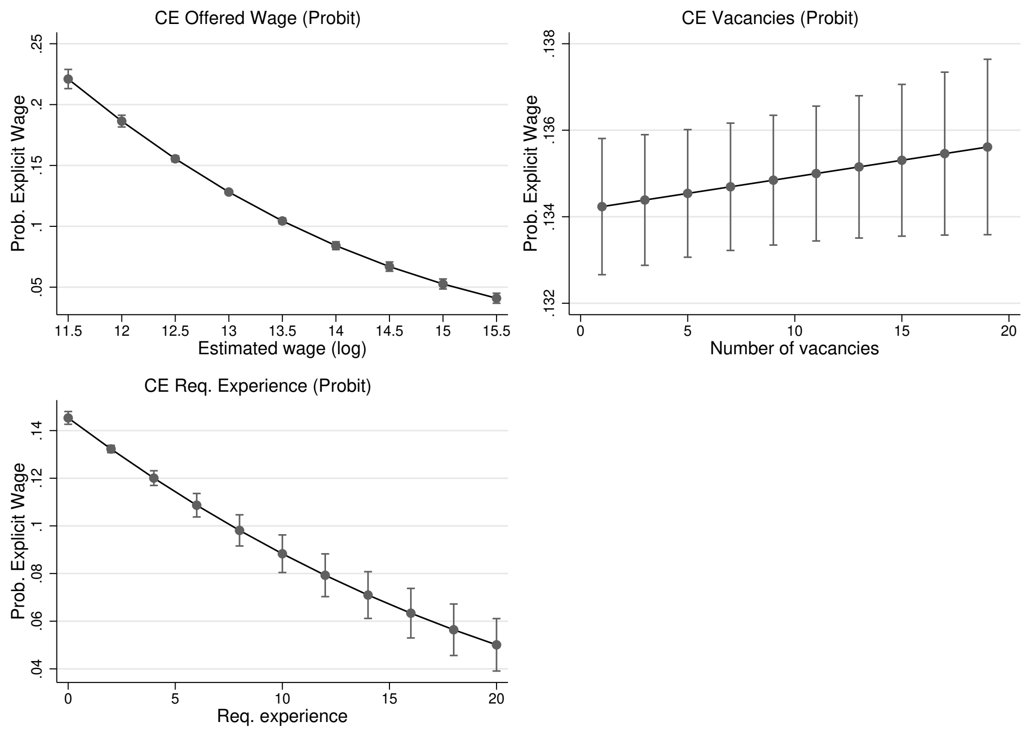
Table 8: Model for probability of explicit wage posting

	Probit		
	β	SE	η
Number of vac.	0.000	0.000	0.000
Req. exper.	-0.034***	0.003	-0.010
log wage	-0.268***	0.010	-0.051
Highest educ			
Primary (1-8 years)	0.211***	0.034	0.052
Tech. High School	-0.108***	0.015	-0.023
Tech. Tertiary Educ.	-0.257***	0.016	-0.052
College	-0.328***	0.019	-0.064
Graduate	-0.276***	0.075	-0.055
Observations	183997		
Avg. Probability	0.135		
pseudo - R^2	0.131		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.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 8, 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

Figure 4: Conditional probability of explicit wage posting (Table 8)



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

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.

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 1% on average. In Figure 4, we show that ads without an experience requirement have a 14% of probability of having an explicit wage, while positions with experience requirements over 20 years have a probability close to 5%. 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 abundant in the market.

An increase of one log point of offered wage decreases the probability of explicit wage posting by 5.1%. In Figure 4, we plot the average conditional probability of posting an explicit wage. We show that for wages close to CLP 100,000 (below the minimum legal net 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%. On top of this, job ads with explicit wages tend to target unskilled workers because the probability of explicit wage posting decreases in the required education level.

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 *et al.* (2013) and Marinescu & 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.

A wage increase not only affects the number of applicants received, but also the probability that the employer makes the wage offer explicit. In the OA, Section A.7, we derive a theoretical condition to obtain an unbiased estimate for application-wage sensitivity solely based on explicit wages ads. Such condition, involving application-wage elasticities and other estimated magnitudes, does not empirically hold. Thus, we conclude that the estimated application-wage sensitivity for only explicit wages overestimates the average value for all ads.

Our facts are consistent with the Michelacci & 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 by 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.

Our results are robust. In the OA, Section A.6, Tables A13 and A14, besides probit estimates, we report OLS linear probability and firm fixed effects (OLS-FE) to account for all firm idiosyncratic unobserved factors affecting the wage explicitness decision, such as corporate culture, or specific managerial standards. If explicit-wage posting is a corporate policy, controlling for unobserved heterogeneity is important. While the effect of wage level on wage-explicitness decreases noticeably if we control for firm-fixed effects, it remains negative and significant. Hence, job characteristics affect explicit wage-posting even within the same firm.

We also show that these linear models controlling for recruiting firms since they may be hired to post ads for a particular type of jobs. In the OA, Section A.6, Tables A15 and A16 we show that the average marginal effects barely change with respect to the baseline.

4 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 a sizable share of ads in the job board studied, we can circumvent the large selection bias arising in other databases, which typically cannot analyze 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 as well.

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 & 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 & Schaefer, 2011; Muehlemann & Pfeifer, 2016).

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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 if it is a suspicious number due to its pattern (CLP 123,456; CLP 123,123, and CLP 111,111). This procedure discards 18.46% of the job ads.
  2. Wage values below 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.

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%

A.2 Additional data description

Table A2: 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 70,000 $\leq$	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 A3: 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

Note: The years of inactivity is estimated as inactivity = age − schooling − experience − 6, which assumes that school starts at age six. Nevertheless, this number is an overestimation because completing a college degree often takes more time than the theoretical years for completing coursework in the Chilean educational system (Servicio de Información de Educación Superior, 2017).

Table A4: 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).

Table A5: 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 an explicit time frame for the job. Undefined-term jobs post no finishing date. These are legal distinctions in Chilean labor law.

Table A6: 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

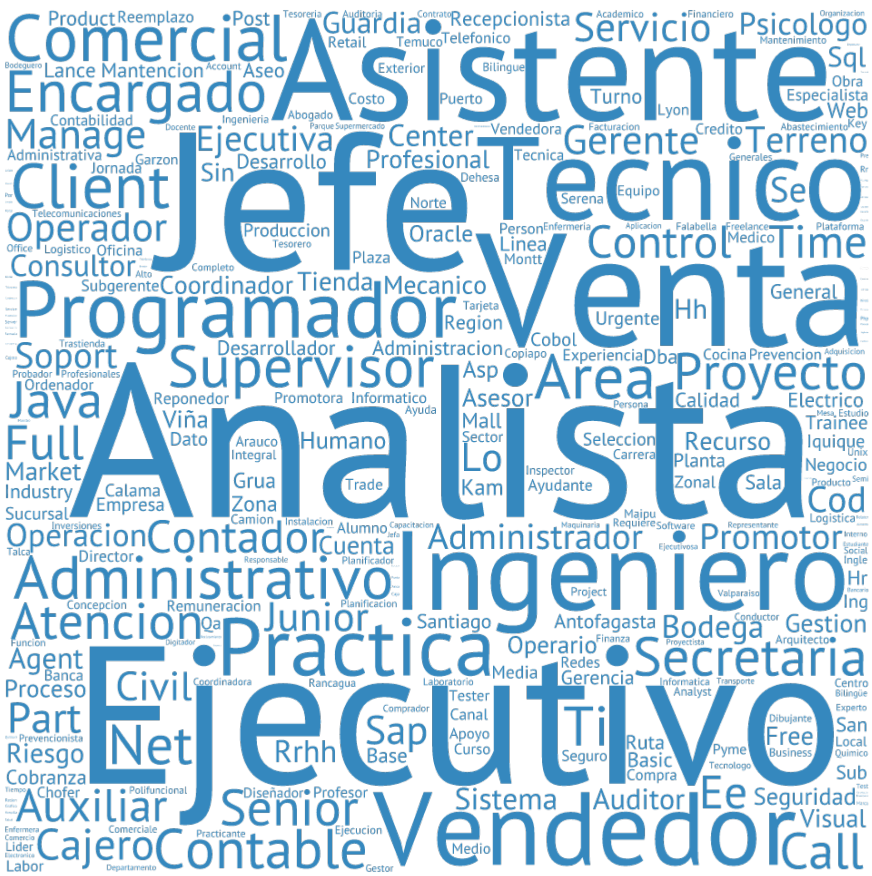
Table A7: Job Ads Characteristics (III)

	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 (%)			
Commission-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.

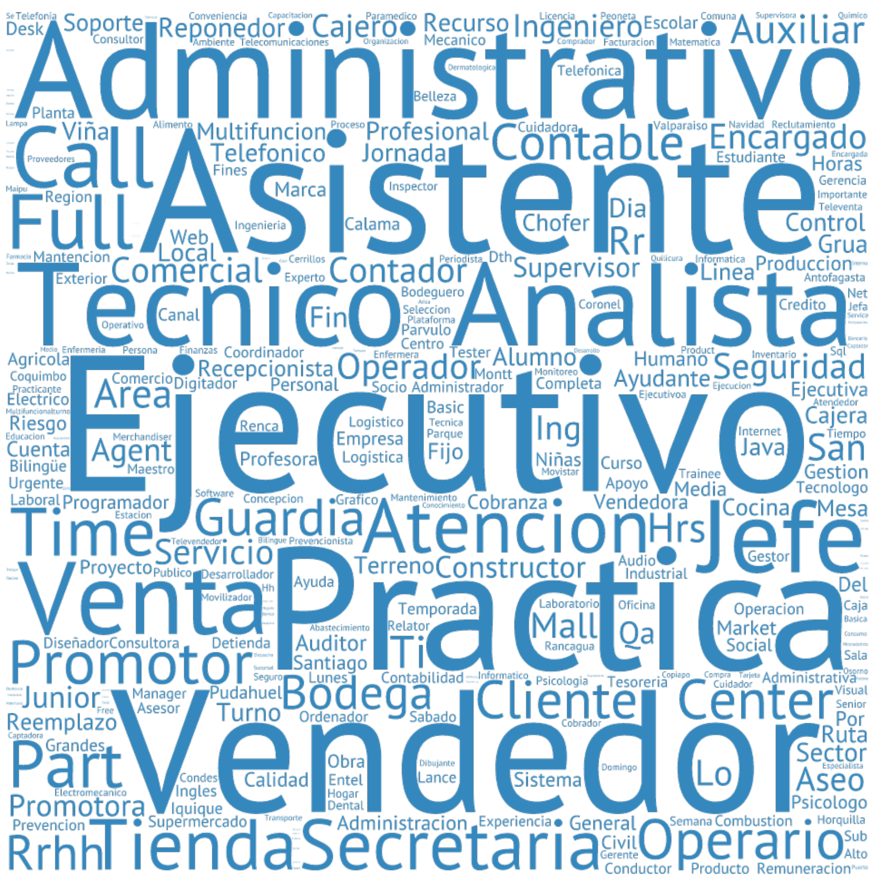
A.3 Word cloud for job titles

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 A8: 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 A9 continues the estimated results.

Table A9: 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									
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
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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.All estimates based on Table 4 in the main text, which do not distinguish recruiting firms. For OLS and OLS-FE models, the dependent variable is $\log(1 + \text{number of applicants})$. 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 A10: 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		

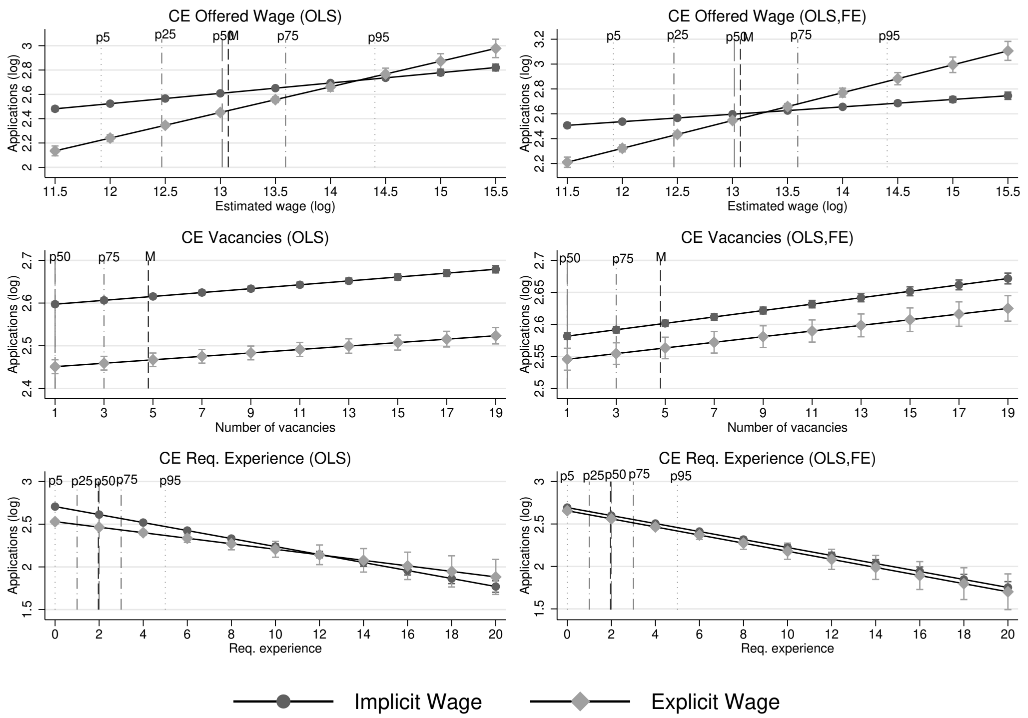
Note: Table A11 continues the estimated results.

Table A11: 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		

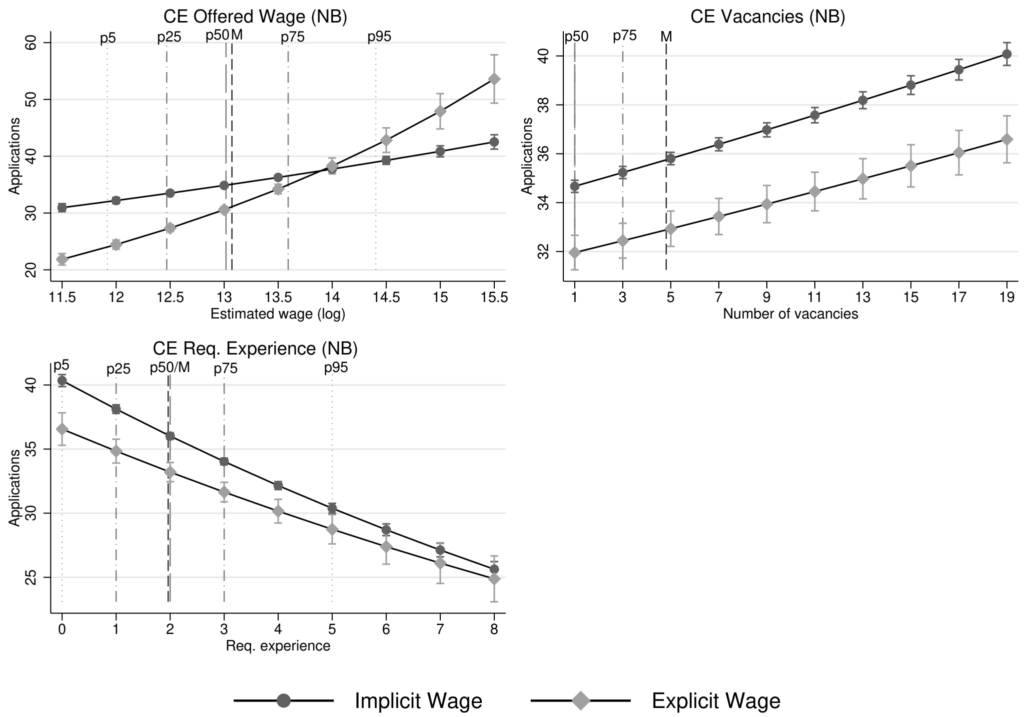
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.All estimates, implementing a recruiting firm dummy as defined in Section 2.2. For OLS and OLS-FE models, the dependent variable is $\log(1+\text{number of applicants})$. Omitted or reference groups: *Highest educ:* Science-humanity high-school; *Contract 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 A8 and A9, OLS and OLS Firm FE)



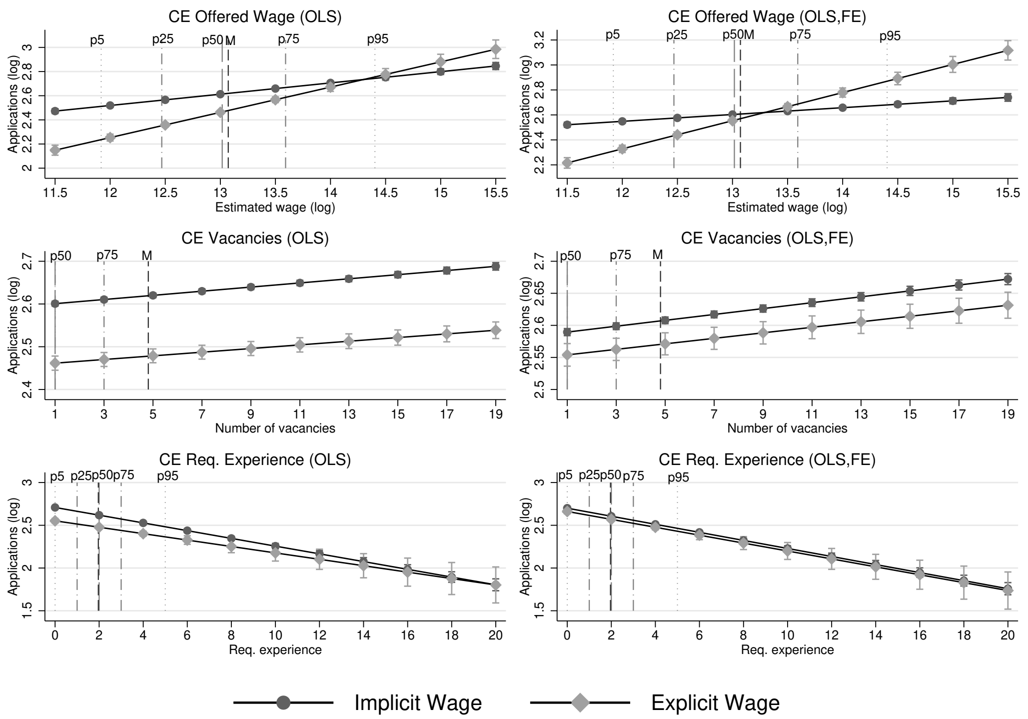
Note: Model without controlling for recruiting firms. Vertical bars indicate 95% confidence intervals.

Figure A4: Conditional expectations of applications by explicitness of wage (Tables A10 and A11, NB Model)



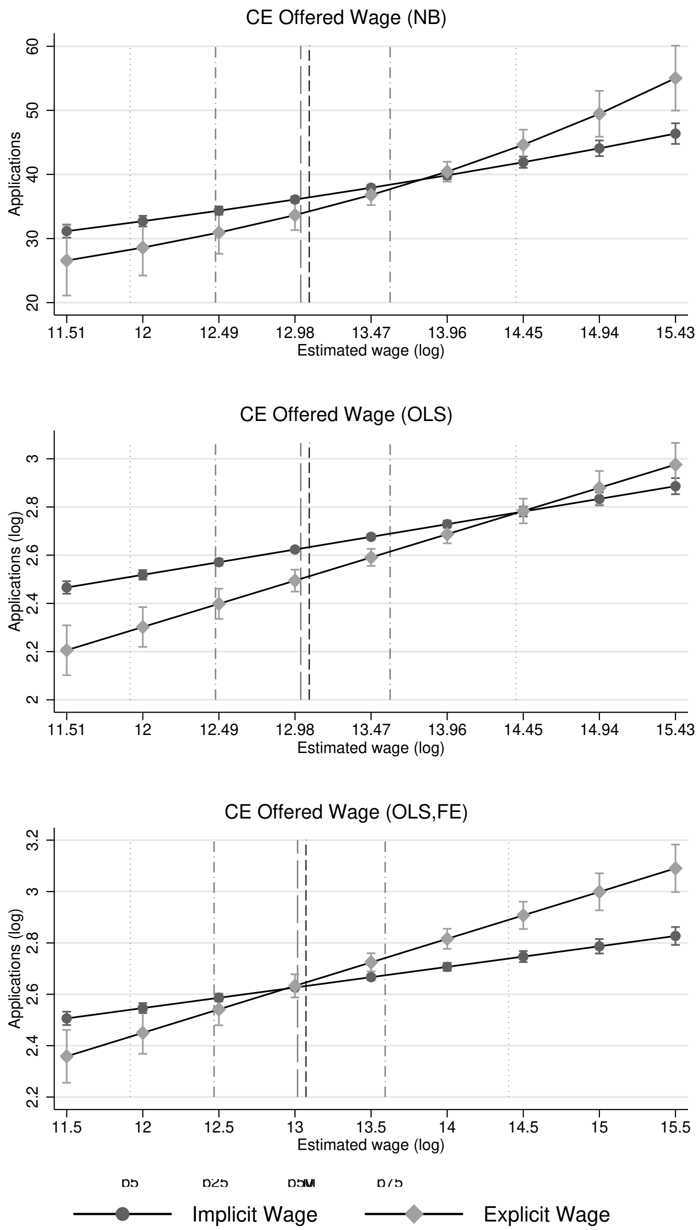
Note: Model controlling for recruiting firms. Vertical bars indicate 95% confidence intervals.

Figure A5: Conditional expectations of applications by explicitness of wage (Tables A10 and A11, 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 × explicit-wage dummy. Vertical bars indicate 95% confidence intervals.

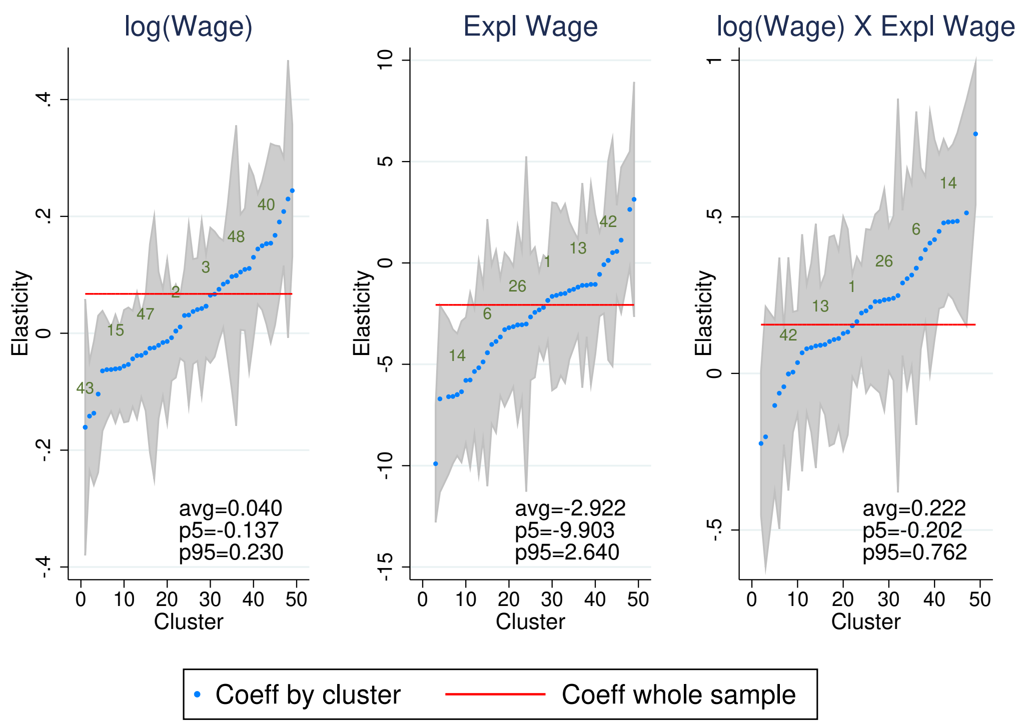
A.5 Additional information for testing random search in segmented markets, Section 3.3

The k-means algorithm is an old non-supervised machine-learning technique (Everitt *et al.* , 2011) that 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 A7 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 4. The Figures also report the mean, 5th, and 95th percentile of the estimates. In Table A12, we present a 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.

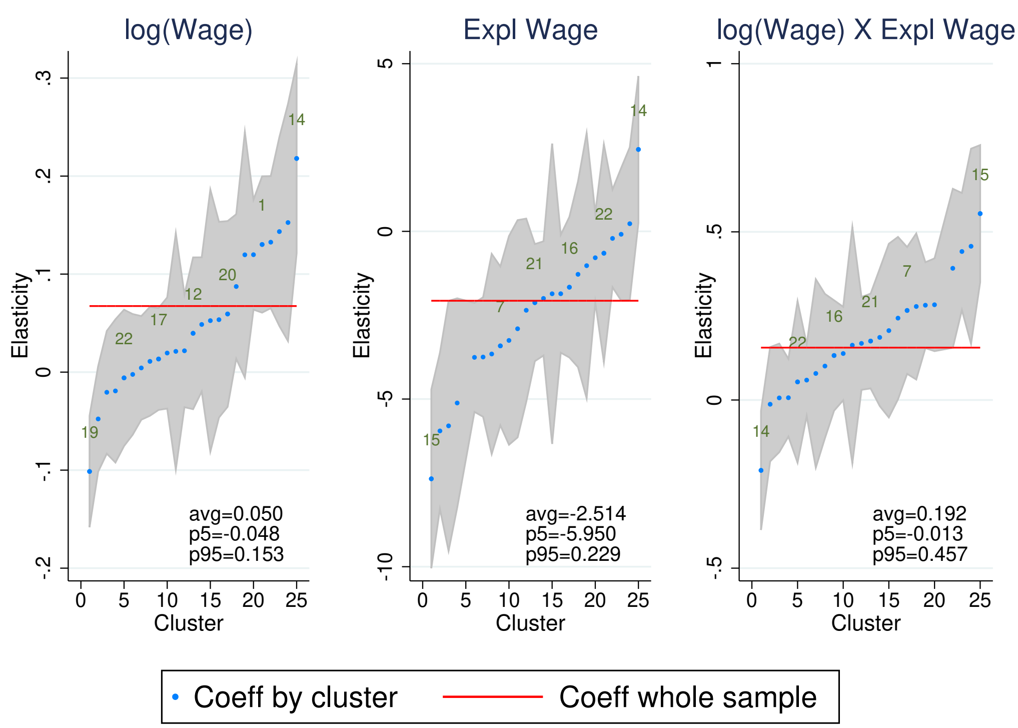
Figure A7: Distribution of estimated coefficients by cluster (k=50)



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 Section A.5, Table A12. 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 & Harabasz (1974) statistic among 15 stochastic realizations of the k-means algorithm.

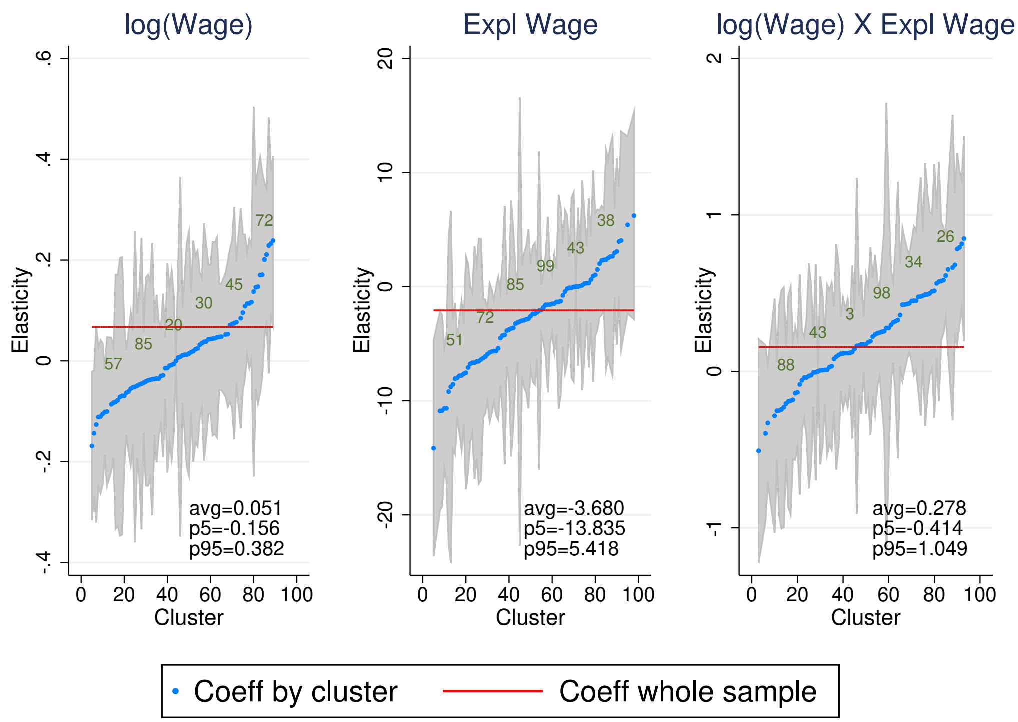
In the literature, there are several methods to determine the "best" number of clusters, k. Since the right choice of k is highly dependent on many tuning choices such as variables defining clusters, distance metric, and selection method, we simply verify that our conclusions remain intact if (1) we consider a different number of segments ($k = 25, 50$, and 100) and (2) we define segments based on larger sets of job ad characteristics. Besides our benchmark k-means exercise in Figure A7, we present additional results in Figures A8 - A15.

Figure A8: Distribution of estimated coefficients by cluster (k=25)



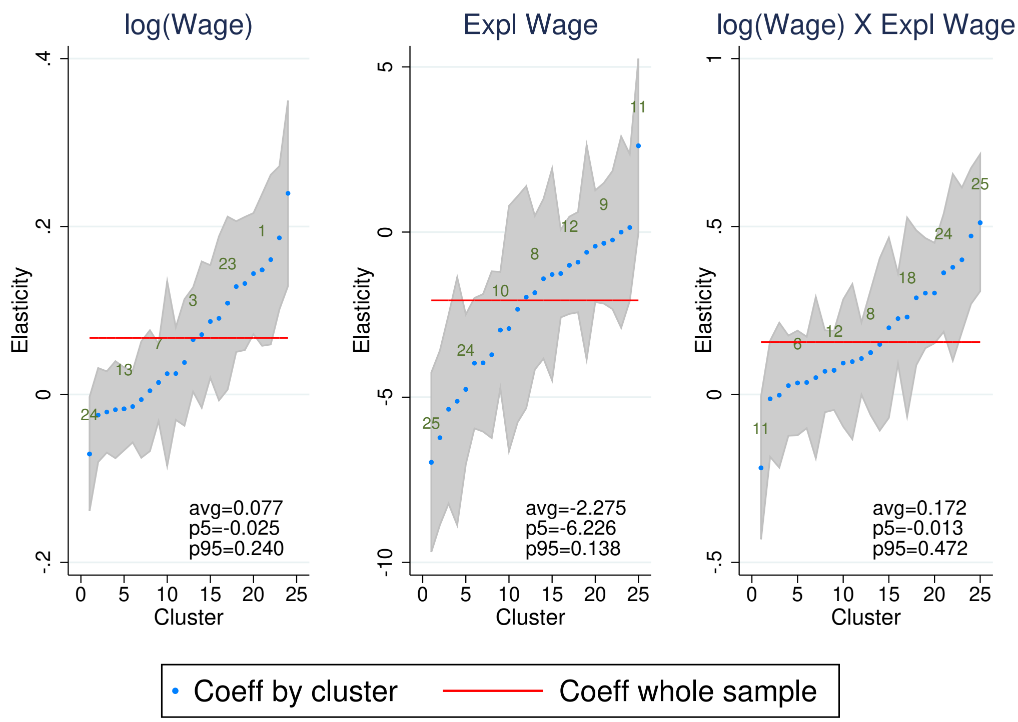
Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński & Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are 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=100)



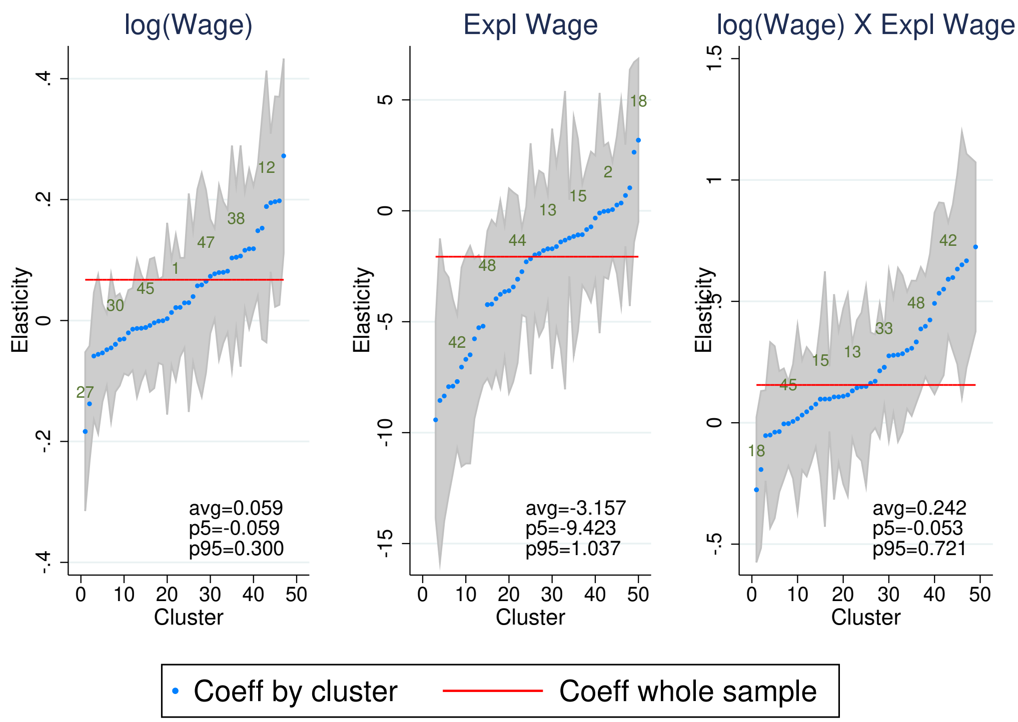
Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński & Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are 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 A10: Distribution of estimated coefficients by cluster (*k*=25)



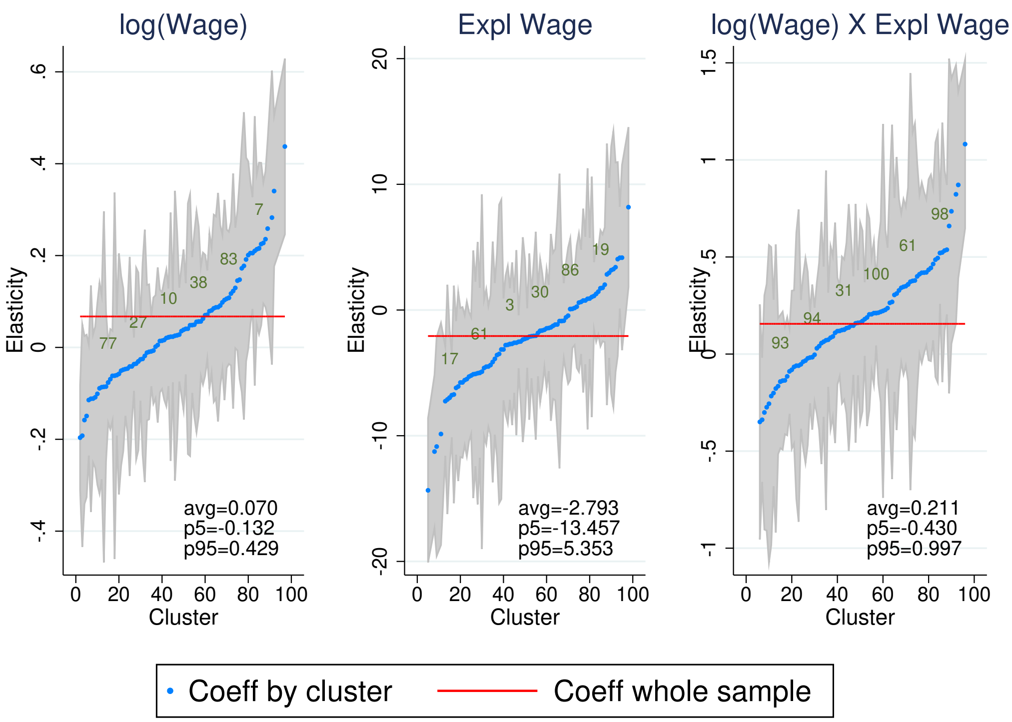
Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński & Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are 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=50)



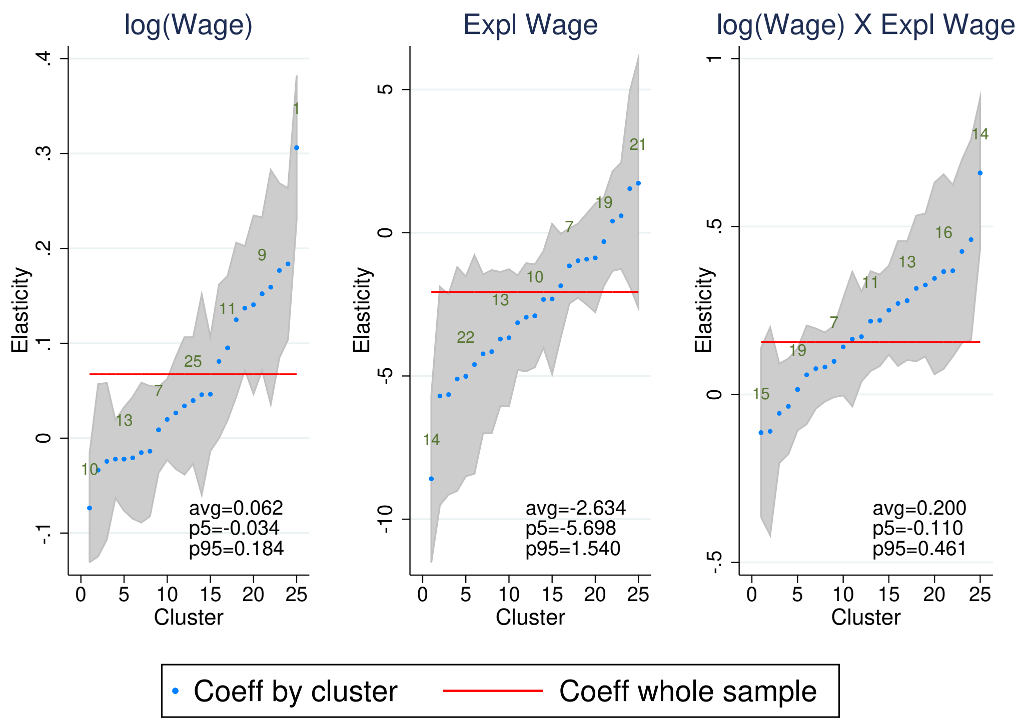
Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński & Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are 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=100)



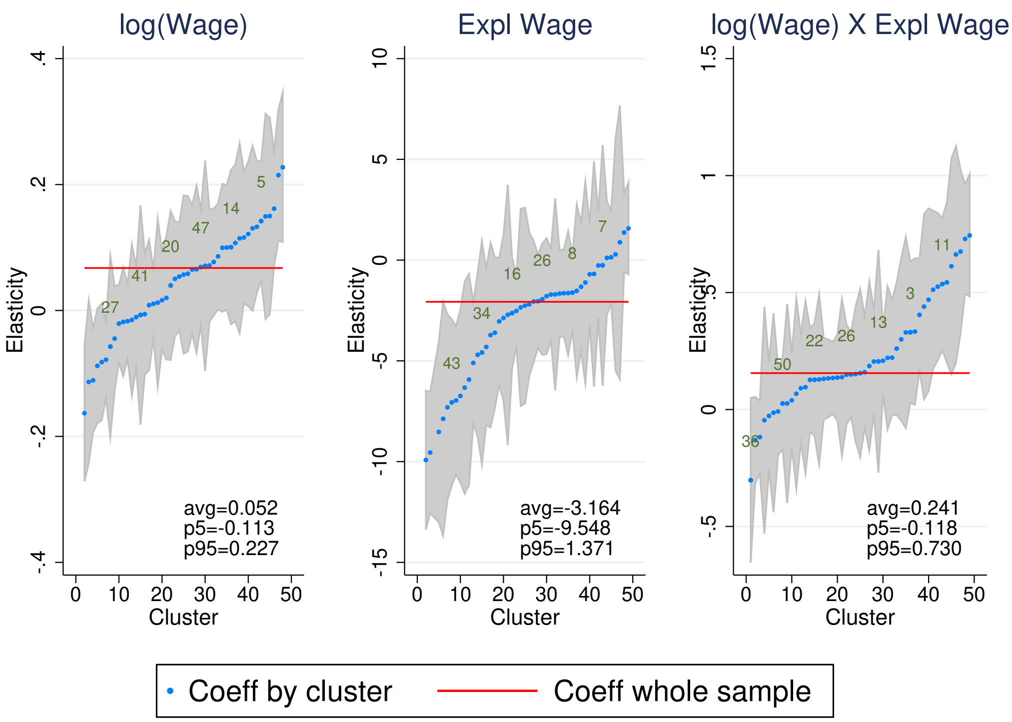
Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński & Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are 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 A13: Distribution of estimated coefficients by cluster (k=25)



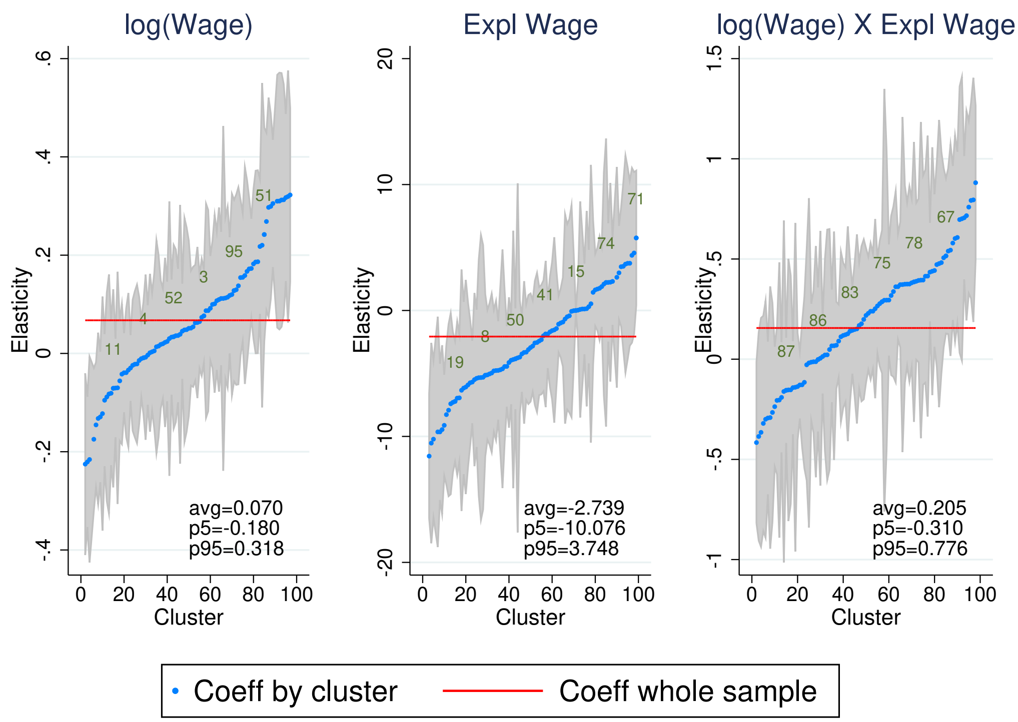
Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński & Harabasz (1974) statistic obtained among 15 stochastic realizations of the k-means algorithm. Variables used to define clusters are 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=50)



Note: Estimated coefficients of linear models by segment (cluster) are plotted. Shaded areas indicate 95% confidence intervals. Segments defined by the highest Caliński & 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 A15: 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 & 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.

Table A12: Description of clusters used in estimating coefficients for Figure A7

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 & Harabasz (1974) statistic among 15 computations of the *k*-means method.

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

Table A13: 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 A14 continues the estimated results.

Table A14: 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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.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 A15: 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		

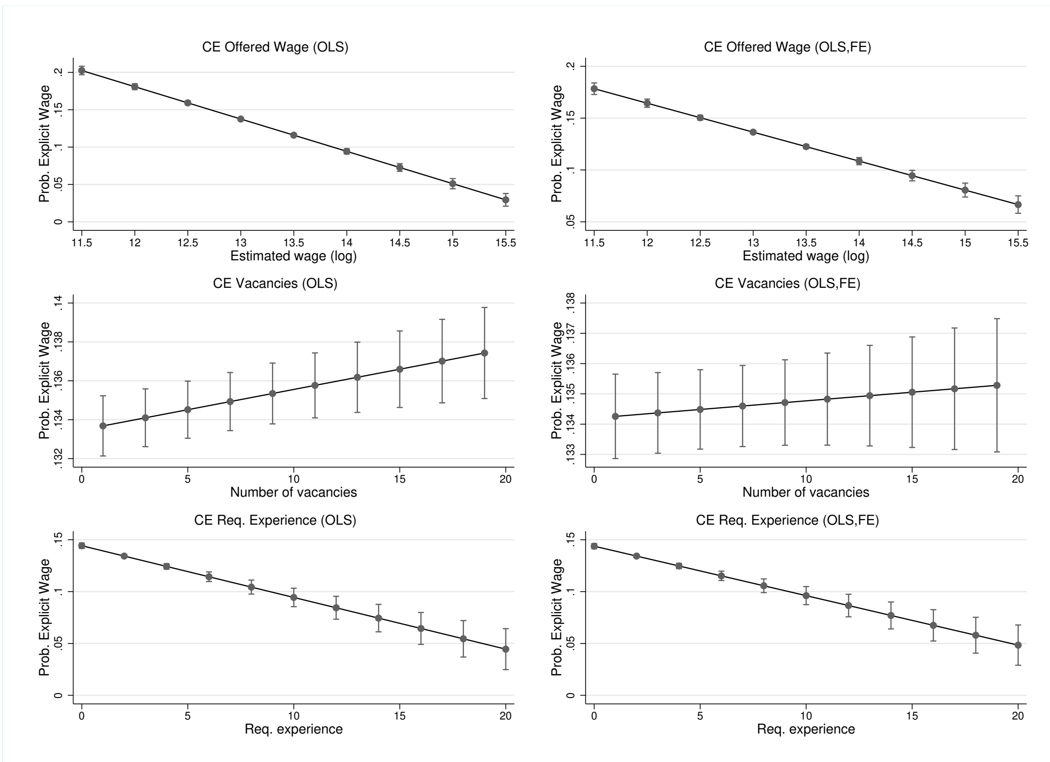
Note: Table A16 continues the estimated results.

Table A16: 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									
Commission 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		

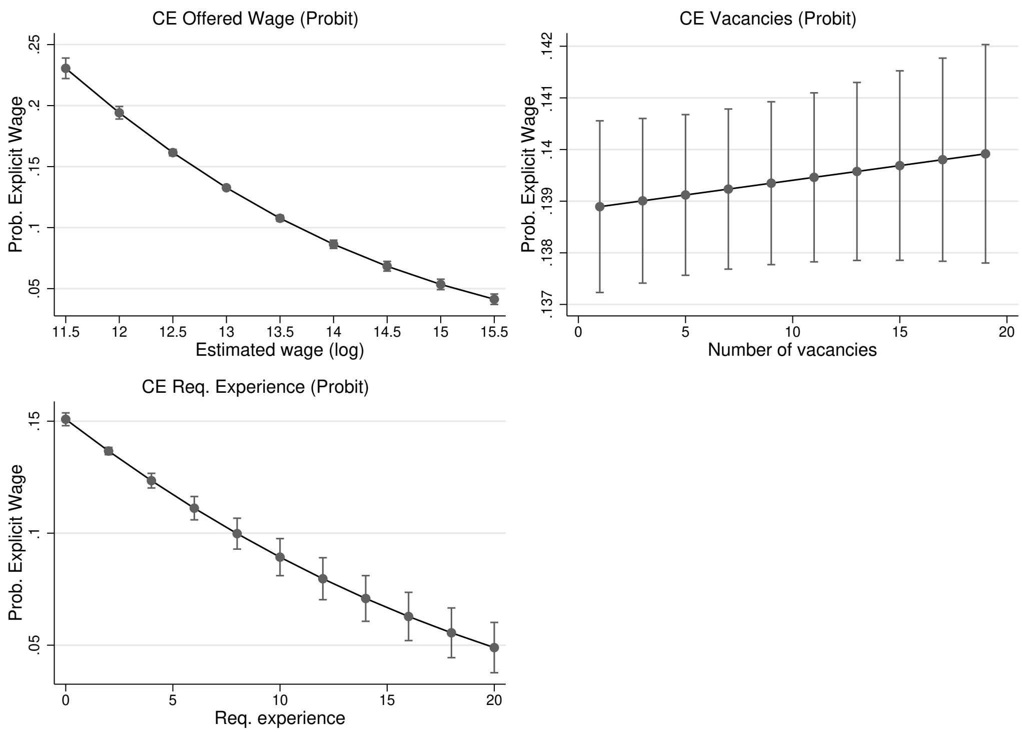
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.Estimated coefficients of models controlling for recruiting firms. Omitted groups: *Highest educ:* Science-humanity high-school; *Contract law* Other. *Availabilty:* Full-time. *Computer knowledge level:* None. In all the equations, we control for profession/occupation 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 A16: Conditional probability of explicit wage posting (Tables A13 and A14, OLS and OLS Firm FE)



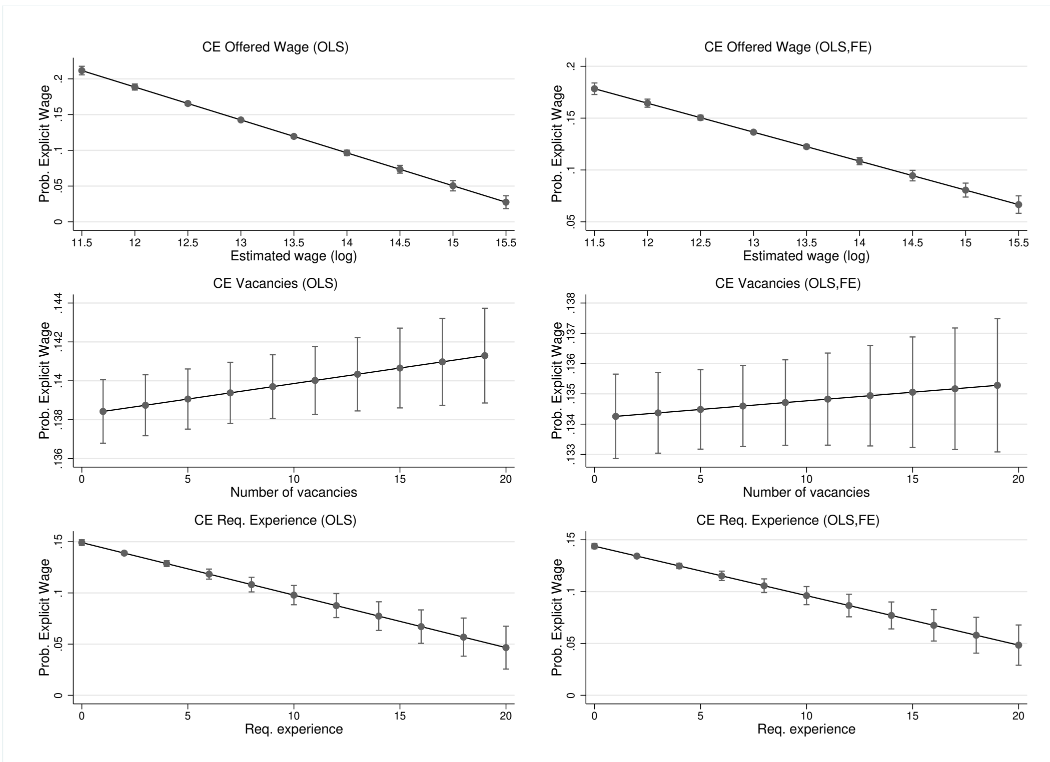
Note: Effects computed *without* controlling for recruiting firms. Vertical bars indicate 95% confidence intervals.

Figure A17: Conditional probability of explicit wage posting (Tables A15 and A16, probit)



Note: Effects computed controlling for recruiting firms. Vertical bars indicate 95% confidence intervals.

Figure A18: Conditional probability of explicit wage posting (Tables A15 and A16, OLS and OLS Firm FE)



Note: Effects computed controlling for recruiting firms. Vertical bars indicate 95% confidence intervals.

A.7 Condition for unbiased estimation of wage-sensitivity of applicants using explicit wages only

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 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 see 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

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

Rearranging terms, we obtain that only if condition

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

holds would we obtain the true response of applications to wages just by estimating the effect with explicit wage job ads.

To evaluate (1), we use the NB model in Table 4. 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 8 and the expected implicit-explicit log wage gap in Table 4 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.