Directed Search, Pay, and Non-Wage Amenities: Evidence from an Online Job Board*

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Abstract

We leverage data from a prominent online job board in Uruguay to study how job seekers respond to posted wages, advertised variable pay, and advertised non-wage amenities. Posted wages predict applications to vacancies attached to lower-skill occupations, but not those attached to higher-skill occupations. Non-wage amenities increase applications to all vacancies, whereas variable pay decreases applications to lower-skill vacancies but increases applications to higher-skill vacancies. Difference-in-differences estimates exploiting industry-by-occupation minimum wages causally support the finding that responses to posted wages vary by occupation. Our results suggest that directed search in the labor market extends beyond the targeting of higher wages.

JEL codes: E24, J31, J32, J62, J63

Keywords: Directed Search, Vacancies, Wages, Variable Pay, Non-Wage Amenities, Minimum Wages

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"I remember you were asking me: 'Guess what? Employers can't find workers.'
I said, 'Yeah, pay them more!."' Joe Biden, June 24, 2021.

1 Introduction

How responsive are job seekers to the characteristics of vacancies? Unpacking the "black box" of job applications informs about the presence of labor market frictions and helps to assess key assumptions in related theoretical work, for example, about random versus directed search, wage posting versus wage bargaining, or the role of non-wage amenities. Understanding the job application process is particularly relevant given recent documentation of imperfect information and beliefs in the labor market, from both workers and employers (Cullen, 2024; Jäger et al., 2024; Agan et al., 2025). Moreover, as argued by Holzer et al. (1991), job queuing behavior suggests the existence of ex-ante rents in the labor market. Hence, job seekers' responses to changes in the characteristics of posted vacancies can shed light on the degree to which the documented industry- and firm-level wage premia constitute evidence of rents in the labor market.

Despite its importance, the empirical study of job applications is challenging because most datasets record equilibrium outcomes which, by definition, are only observed once the job application process is completed. To overcome this challenge, researchers have switched gears to gather direct information on the application process. Hall and Krueger (2012) and Krueger and Mueller (2016) pioneered using survey data on workers and job seekers, an approach recently adopted by Caldwell et al. (2025). Economists have also started using vacancy-level data from private online job boards to study how firms advertise jobs and recruit workers and how job seekers search and make application decisions (e.g., Banfi and Villena-Roldan, 2019; Marinescu and Wolthoff, 2020; Skoda, 2022; Batra et al., 2023; Arnold et al., 2025).

This paper builds on this latter literature and uses data from a large online job board in Uruguay to study directed search patterns in job applications (that is, the extent to which job seekers direct their search toward vacancies with specific attributes), focusing on the role of posted wages, advertised variable pay (in the form of bonuses and commissions), and advertised non-wage amenities. The data comes from BuscoJobs (BJ), a prominent online job search platform that operates in more than 30 countries. In Uruguay, BJ covers a broad set of industries and occupations and is estimated to contain around 60% of total online private sector vacancies in the country (Escudero et al., 2024). We have access to data on vacancies, applicants, and applications for the period 2011-2020, which we link using unique identifiers of applicant profiles and vacancies. Applicant profiles contain information on gender, age, employment status, employment histories, education, and training. Vacancies contain information on the number of positions they seek to fill, formal requirements, and firm and industry identifiers. Also, 20% of vacancies post a monthly wage. Important for our analysis, we have access to the full job ad text, which is processed using Natural Language Processing (NLP) techniques to elicit the following additional variables: the skills required by vacancies and the occupations vacancies seek to recruit (Escudero et al., 2024); and whether the vacancy advertise variable pay and non-wage amenities (Adamczyk et al., 2025).

We first develop an extensive cross-sectional analysis that explores whether certain vacancy attributes predict applications. We start by assessing directed search patterns based on posted wages and then study the effects of advertised variable pay and non-wage amenities on application patterns. The second part of our analysis leverages the fact that Collective Bargaining Agreements (CBAs) in Uruguay dictate and frequently adjust minimum wages, which vary at the industry-by-occupation level. We exploit this feature to complement the cross-sectional analysis of posted wages with causal differences-in-differences estimates of wage effects on job applications.

The cross-sectional analysis is structured in two exercises. First, we study directed search based on posted wages. Consistent with Banfi and Villena-Roldan (2019) and Marinescu and Wolthoff (2020), we find a positive and significant correlation between posted wages and vacancy-level applications once appropriate skill controls (in our case, occupation codes) are included. The main contribution of this section, however, is to document a stark heterogeneity by occupation in the wage-application elasticity. We find that for vacancies attached to a subset of occupations, which we label as *lower-skill occupations* (clerical support, services and sales, plant and machine operators, and elementary occupations), the elasticity of applications to posted wages is large, significant, and highly robust to the inclusion of controls and sample selections. On the contrary, for the vacancies attached to the remaining occupations, which we label as *higher-skill occupations* (managers, professionals, technicians and associate professionals, and craft workers), the relationship between applications and posted wages is absent.

The heterogeneous response to posted wages by occupation is consistent with wage posting being more prevalent in lower-skill occupations and wage bargaining and individual offer tailoring being more prevalent in higher-skill occupations (e.g., Hall and Krueger, 2012; Caldwell and Harmon, 2019; Lachowska et al., 2022; Caldwell et al., 2025). This result suggests that applications to vacancies attached to higher-skill occupations react to other features of the posting, such as additional components of pay and non-wage attributes. In other words, the relevant information contained in the posted wage may differ by occupation if the post-matching wage determination process is different. This heterogeneity is also consistent with recent evidence on employers being more likely to use aggregate information to set wages (i.e., engage in "salary benchmarking") when positions are attached to lower-skill occupations (Cullen et al., Forthcoming).

We then explore whether the responsiveness of applications to posted wages varies with applicant characteristics. We find that applications to lower-skill vacancies made by male, employed, older, college-educated, and job seekers reporting various types of skills are significantly more responsive to wages than applications made by female, unemployed, young, non-college-educated, and job seekers not reporting skills, respectively. The fact that more educated applicants are more responsive while higher-skill vacancies show no responsiveness in the aggregate can be rationalized by more educated applicants applying to vacancies attached to lower-skill occupations only if wages are attractive, given their possibly better outside options. We also find that applicants with presumably worse labor market prospects (female, unemployed, young, and non-educated) display negative wage elasticities when applying to vacancies attached to higher-skill occupations. This finding is consistent with models with on-the-job search where worse outside options may encourage workers to apply to low-wage jobs to climb the job ladder in future job transitions (e.g., Burdett and Mortensen, 1998; Postel-Vinay and Robin, 2002a,b).

The second cross-sectional exercise assesses the role of advertised variable pay (bonuses and commissions) and non-wage amenities in the job application process. Regarding the latter, we exploit information on four elicited non-wage amenities (schedule flexibility, work environment and impact on society, working in teams, and possibilities for human capital development). We show that advertising at least one non-wage amenity has a positive effect on applications across all occupations. However, the effect is attenuated within the sample of vacancies that post a wage (conditional on the posted wage), suggesting a mild lexicographic preference for wages over amenities among job applicants. The relevance of non-wage amenities for job applications echoes the findings in Banfi and Villena-Roldan (2019), who show that applicants rely on job ad descriptions when no wages are posted, and in Audoly et al. (2024), who find that non-pay attributes advertised in job ads are as predictive of employer attractiveness as pay-related factors. Likewise, the results are consistent with Belot et al. (2022), who show that applicants predict non-wage attributes based on the posted wage even when job ads are equal. We also document substantial heterogeneity in amenity valuation across applicants and amenities, suggesting that heterogeneous preferences for non-wage amenities may be a relevant source of monopsony power (Card et al., 2018).

We also provide novel evidence that the role of advertised variable pay on applications is large and heterogeneous across occupations, especially when wages are posted: the significant effect on applications is negative in vacancies attached to lower-skill occupations and positive for vacancies attached to higher-skill occupations. One explanation is that, in lower-skill occupations, bonuses and commissions constitute the primary source of earnings, introducing income volatility and uncertainty. On the contrary, in higher-skill occupations, bonuses and commissions may represent a part of incentive schemes that supplement (rather than replace) base salary. This difference would then mediate how workers value the presence of variable pay when selecting where to apply.

Our cross-sectional analysis is only correlational because applications can respond to additional vacancy characteristics than those observed by the econometrician. Moreover, and despite the fact that, in our setting, the distribution of industries and occupations is similar between vacancies that post and do not post wages, the sample of vacancies with posted wages may be selected within industries and occupations (Skoda, 2022; Batra et al., 2023; Arnold et al., 2025). The second part of the paper thus presents causal estimates of the effect of wages on applications by leveraging plausibly exogenous variation in minimum wages at the 2-digit industry-by-1-digit occupation level. In addition to providing grounds for a causal interpretation, a benefit of this strategy results from its independence of firms' wage-posting decisions, allowing us to consider all vacancies in our sample. We test whether the occupational heterogeneity in directed search based on posted wages documented in the cross-section is confirmed in the quasi-experimental framework.

Uruguay implemented several labor market institutions in 2005, including wage councils that carried out frequent tripartite bargaining rounds (between workers, employers, and the government) at the industry level to define a range of minimum wages attached to different occupations specified in CBAs. These CBAs were gradually expanded, yielding almost complete industry coverage by 2010, and played an economically significant role across the different occupational groups we study.

CBAs are heterogeneous across industries, both in terms of the minimum wage levels and the number of occupations that they cover. This diversity results in variation in minimum wages across industries within occupations. While we cannot match each vacancy to the exact minimum wage set by the CBAs (as these agreements encompass occupations and industries that do not align directly with the classifications in our data), we exploit the heterogeneity in minimum wages by measuring exposure to minimum wage increases at the industry-by-occupation level after collapsing the variation present in the CBAs at the occupation and industry categories observed in the vacancy data. The variation in exposure to minimum wage increases, combined with the regularity of bargaining rounds (resulting in several minimum wage adjustments every 6 months), offers a natural source of variation to estimate the causal (intent-to-treat, ITT) effects of wages on applications. We implement a stacked difference-in-differences (DID) design that compares, within each minimum wage adjustment window, the applications to vacancies in industry-by-occupation cells that are exposed to minimum wage increases to vacancies in industry-by-occupation cells that are not. This latter situation may arise either because the specific cell does not adjust the wage in a given semester or because certain occupations are not covered in certain contracts.

We find that vacancies attached to lower-skill occupations in industry-by-occupation cells exposed to minimum wage increases face an increase in applications, while exposed vacancies attached to higher-skill occupations show no response to the policy change. That is, the quasi-experimental DID results confirm our cross-sectional finding of occupational heterogenitiy in directed search based on posted wages. The implied wage-application elasticity in vacancies attached to lower-skill occupations – which, we argue, is conservatively estimated due to our ITT approach – is around 1.5. This aligns with the lower end of the useful benchmark provided by the empirical literature on labor supply elasticities (Sokolova and Sorensen, 2021). We also provide evidence that suggests that minimum wage increases generated no change in vacancies, openings, advertised non-wage amenities, or vacancy requirements. In the spirit of Holzer et al. (1991), the documented queuing for high-paying jobs in lower-skill occupations paired with the absence of changes in other margins suggests the presence of rents in the Uruguayan lower-skill labor market.

This paper contributes to the growing literature that uses online job board data to characterize empirical patterns in job applications, in particular, related to directed search.[1] For Chile and the United States, respectively, Banfi and Villena-Roldan (2019) and Marinescu and Wolthoff (2020) document that, conditional on appropriate vacancy-level skill controls, vacancies posting higher

[1]Online job board data has also been used to analyze the wage posting decision by firms and the effect of job transparency policies (Skoda, 2022; Batra et al., 2023; Arnold et al., 2025), job-specific skill requirements (Deming and Kahn, 2018; Hershbein and Kahn, 2018), and the role of information in job applications (Belot et al., 2019).

wages receive more applications.[2] We replicate this finding in the cross-section and document novel heterogeneities by vacancies' occupations and applicants' characteristics. We also show that directed search extends beyond posted wages to include advertised variable pay and non-wage amenities, and confirm the directed search pattern based on posted wages using quasi-experimental variation. The two papers additionally document that applicants use the information displayed in job titles and job ads to direct their search. We provide an interpretation of that behavior by eliciting advertised features from job ad texts and detecting directed search patterns based on them. While the aforementioned papers exclusively rely on cross-sectional variation in wages, another literature causally establishes directed search patterns using experimental variation in controlled settings (Dal Bó et al., 2013; Belot et al., 2022; He et al., 2023). Our quasi-experimental results based on minimum wage variation add to the causal estimates of directed search behavior.

This paper also contributes to the literature on non-wage amenities and compensating differentials. Recent analyses of the role of non-wage amenities in wage determination add structure to a wage residual, usually giving form to an "amenity index" estimated from equilibrium data (e.g., Sorkin, 2018; Taber and Vejlin, 2020; Lamadon et al., 2022; Morchio and Moser, 2024; Roussille and Scuderi, 2024). To open the "black box" of amenities, different papers have explicitly elicited willingness to pay for specific non-wage job attributes, using survey data, quasi-experimental designs, structural work, or controlled experiments (e.g., Bonhomme and Jolivet, 2009; Mas and Pallais, 2017, 2019; Wiswall and Zafar, 2018; Le Barbanchon et al., 2021; Dube et al., 2022; Lindenlaub and Postel-Vinay, 2022; Maestas et al., 2023; Sockin, 2024). We add to this literature by providing estimates of variable pay and advertised amenities from job ad texts using the methodology outlined in Adamczyk et al. (2025). Our estimated effects of advertised amenities on applications are consistent with estimates of willingness to pay for non-wage job attributes and additionally suggest that the role of amenities masks substantial heterogeneity by vacancy occupation, applicant characteristics, and amenity type. We also show that the role of variable pay helps rationalize the occupational heterogeneity in directed search based on posted wages.

Finally, this paper contributes to the vast literature on minimum wages, which has mostly focused on the employment and wage effects of minimum wage increases, usually finding significant wage effects on exposed workers with small disemployment consequences (Manning, 2021a). Our estimated null effects on posted vacancies are consistent with the absence of significant disemployment effects. To rationalize limited employment effects, other margins of adjustment have been studied, such as prices, productivity, and profits (Dube and Lindner, 2024). We provide evidence on a complementary margin that can help firms buffer minimum wage shocks: the effect on job applications (Holzer et al., 1991; Flinn, 2006; Vergara, 2023). This margin is consistent with the dynamic effects on employment flows and turnover estimated by Dube et al. (2016), Gittings and Schmutte (2016), and Wiltshire et al. (Forthcoming), and with recent evidence on positive effects of minimum wages on search effort (Piqueras, 2023). Following Clemens (2021), we estimate effects on advertised amenities, finding null effects in our case. Finally, the fact that the estimated

[2]Relatedly, Mueller et al. (2023) and Bassier et al. (Forthcoming) study the vacancy duration-wages relationship.

additional applicants are relatively unskilled together with the lack of estimated effects on vacancy requirements does not suggest skill upgrading in our setting (Butschek, 2021; Clemens et al., 2021).[3]

2 General Context, Data, and Descriptive Statistics

Uruguay is located in South America and its population reached 3.5 million in 2020. The country performs above the Latin American average for various socio-economic indicators (UNDP, 2022) and has been classified since 2012 as a high-income country, according to the World Bank. A large majority of the Uruguayan population lives in urban areas. In 2020, 73.5% of employment was in services, followed by manufacturing (18.2%) and agriculture (8.3%). The public sector represents around 15% of employment. Informal employment in Uruguay is comparatively low for the region, and 93.8% of the population is covered by at least one type of social protection benefit (ILO, 2022). Since 2005, Uruguay's labor market has been characterized by strong labor market institutions, including wage councils that set industry-by-occupation minimum wages in tripartite collective bargaining agreements (CBAs). We provide a detailed description of the CBAs in Section 4 when discussing our quasi-experimental framework based on this minimum wage variation.

2.1 Data

We use data on vacancies, applicants, and applications from BuscoJobs (BJ), a private online job board that contains detailed information on vacancies posted by firms, applicants searching for jobs, and the applications job seekers made to those vacancies between 2010 and 2020. As the leading job board in Uruguay, it covers around 60% of Uruguayan online vacancies (Escudero et al., 2024). To post vacancies in BJ, firms have to register and pay a fee. Subscribed firms provide information on their characteristics, including their name and industry. For each vacancy, they provide a job title, a detailed open-text description of the vacancy, dates when the job ad will be open, and, in some cases, a salary range. Vacancies may also include information on application requirements related to the applicant's age, gender, education, experience, or language skills. Job seekers have to register on the portal to search and apply for vacancies, but they can do so for free. Once they register, they must include in their profile their personal information, employment histories, employment status, educational attainment, and languages spoken. To build their employment histories, applicants must provide dates of entry and exit for each job spell and details about the previous positions, including an open-text description of the duties carried out.

In addition to the information that is directly reported on the BJ platform, we use variables derived through NLP models as described by Escudero et al. (2024) and Adamczyk et al. (2025). These procedures leverage the rich open-text descriptions available in the platform's raw data entries. In what follows, we provide a high-level description of these procedures; a detailed description is available in Appendix A and the corresponding references.

[3] Our estimates of positive and finite elasticities of applications to wages are also consistent with the empirical literature on monopsony power (Manning, 2021b; Sokolova and Sorensen, 2021; Azar et al., 2022; Card, 2022).

First, we estimate whether job ads advertise variable pay and non-wage amenities by looking at keywords and expressions that are unique to specific attribute categories. We predefine a list of categories, adapting the definitions of Maestas et al. (2023) and Sockin (2024) to vacancy data and the Uruguayan context. Variable pay is proxied by "bonuses and commissions" and includes financial incentives and rewards aimed at compensating employees' achievements. Regarding non-wage amenities, we start with a list of 15 amenities but, throughout the paper, we focus on the 4 amenities that are estimated to be advertised on at least 5% of the vacancies in our sample: "schedule flexibility" (including arrangements that allow for telecommuting, remote work, part-time employment, and flexible hours, as well as practices that support a better work-life balance), "work environment/impact on society" (aspects that provide insights into the firms' commitment to creating a positive workplace environment and contributing positively to the community and society as a whole), "working in teams" (providing insights into the collaborative aspects of the job and team-oriented nature of the work environment), and "human capital development" (including opportunities for personal and professional growth and development within the firm).[4] The NLP procedure requires job ads' texts to have at least 15 words (Atalay et al., 2020). The 1.1% of the vacancies in our sample that do not meet this requirement are coded as not advertising any amenity. For the remaining 98.9%, we can properly implement the text analysis.

In addition to standard robustness checks (e.g., verifying the inclusion of words in between, testing various methods for reducing words to their root form, and identifying reverse expression forms), this process underwent multiple rounds of manual verification to ensure contextual accuracy of words and expressions. Beyond the fact that keywords were carefully selected and contextualized within broader sentences to minimize errors, manual verification was feasible as few dominant keywords typically account for the majority of matches in each subcategory, with other terms making smaller contributions (see the word clouds displayed in Figure A.1 of Appendix A). This verification also involved manual checks for a random sample of vacancies for each amenity group.

We additionally use measures of applicants' skills beyond formal educational attainment. These variables, also developed using NLP methods and similar robustness checks and verification procedures by Escudero et al. (2024), are derived from applicants' descriptions of duties performed in current or previous employment spells. The taxonomy focuses on three categories of skills (cognitive, socio-emotional, and manual).[5] The same procedures are applied to vacancies' descriptions to identify skills requirements that extend beyond formal educational degrees.

Finally, the NLP procedures combined with additional machine learning techniques were also used to identify the vacancy-level and applicant-job-spell level occupation according to ISCO-08 (Escudero et al., 2024). Vacancy-level occupations were recovered using both job ads and job

[4]Other amenities are rarely advertised (Table B.1 of Appendix B), with only 5% of vacancies advertising at least one of the remaining 11 amenities. Importantly, the advertisement of fringe benefits is mostly absent from job ads because benefits and contributions are very regulated in Uruguay, giving little discretion to firms to manipulate them.

[5]These categories are further divided into 14 subcategories. "Cognitive skills" include general cognitive skills, general computer skills, software skills and technical support, machine learning and AI, financial skills, writing skills, and project management skills. "Socio-emotional skills" include character skills, social skills, people management, and customer service skills. "Manual skills" include finger-dexterity, hand-foot-eye coordination, and physical skills.

titles of the posted vacancy, while applicant-job-spell-level occupations were recovered from analog entries reported in the applicant-level employment status and employment histories.

2.2 Descriptive statistics

For the period 2010-2020, 87,030 vacancies were posted on the BJ platform. We drop 134 vacancies for which we cannot identify the applicants, which have miscoded opening dates, are for jobs outside Uruguay, and/or for which it is not possible to identify the 2-digit industry code and/or the 1-digit occupation code. Figure B.1 of Appendix B shows that the number of applicants and vacancies grew steadily during 2010 but stabilized during the second half of 2011. Hence, our empirical strategy only considers the period from October 2011 to September 2020. This restriction leads us to drop 8,916 additional vacancies.

Figure B.2 of Appendix B plots the industry and occupation distributions of the vacancies. Panel (a) shows that the five industries with the majority of posted vacancies are administrative and support service activities; wholesale and retail trade; professional, scientific, and technical activities; information and communication; and manufacturing. When comparing these figures to the national employment distribution, the five mentioned industries - with the exception of manufacturing, which closely matches the national share - are overrepresented in the BJ platform (Escudero et al., 2024). On the contrary, primary sectors (agriculture, mining, and quarrying), energy and water management services, and public services and defense are severely underrepresented. Therefore, we drop the posted vacancies in these industries in all subsequent analyses (106 vacancies, leaving a final sample of 77,874 vacancies). Panel (b) shows that posted vacancies are not concentrated in a few occupations. The BJ platform encompasses a variety of occupations with different implied skills and formal qualification levels, spanning from managers and professionals to clerical support and elementary occupations. Panels (c) and (d) show that the distributions of industries and occupations are similar between vacancies that post and do not post wages.

Panel (a) of Table 1 presents descriptive statistics of the final sample of posted vacancies. The modal number of openings per vacancy (i.e., the number of jobs the vacancy is expected to fill) is 1, although there are a few vacancies advertising several positions, with a mean number of openings of 1.7. The median vacancy receives 97 applications per opening, but there is substantial variation, again, with a few vacancies receiving large numbers of applications (the mean number of applications per opening is 179). 78% of vacancies are open for exactly 31 days, 19% are open for less than 31 days – with 8% being open for 8 days and 9.25% for 16 days – and only 3.5% of vacancies are open for exactly 2 months. Finally, 20% of vacancies post a wage. This number is computed as follows. Vacancies are allowed to advertise a monthly wage range. Throughout the paper, we define the posted wage as the minimum of the range posted, since 8.6% of vacancies that provide a lower bound do not provide an upper bound. Some vacancies attach a minimum value that is non-informative (i.e., close to zero), so we impute the wage reference as missing whenever the advertised wage is lower than 1,000 Uruguayan pesos (as of 2020).[6]

[6]As a reference, the mean (median) posted wage conditional on posting is 20,942 (25,482) Uruguayan pesos.

Table 1: Descriptive Statistics for Vacancies, Applicants, and Applications

Panel (a): Vacancies

	Obs.	Mean	Std. Dev.	p25	p50	p75
Openings attached to vacancies	77,874	1.70	2.87	1	1	1
Total applications (per job opening)	77,874	178.50	253.22	38	97	216
Days open	77,874	28.56	9.71	31	31	31
Posts wage? (1 = yes)	77,874	0.20	0.40	0	0	0
Requires vocational training? (1 = yes)	77,874	0.14	0.35	0	0	0
Requires college degree? (1 = yes)	77,874	0.21	0.40	0	0	0
Requires foreign language? (1 = yes)	77,874	0.19	0.39	0	0	0
Requires cognitive skills? (1 = yes)	77,874	0.80	0.40	1	1	1
Requires socio-emotional skills? (1 = yes)	77,874	0.83	0.38	1	1	1
Requires manual skills? (1 = yes)	77,874	0.38	0.49	0	0	1

Panel (b): Applicants

	Obs.	Mean	Std. Dev.	p25	p50	p75
Total profiles (698,880):						
Female	665,710	0.55	0.50	0	1	1
Share completed voc. training	666,797	0.08	0.27	0	0	0
Share completed college	666,797	0.12	0.32	0	0	0
Year of birth	665,830	1987.31	9.69	1982	1990	1994
Total applications	698,880	23.35	71.98	0	2	16
Profiles with positive applications (410,955):						
Female	388,007	0.55	0.50	0	1	1
Share completed voc. training	388,871	0.11	0.31	0	0	0
Share completed college	388,871	0.16	0.37	0	0	0
Year of birth	388,012	1987.76	9.16	1983	1990	1994
Total applications	410,955	39.71	90.34	3	11	37

Panel (c): Characteristics of Applicants when making an Application

	Obs.	Mean	Std. Dev.	p25	p50	p75
Employed	16,320,466	0.42	0.49	0	0	1
Age	15,223,577	27.67	7.62	22	26	31
Cognitive tasks in current/previous job?	16,320,466	0.31	0.46	0	0	1
Socio-emotional tasks in current/previous job?	16,320,466	0.45	0.50	0	0	1
Manual tasks in current/previous job?	16,320,466	0.13	0.34	0	0	0

Notes: This table shows summary statistics of the BJ data. Panel (a) reports statistics for vacancies in our final sample (see Section 2 for sample restrictions). Panel (b) shows statistics for applicants registered on the BJ platform. Panel (c) focuses on applicants at the time of application, considering only applications to vacancies in the final sample. In Panel (a), "vocational training" refers to tertiary-level training, whereas in Panel (b), it also includes lower levels of vocational training.

Panel (a) of Table 1 also shows the shares of vacancies that specify requirements for applicants. 14% of vacancies require a vocational training certificate, while 21% require a college degree, and 19% of vacancies require knowledge of a language other than Spanish (in most cases, English). These requirements are directly specified by firms in related entries when posting a vacancy. Other requirements are specified in the open text of job ads, which are elicited using NLP techniques as described in Section 2.1. We observe that 80% of vacancies require at least one cognitive skill, 83% require at least one socio-emotional skill, and 38% require at least one manual skill.

Panel (b) of Table 1 presents descriptive statistics of the applicants registered on BJ. We identify

Table 2: Descriptive Statistics for Advertised Variable Pay and Amenities

	All Vacancies (1)	Posts Wage (2)	Does not post wage (3)
Bonuses and commissions	0.07	0.07	0.06
At least one amenity	0.42	0.36	0.44
Number of amenities	0.63	0.50	0.66
<u>Individual amenities:</u>			
Schedule flexibility	0.05	0.04	0.06
Work environment/Impact on society	0.16	0.14	0.16
Working in teams	0.19	0.14	0.20
Human capital development	0.23	0.18	0.24
Number of vacancies	77,874	15,835	62,039

Notes: This table shows summary statistics for advertised variable pay and amenities in the final vacancy sample, where attributes were elicited following Adamczyk et al. (2025). It reports the share of vacancies advertising at least one amenity, the number of amenities advertised per vacancy, and details on each amenity. Statistics are also disaggregated by whether vacancies post a wage.

698,880 profiles in the 2010-2020 period, of which 410,955 are "active" profiles, i.e., individuals who made at least one application between October 2011 and September 2020. To get a sense of the order of magnitude, the population in Uruguay was estimated at 3,530,912 in 2020, of which 2,067,384 (59%) were between 20 and 64 years old (INE, 2021). Thus, the total number of profiles created between 2010 and 2020 represents approximately 34% of the working-age population in 2020.[7] Among the active profiles, the mean number of applications made between October 2011 and September 2020 is 39.7, and the corresponding median is 11. Among active applicants, 55% are female. 11% report having a vocational training degree, and 16% a college degree. The median applicant was born in 1990. Overall, the educational structure of BJ applicants closely resembles that of the national labor force, although BJ applicants are slightly more likely to be college graduates. They are also younger on average (Escudero et al., 2024).

We identify 16,320,466 applications for vacancies made between October 2011 and September 2020. Panel (c) of Table 1 shows that 42% of applications are made by individuals who report being employed at the time of the application. The average age at the time of application is relatively young at 27.7 years with moderate dispersion. Finally, based on the open-text descriptions of current and previous jobs, we estimate that 31% report having performed cognitive tasks, 45% report having performed socio-emotional tasks, and 13% report having performed manual tasks.

Table 2 shows that 7% of vacancies in our sample advertise "bonuses and commissions", while 42% advertise at least one of the four amenities described in Section 2.1. The average number of amenities advertised is 0.63, with 58% of vacancies advertising zero amenities, 26% advertising one, 12% advertising two, 4% advertising three, and less than 1% advertising four amenities. The share of vacancies advertising amenities is larger among vacancies that do not post wages (44% versus 36%). The three most commonly advertised amenities are "human capital development", "working

[7] As an alternative benchmark, 114,392 individuals made at least one job application on the platform in 2020, which corresponds to 6% of the population aged 20 to 64.

in teams", and "work environment/impact on society", which are featured in 23%, 19%, and 16% of vacancies, respectively. "Schedule flexibility" is advertised only in 5% of the vacancies.

Application portfolios. Appendix C characterizes the application portfolios at the applicant level. Application portfolios are, to a significant extent, diversified in terms of the number of applications sent and the industry and occupation attached to the targeted vacancies. This suggests that characteristics other than occupation and industry can affect applications.

Figure C.1 of Appendix C shows that, while 23% of applicants with positive applications make a unique application within an application spell, 51% of applicants submit between 2 and 10 applications in a given spell, and 13% submit between 11 and 20 applications. Only 3% of applicants submit more than 50 applications. The distributions of the number of applications per spell are remarkably similar across groups of applicants (defined in terms of gender, education, and employment status). Figure C.2 of Appendix C shows that applicants diversify vacancies' occupations and industries. Almost everyone who applies to 2 vacancies applies to vacancies in 2 different 2-digit industry-by-one-digit occupation cells. Individuals making 5 and 10 applications span 4.6 and 8.7 industry-by-occupation cells, respectively. While mechanically smaller, diversification remains large when considering broader groups (2-digit industries, 1-digit industries, and 1-digit occupations alone). Applicants who make 2 applications span, on average, 1.90 2-digit industries, 1.79 1-digit industries, and 1.66 1-digit occupations. Applicants who make 5 applications span, on average, 4.2 2-digit industries, 3.5 1-digit industries, and 2.8 1-digit occupations. Applicants who make 10 applications span, on average, 7.1 2-digit industries, 5.1 1-digit industries, and 3.8 1-digit occupations. Finally, Figure C.3 of Appendix C shows, consistent with recent findings in Altmann et al. (2024) and Fluchtmann et al. (2024a), that employed job seekers frequently apply to vacancies attached to occupations different from the ones attached to their current employment.

3 Cross-Sectional Facts on Job Applications

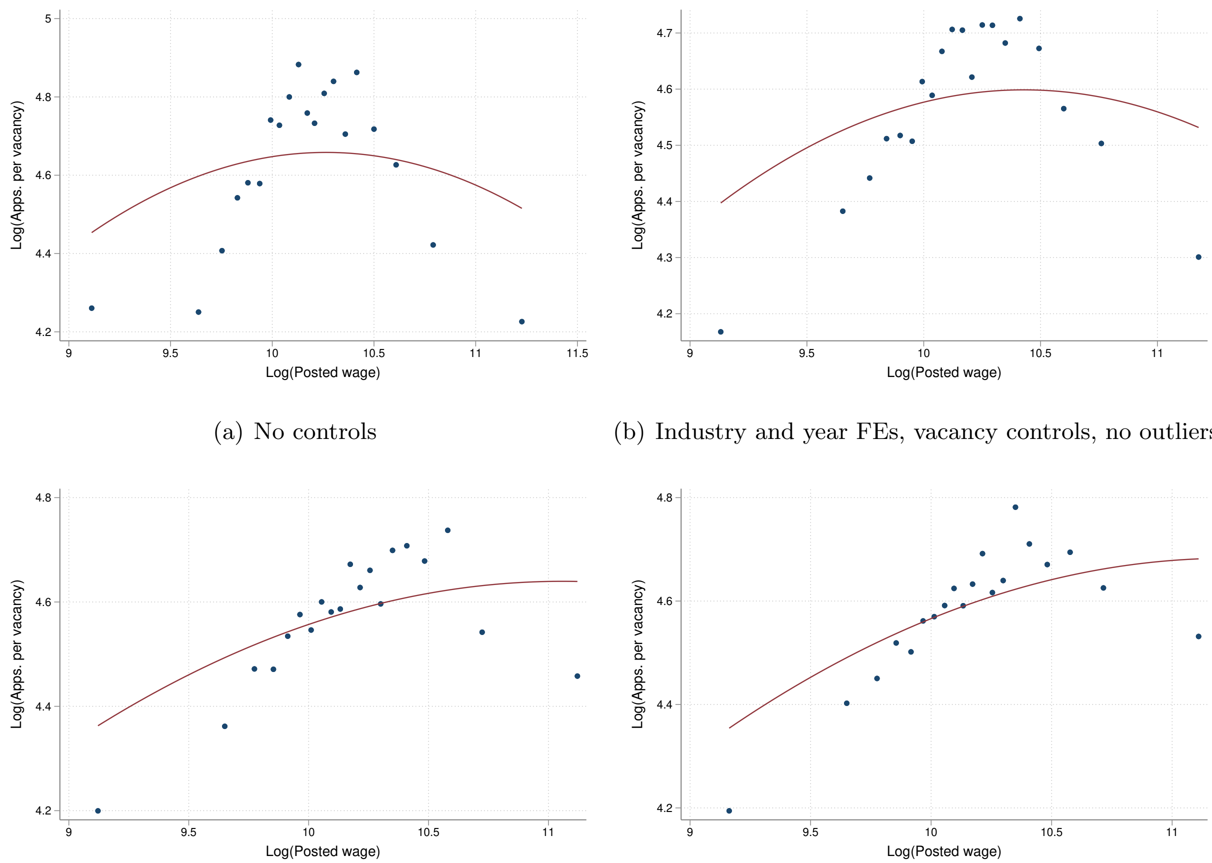
We perform two cross-sectional exercises using the BJ data. First, we explore whether posted wages affect applications. Second, we explore the role of advertised variable pay and non-wage amenities.

3.1 Directed search based on posted wages

This subsection explores directed search patterns based on posted wages. As mentioned previously, among our sample of 77,874 vacancies, 15,835 (20.3%) post a wage in the job ad.

We start by non-parametrically analyzing the relationship between log applications and log posted wages, pooling all vacancies that post a wage. Figure 1 shows different binned scatter plots that vary in the controls considered. Panel (a) shows the raw relationship between log applications and log posted wages. The plot shows a noisy and inverse U-shaped relationship: vacancies that post very low or very high wages tend to receive fewer applications. Panel (b) shows that the same relationship is observed when excluding the 3% of outlier vacancies that received more than 1,000 applications and controlling for 2-digit industry fixed effects, year fixed effects, and the

Figure 1: Cross-Sectional Relationship Between Applications and Posted Wages (All Vacancies)



(a) No controls

(b) Industry and year FEs, vacancy controls, no outliers

(c) Panel (b) + 1-digit occupation FEs

(d) Panel (b) + 2-digit occupation FEs

Notes: This figure shows binned scatter plots with quadratic fits for the relationship between log applications per vacancy and log posted wages, considering the sample of vacancies that post a wage. Panel (a) does not include controls. Panel (b) excludes vacancies with over 1,000 applications and includes 2-digit industry and year fixed effects, along with controls for advertised variable pay and the four amenities. Panels (c) and (d) augment Panel (b) by including 1-digit and 2-digit occupational fixed effects, respectively.

advertised variable pay and non-wage amenities. As stressed by Banfi and Villena-Roldan (2019) and Marinescu and Wolthoff (2020), the cross-sectional relationship may be spurious when not properly controlling for the skills associated with the job tasks. Panels (c) and (d) add 1-digit and 2-digit occupation fixed effects, respectively, and indicate that, with the exception of the vacancies at the very top of the posted wage distribution, the relationship between applications and posted wages becomes positive, suggesting the presence of a within-occupation directed search pattern in a wide range of the posted wage distribution.

To summarize these patterns, we run OLS regressions of the following type:

$$\log \text{App}_j = \alpha \log w_j + X_j'\beta + \epsilon_j, \tag{1}$$

where App_j is the number of applications per opening for vacancy j, w_j is the posted wage of

Table 3: Cross-Sectional Patterns of Directed Search: Posted Wages

Panel (a): All vacancies

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Posted wage)	0.086	0.111	0.167	0.194	0.332	0.207
	(0.081)	(0.055)	(0.053)	(0.055)	(0.056)	(0.053)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	No	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	15,575	15,241	15,241	14,378	13,677	10,625
Adj. R^2	0.001	0.064	0.124	0.159	0.164	0.371

Panel (b): Interactions with low- and higher-skill occupations

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Posted wage) (LS)	0.497	0.464	0.414	0.401	0.531	0.322
	(0.047)	(0.047)	(0.051)	(0.048)	(0.055)	(0.049)
Log(Posted wage) (HS)	-0.100	-0.069	-0.067	-0.044	0.055	0.036
	(0.061)	(0.048)	(0.047)	(0.052)	(0.049)	(0.065)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	No	Yes	Yes	Yes	Yes	Yes
Occupation group	Yes	Yes	No	No	No	No
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	15,575	15,241	15,241	14,378	13,677	10,625
Adj. R^2	0.051	0.104	0.131	0.165	0.169	0.373

Notes: Panel (a) presents the estimated α coefficient from equation (1). Panel (b) presents the estimated $(\alpha_{LS}, \alpha_{HS})$ coefficients from equation (2), where LS and HS correspond to lower- and higher-skill occupations, respectively. The dependent variable is log applications, and the key regressor is log posted wage. Column (1) includes no controls in Panel (a) and controls for broad occupational groups in Panel (b). Column (2) excludes vacancies with over 1,000 applications and includes 2-digit industry and year fixed effects, and controls for advertised variable pay and the four amenities. Columns (3) and (4) add 1-digit and 2-digit occupational fixed effects, respectively. Column (5) excludes the top 5% posted wages. Column (6) restricts the sample to vacancies of firms posting at least 10 vacancies on the BJ platform and includes firm fixed effects. Standard errors (in parentheses) are clustered at the 2-digit industry level.

vacancy j, and X_j are vacancy controls. We cluster standard errors at the 2-digit industry level.

Panel (a) of Table 3 shows the estimate of α with different controls. Column (1) shows the raw correlation, which is positive but small and not statistically significant. Column (2) excludes outliers, includes industry and year fixed effects, and controls for the advertised variable pay and amenities. Including these controls has a small effect on the coefficient but slightly increases precision. Columns (3) and (4) add 1-digit and 2-digit occupation fixed effects, respectively, generating an increase in the estimated coefficient that is statistically significant at conventional levels. The cross-sectional application-wage elasticity in these columns is 0.17 and 0.19, respectively. Column (5) excludes the vacancies at the top 5% of the posted wage distribution. Consistent with Figure 1, omitting the upper tail increases the elasticity to 0.33. Finally, Column (6) leverages the fact that several firms post multiple vacancies in the platform and, therefore, only considers vacancies posted by firms with 10 or more posted vacancies and includes firm fixed effects.[8] While it is not clear whether firm fixed effects are good controls (directed search may reflect job ladders between firms), it is reassuring that the elasticity remains positive and significant, with a value of 0.21. Our analysis replicates the main conclusions in Banfi and Villena-Roldan (2019) and Marinescu and Wolthoff (2020): directed search arises after including appropriate controls for the skill attached to the vacancy, which we approximate with occupation codes. Our estimated elasticities are smaller than the ones estimated in these papers, possibly because they use job titles as the skill control which are narrower than 1-digit or 2-digit occupation codes. The sensibility of the estimated elasticity to the included controls, however, provides a similar narrative in qualitative terms.[9,10]

In most of the exercises that follow, we report results for the same sets of controls and sample refinements. Given the lessons from related literature and the results of Panel (a) in Table 3, we designate the specification of Column (3) (no outliers, 2-digit industry fixed effects, year fixed effects, advertised variable pay and amenities, and 1-digit occupation fixed effects) as our preferred specification. The choice of 1-digit over 2-digit occupation codes rests solely on the fact that 2-digit codes are not available for all vacancies and, therefore, using 1-digit codes increases the sample size.

Occupational heterogeneity. The analysis above pools all vacancies when estimating the cross-sectional wage-application relationship. However, different occupations may react differently to posted wages. Findings in Hall and Krueger (2012), Caldwell and Harmon (2019), Lachowska et al. (2022), and Caldwell et al. (2025) suggest that wage bargaining is more prevalent in higher-skill occupations, which could mediate how job seekers attached to different occupations interpret and react to posted wages in online job ads. To study occupational heterogeneities, we replicate the analysis separately by 1-digit occupation categories.

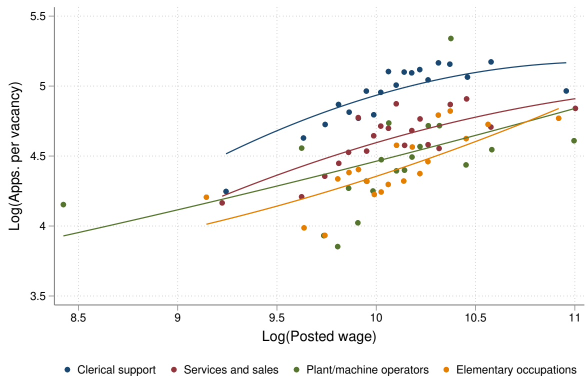
Figure 2 presents binned scatter plots for the relationship between applications and posted wages by occupation. These figures exclude outliers and include industry fixed effects, year fixed effects, and controls for advertised variable pay and amenities. The data reveals the existence of two groups of occupations that display opposite patterns. Panel (a) shows results for vacancies

[8] The 77,874 vacancies are posted by 6,214 firms. 2,341 firms only post one vacancy, 2,578 firms post 2 to 9 vacancies, and 1,295 firms post 10 or more. 2,682 firms are responsible for the 20% of vacancies that post wages.

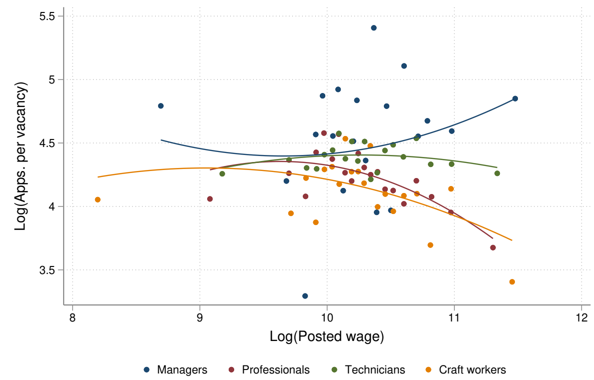
[9] Table B.3 of Appendix B replicates Panel (a) of Table 3 using different definitions of posted wage. Panel (a) uses the midpoint of the salary range. Panel (b) uses the midpoint of the salary range but excludes vacancies with ranges larger than 50% of the midpoint. Panel (c) uses the maximum of the salary range. In these cases, and consistent with Banfi and Villena-Roldan (2019) and Marinescu and Wolthoff (2020), elasticities are negative in the absence of skill controls but become positive when adding the occupation fixed effects. When using the midpoint of the salary range, the qualitative pattern of Table 3 is confirmed and the resulting elasticities are significant. When using the maximum of the salary range, the same qualitative pattern is observed but with smaller and non-significant estimates. These results suggest that the minimum of the salary range is more relevant to job seekers than the maximum.

[10] 1.6% (260) of vacancies advertising a wage had zero applications, so are excluded from the main analysis. Table B.2 of Appendix B shows that a Poisson model that includes these vacancies yields similar results.

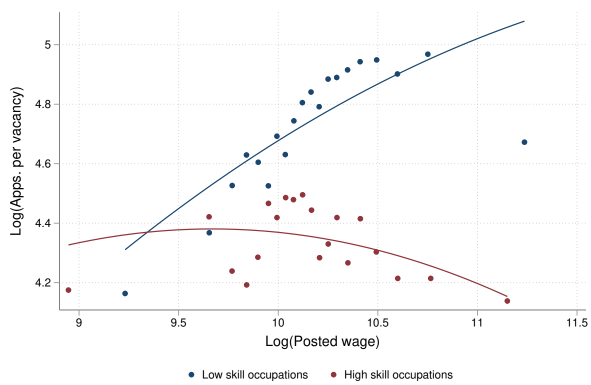
Figure 2: Cross-Sectional Relationship Between Applications and Posted Wages (By Occupation)



(a) Lower-skill occupations



(b) Higher-skill occupations



(c) By broad group

Notes: This figure presents binned scatter plots with quadratic fits for the relationship between log applications per vacancy and log posted wage, by occupation. The analysis considers all vacancies in our final sample that post a wage. All plots exclude vacancies with over 1,000 applications, include 2-digit industry and year fixed effects, and control for advertised variable pay and the four amenities. Panel (a) focuses on vacancies attached to lower-skill occupations (clerical support, services and sales, plant and machine operators, and elementary occupations), Panel (b) on higher-skill occupations (managers, professionals, technicians and associate professionals, and craft workers) and Panel (c) on both occupational groups.

attached to clerical support, services and sales, plant and machine operators, and elementary occupations. We denote this group of occupations as *lower-skill* and refer to vacancies attached to these occupations as "lower-skill vacancies". Vacancies in this group exhibit a monotone and positive relationship between applications and posted wages. Panel (b) shows results for vacancies attached to managers, professionals, technicians and associate professionals, and craft workers. We denote this group of occupations as *higher-skill* and refer to vacancies attached to these occupations as "higher-skill vacancies". The relationship between applications and posted wages is essentially flat for this group of occupations. Panel (c) reproduces the analysis after grouping lower- and higher-skill occupations into the two broad groups. The lower-skill group exhibits a clear positive correlation between applications and posted wages, whereas the higher-skill group displays no such relationship.[11]

Table B.4 in Appendix B presents estimates of equation (1) separately by 1-digit occupation group, confirming the patterns displayed in Figure 2. Panel (b) of Table 3 summarizes the results by replicating Panel (a) of Table 3 using a model with interactions:

$$\log \text{App}_j = \alpha_{LS} \log w_j \times 1\{\text{Occ}_j \in LS\} + \alpha_{HS} \log w_j \times 1\{\text{Occ}_j \in HS\} + X_j' \beta + \epsilon_j, \tag{2}$$

where LS and HS account for lower- and higher-skill occupation, respectively. When X_j does not include 1-digit or 2-digit occupation fixed effects (Columns (1) and (2)), the regression controls for $1\{\text{Occ}_j \in LS\}$. The results are remarkably stable across columns and confirm the pattern documented in Figure 2. Vacancies attached to lower-skill occupations consistently display a positive and significant elasticity of applications to posted wages, with larger magnitudes closer to the values reported in Banfi and Villena-Roldan (2019) and Marinescu and Wolthoff (2020), while vacancies attached to higher-skill occupations show no significant relationship between posted wages and applications. In our preferred specification (Column (3)), the point estimates are $\widehat{\alpha}_{LS} = 0.41$ and $\widehat{\alpha}_{HS} = -0.07$, compared to the estimated $\widehat{\alpha} = 0.17$ from the pooled regression with no interactions.

One possible explanation is that higher-skill vacancies impose more requirements on applicants in terms of formal qualifications or skills, which could prevent job seekers from applying to high-wage higher-skill vacancies. Table B.5 of Appendix B shows that requirements are more prevalent in higher-skill vacancies. Table B.6 of Appendix B, however, shows that the absence of directed search based on posted wages in higher-skill vacancies holds regardless of whether we restrict the sample to vacancies that post or do not post requirements. This is true in terms of formal requirements (see Panels (a) and (c)) and skill requirements (see Panels (b) and (d)). Conversely, we continue to find evidence of directed search among vacancies attached to lower-skill occupations independent of vacancy requirements. Yet, for vacancies attached to these occupations, the responsiveness to posted wages is stronger when no formal requirements are posted (Panels (a) and (c)).

Applicant-level heterogeneity. Finally, we leverage our applicant-level data and test whether directed search patterns are heterogeneous by applicant characteristics. Specifically, we estimate equation (2) using applications from particular groups of applicants as dependent variables. Table 4 presents the results. Regressions exclude outliers and include 2-digit industry fixed effects, year fixed effects, variable pay and amenity controls, and 1-digit occupation fixed effects.

While the larger responsiveness in vacancies attached to lower-skill occupations relative to

[11] We use the terms lower- and higher-skill for clarity and consistency with existing literature (e.g., Kunst et al., 2022; Montobbio et al., 2023), while acknowledging the limitations of inferring skill levels from broad occupations. This categorization aligns with ISCO-08 guidelines (ILO, 2012), which classify the four 1-digit occupations in our lower-skill group at the lowest skill levels 1 and 2, and three of the four 1-digit occupations in our higher-skill group at the highest skill levels 3 and 4. ISCO-08 guidelines determine skill levels based on the complexity and range of tasks and duties typically associated with an occupation, and the level of formal education required to perform those tasks. As such, it does not account for variation in task complexity across different jobs within the same occupation or between countries. Moreover, it places greater emphasis on formal educational qualifications despite the importance of other types of learning, for example, on-the-job (e.g., Alfonsi et al., 2020). Finally, our higher-skill group includes craft and related trades workers which ISCO-08 classifies at skill level 2, possibly because this occupation commands a higher average salary than other occupations with ISCO skill level 2 (see Table B.10 of Appendix B).

Table 4: Cross-Sectional Patterns of Directed Search: Heterogeneity by Applicants Characteristics

Panel (a): Gender, employment status, and age

	Female (1)	Male (2)	Emp. (3)	Unemp. (4)	Age≤25 (5)	Age>25 (6)
Log(Posted wage) (LS)	0.142	0.631	0.616	0.281	0.006	0.738
	(0.075)	(0.041)	(0.051)	(0.052)	(0.074)	(0.041)
Log(Posted wage) (HS)	-0.278	0.045	0.087	-0.221	-0.502	0.195
	(0.080)	(0.052)	(0.056)	(0.044)	(0.054)	(0.056)
No outliers	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,018	13,748	15,199	15,216	15,166	15,204
Adj. R^2	0.181	0.098	0.141	0.138	0.137	0.207

Panel (b): Education and skills

	No tert. (1)	Voc. trn. (2)	College (3)	Cogn. sk. (4)	Soc. sk. (5)	Man. sk. (6)
Log(Posted wage) (LS)	0.203	0.654	0.833	0.824	0.629	0.664
	(0.057)	(0.044)	(0.050)	(0.053)	(0.051)	(0.042)
Log(Posted wage) (HS)	-0.393	-0.003	0.460	0.341	0.096	0.136
	(0.046)	(0.060)	(0.085)	(0.066)	(0.061)	(0.070)
No outliers	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,198	14,934	14,799	15,142	15,194	14,943
Adj. R^2	0.162	0.156	0.243	0.229	0.187	0.172

Notes: This table presents the estimated $(\alpha_{LS}, \alpha_{HS})$ coefficients from equation (2), where LS and HS correspond to lower-skill and higher-skill, respectively. The dependent variable is the log number of applications made by applicants with the characteristic depicted in each column. The key regressor is the log posted wage. Panel (a) presents results by gender, employment status, and age. Panel (b) reports results by educational attainment (no tertiary education, vocational training, and college degree) and skill category (cognitive, socio-emotional, and manual skills). Regressions exclude vacancies with over 1,000 applications and include 2-digit industry and year fixed effects, controls for advertised variable pay and the four amenities, and 1-digit occupation fixed effects. Standard errors (in parentheses) are clustered at the 2-digit industry level.

higher-skill occupations is seen across all groups of applicants, point estimates reveal substantial heterogeneity by group of applicants. Columns (1) and (2) of Panel (a) show results for female and male applicants, respectively. Male applicants are substantially more responsive to posted wages than female applicants. While the lower-skill elasticity is 0.63 for male applicants, female applicants reveal a non-significant lower-skill elasticity of 0.14 and a negative higher-skill elasticity of -0.27. Columns (3) and (4) of Panel (a) provide a similar comparison between employed and unemployed applicants, with employed applicants showing a much larger responsiveness to posted wages in lower-skill vacancies ($\widehat{\alpha}_{LS} = 0.61$) than unemployed applicants ($\widehat{\alpha}_{LS} = 0.28$). The latter group also reveals a negative higher-skill elasticity of -0.22. Columns (5) and (6) of Panel (a) compare applications from job seekers aged 25 or less with applications from job seekers older than

25. Younger applicants show a precisely estimated zero lower-skill elasticity and a large negative higher-skill elasticity of -0.50. On the contrary, the estimated elasticities for older applicants resemble the findings for male and employed applicants ($\widehat{\alpha}_{LS} = 0.74$ and $\widehat{\alpha}_{HS} = 0.20$). Panel (b) shows heterogeneities by applicants' education level and skill types. Columns (1) to (3) of Panel (b) reveal larger responsiveness for applicants with tertiary education, especially for job seekers with a college degree in lower-skill occupations ($\widehat{\alpha}_{LS} = 0.83$). This finding may reflect the fact that more educated applicants apply to vacancies attached to lower-skill occupations only if wages are attractive (given their possibly better outside options), while they may prioritize factors other than posted wages when applying to vacancies attached to higher-skill occupations. Columns (4) to (6) show that applicants with cognitive, socio-emotional, and manual skills, are also more responsive to posted wages than the average applicant, both in lower- and higher-skill vacancies.[12]

It is noteworthy that the groups of applicants with presumably worse labor market prospects exhibit negative higher-skill elasticities. The finding for these groups is consistent with models with on-the-job search where the lack of outside employment options may encourage workers to apply to low-wage jobs with the aim of climbing the job ladder in future job transitions (e.g., Burdett and Mortensen, 1998; Postel-Vinay and Robin, 2002a,b). The particularly negative response observed for the younger applicants may also reflect that these workers internalize in their application choices the importance of labor market experience to access higher-paying jobs. On the contrary, and consistent with related theory, results generally suggest that applicants with better outside options are more selective about the vacancies they choose to apply for in terms of the posted wage.

3.2 The role of variable pay and non-wage amenities

In this second exercise, we explore correlations that inform the role of variable pay and non-wage amenities in the application process. We first estimate the analog of equation (2) but using the variable pay and amenity indicators as the main right-hand-side variables of interest:

$$\begin{aligned} \log \text{App}_j &= \alpha^v_{LS}\text{VP}_j \times 1\{\text{Occ}_j \in LS\} + \alpha^v_{HS}\text{VP}_j \times 1\{\text{Occ}_j \in HS\} \\ &\quad + \alpha^a_{LS}\text{Am}_j \times 1\{\text{Occ}_j \in LS\} + \alpha^a_{HS}\text{Am}_j \times 1\{\text{Occ}_j \in HS\} + X'_j\beta + \epsilon_j, \end{aligned} \tag{3}$$

where X_j is defined as in equation (2), $\text{VP}_j = 1\{\text{Vacancy } j \text{ advertises bonuses and commissions}\}$, and $\text{Am}_j = 1\{\text{Vacancy } j \text{ advertises at least 1 of the 4 amenities}\}$.

Table 5 shows the results. The role of variable pay is remarkably different across the two occupational groups identified earlier. For vacancies attached to lower-skill occupations, advertising variable pay has a small and imprecisely estimated negative effect on applications. On the contrary, variable pay has a large and significant positive effect on applications to vacancies attached to higher-skill vacancies. One potential explanation of this pattern is that, in lower-skill occupations,

[12] Not all vacancies receive applications that span the complete distribution of applicants observables. Therefore, the number of vacancies considered in each regression is not constant. In Table B.7 of Appendix B, we show that similar results are obtained from a Poisson regression including vacancies with zero applications.

Table 5: Cross-Sectional Patterns of Directed Search: Variable Pay and Amenities

	(1)	(2)	(3)	(4)	(5)
Bonuses and commissions (LS)	-0.103	-0.134	-0.042	-0.083	-0.070
	(0.062)	(0.062)	(0.059)	(0.061)	(0.031)
Bonuses and commissions (HS)	0.403	0.274	0.240	0.158	0.095
	(0.088)	(0.067)	(0.068)	(0.064)	(0.073)
At least one amenitiy (LS)	0.101	0.083	0.066	0.063	0.007
	(0.024)	(0.018)	(0.014)	(0.013)	(0.012)
At least one amenitiy (HS)	0.035	0.073	0.077	0.116	0.082
	(0.048)	(0.033)	(0.032)	(0.028)	(0.017)
No outliers	No	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Occupation group	Yes	Yes	No	No	No
Occupation FE (1-digit)	No	No	Yes	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes
Firm FE	No	No	No	No	Yes
Observations	75,928	74,533	74,533	70,592	59,333
Adj. R^2	0.071	0.113	0.137	0.184	0.327

Notes: This table presents the estimated $(\alpha^v_{LS}, \alpha^v_{HS}, \alpha^a_{LS}, \alpha^a_{HS})$ coefficients from equation (3), where LS and HS denote lower-skill and higher-skill, respectively. The dependent variable is the log number of applications, and key regressors are indicators for advertising variable pay and at least one amenity. Column (1) controls for broad occupational groups. Column (2) excludes vacancies with over 1,000 applications and includes 2-digit industry and year fixed effects. Columns (3) and (4) add 1-digit and 2-digit occupation fixed effects, respectively. Column (5) excludes the top 5% of posted wages. Column (6) only considers vacancies of firms posting at least 10 vacancies on the platform and includes firm fixed effects. Standard errors (in parentheses) are clustered at the 2-digit industry level.

bonuses and commissions constitute the primary source of earnings, presumably introducing income volatility and uncertainty, while in higher-skill occupations, they form part of incentive schemes that supplement (rather than replace) base salary. This difference may mediate how workers value the presence of variable pay when selecting where to apply. As a second result, the table shows that advertising amenities increase applications in both sets of vacancies. Our preferred specification suggests a semi-elasticity of 6.6% for lower-skill vacancies and 7.7% for higher-skill vacancies. This result suggests that workers not only direct their search toward vacancies with higher wages but also toward vacancies with advertised amenities.

The previous regression uses the complete sample of vacancies, implying that we cannot control by the posted wage when vacancies post a wage.[13] This issue may compromise the interpretation of the results if advertised amenities and variable pay correlate with posted wages, a situation that is likely to arise if non-wage features of the job are priced in the posted wage. Table B.8 of Appendix B show that posted wages, variable pay, and amenities are correlated within the sample of vacancies that post a wage. To assess this concern, Table 6 presents estimates of equation (3) separately for the samples of vacancies that post a wage and do not post a wage, respectively. Importantly, we control for the posted wage when using the sample vacancies that post a wage. Results using the sample of vacancies that do not post a wage (Panel (a)) resemble the patterns displayed in Table 5,

[13] For this same reason, these regressions do not consider versions with winsorized wages.

Table 6: Cross-Sectional Directed Search Patterns: Variable Pay and Amenities By Posting Status

Panel (a): No wage posted

	(1)	(2)	(3)	(4)	(5)
Bonuses and commissions (LS)	-0.049	-0.080	0.019	-0.023	-0.060
	(0.073)	(0.069)	(0.067)	(0.069)	(0.040)
Bonuses and commissions (HS)	0.427	0.281	0.249	0.150	0.086
	(0.104)	(0.083)	(0.082)	(0.082)	(0.086)
At least one amenitiy (LS)	0.113	0.095	0.074	0.070	0.002
	(0.023)	(0.017)	(0.015)	(0.014)	(0.017)
At least one amenitiy (HS)	0.044	0.087	0.091	0.132	0.084
	(0.046)	(0.032)	(0.032)	(0.029)	(0.019)
No outliers	No	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Occupation group	Yes	Yes	No	No	No
Occupation FE (1-digit)	No	No	Yes	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes
Firm FE	No	No	No	No	Yes
Observations	60,353	59,292	59,292	56,214	48,133
Adj. R^2	0.079	0.121	0.143	0.193	0.340

Panel (b): Wage posted

	(1)	(2)	(3)	(4)	(5)
Bonuses and commissions (LS)	-0.275	-0.312	-0.241	-0.289	-0.123
	(0.079)	(0.077)	(0.089)	(0.084)	(0.066)
Bonuses and commissions (HS)	0.285	0.221	0.185	0.182	0.083
	(0.138)	(0.131)	(0.131)	(0.087)	(0.097)
At least one amenitiy (LS)	0.058	0.041	0.033	0.035	0.014
	(0.036)	(0.029)	(0.024)	(0.023)	(0.028)
At least one amenitiy (HS)	0.043	0.051	0.046	0.056	0.088
	(0.062)	(0.050)	(0.048)	(0.046)	(0.040)
Posted wage	Yes	Yes	Yes	Yes	Yes
No outliers	No	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Occupation group	Yes	Yes	No	No	No
Occupation FE (1-digit)	No	No	Yes	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes
Firm FE	No	No	No	No	Yes
Observations	15,575	15,241	15,241	14,378	11,200
Adj. R^2	0.042	0.096	0.125	0.160	0.340

Notes: This table presents the estimated $(\alpha^v_{LS}, \alpha^v_{HS}, \alpha^a_{LS}, \alpha^a_{HS})$ coefficients from equation (3), where LS and HS denote lower-skill and higher-skill, respectively. Panel (a) considers vacancies that do not post a wage, while Panel (b) considers vacancies that do, with all regressions controlling for the log posted wage. The dependent variable is the log number of applications and the key regressors are indicators of advertising variable pay and at least one amenity. Column (1) controls for broad occupational groups. Column (2) excludes vacancies with over 1,000 applications and includes 2-digit industry and year fixed effects. Columns (3) and (4) add 1-digit and 2-digit occupation fixed effects, respectively. Column (5) excludes vacancies the top 5% of posted wages. Column (6) only considers vacancies of firms posting at least 10 vacancies on the platform and includes firm fixed effects. Standard errors (in parentheses) are clustered at the 2-digit industry level.

although the effect of variable pay on applications to lower-skill vacancies is more muted (a precise zero semi-elasticity in the preferred specification) and the effect of non-wage amenities is larger (a semi-elasticity of 7.4% for lower-skill vacancies and of 9.1% for higher-skill vacancies). Results using the sample of vacancies that post a wage also show a similar pattern after controlling for the posted wage, with two important differences. First, the negative role of variable pay in lower-skill vacancies increases in magnitude and significance, meaning that, conditional on the wage, applicants to lower-skill vacancies seem to dislike earnings uncertainty. Second, non-wage amenities keep predicting higher applications in both occupation groups, but the coefficients are smaller and noisier. Our preferred specification suggests a semi-elasticity of 3.3% for lower-skill vacancies and of 4.6% for higher-skill vacancies, both non-statistically significant at conventional levels. These results suggest the presence of a mild lexicographic preference for wages over amenities: amenities matter when no wage is posted but become less important conditional on a posted wage.

Two existing papers are consistent with the relevance of non-wage amenities for job applications and the corresponding attenuation of their effect when wages are posted. First, Banfi and Villena-Roldan (2019) show that applicants direct their search to high-wage jobs even when wages are not posted in the job ad. They interpret that result as applicants predicting the wage based on the job ad description. Second, Belot et al. (2022) provide survey evidence that suggests that, when asked to compare two vacancies with different posted wages but equal non-wage attributes (including job description), job seekers systematically perceive the high-wage vacancy to have better non-wage attributes, suggesting that information contained in job ads may be secondary to the posted wage.

Table B.9 of Appendix B shows additional differences between lower- and higher-skill vacancies when looking at individual amenities. Schedule flexibility negatively affects applications to lower-skill vacancies ($\widehat{\alpha}^a_{LS} = -0.029$), while having a large positive relationship on applications to higher-skill vacancies ($\widehat{\alpha}^a_{HS} = 0.043$), although the semi-elasticities are non-statistically significant in most of the specifications. These results suggest that, as in the case of variable pay, schedule flexibility has different implications for utility depending on the occupation. For example, in lower-skill occupations, schedule flexibility may reflect the ability of supervisors to determine working schedules while leaving less autonomy for the employees. In contrast, for higher-skill occupations, schedule flexibility may represent allowances to accommodate family responsibilities and remote work opportunities. Work environment/impact on society shows a large and significant positive effect on lower-skill vacancies ($\widehat{\alpha}^a_{LS} = 0.105$) and a small, unstable, and non-significant effect on higher-skill vacancies. Working in teams shows a stable positive effect on applications for both groups ($\widehat{\alpha}^a_{LS} = 0.071$ and $\widehat{\alpha}^a_{HS} = 0.074$). The same pattern is observed for human capital development, although the estimated effects are small and non-significant.

Applicant-level heterogeneity. As above, we study heterogeneities by applicants' characteristics using the vacancy-level strategy previously illustrated in Table 4, but with the variable pay and amenity indicators as the main variables of interest. Table 7 shows the results, where we estimate analogs of equation (1) using applications from specific groups of applicants as the dependent variable, and variable pay and amenity indicators as the right-hand-side variables.

The analysis shows two results. First, there is little heterogeneity across applicants on the relationship between applications and advertising at least one amenity. The effect is positive and

Table 7: Applications, Variable Pay, and At Least One Amenity: Applicant Heterogeneity

Panel (a): Gender, employment status, and age

	Female (1)	Male (2)	Emp. (3)	Unemp. (4)	Age≤25 (5)	Age>25 (6)
Bonuses and commissions	0.191	-0.067	-0.038	0.070	0.104	-0.025
	(0.072)	(0.043)	(0.045)	(0.051)	(0.069)	(0.037)
At least one amenity	0.049	0.091	0.083	0.051	0.097	0.019
	(0.028)	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)
No outliers	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,545	69,922	74,253	74,332	73,750	74,231
Adj. R^2	0.188	0.084	0.118	0.159	0.153	0.170

Panel (b): Education and skills

	No tert. (1)	Voc. trn. (2)	College (3)	Cogn. sk. (4)	Soc. sk. (5)	Man. sk. (6)
Bonuses and commissions	0.144	-0.067	-0.163	-0.163	0.021	-0.081
	(0.054)	(0.037)	(0.045)	(0.050)	(0.047)	(0.039)
At least one amenity	0.034	0.044	0.132	0.137	0.092	0.026
	(0.016)	(0.018)	(0.020)	(0.021)	(0.023)	(0.019)
No outliers	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74,206	72,179	72,598	73,898	74,128	72,521
Adj. R^2	0.198	0.132	0.166	0.158	0.167	0.146

Notes: This table presents the estimated α coefficients from analogs of equation (1), using applications from specific applicant groups (specified in column titles) as the dependent variable and indicators for variable pay and at least one amenity as key regressors. Panel (a) presents results by gender, employment status, and age. Panel (b) presents results by educational attainment (no tertiary education, vocational training, and college degree) and skill categories (cognitive, socio-emotional, and manual skills). Regressions exclude vacancies with over 1,000 applications and include 2-digit industry, year, and 1-digit occupation fixed effects. Standard errors (in parentheses) are clustered at the 2-digit industry level.

significant across groups of applicants, with male, employed, young, more educated, and applicants reporting cognitive and socio-emotional skills showing slightly stronger relationships. The exception is age, where young workers show large responsiveness (semi-elasticity of 9.5%), contrary to older workers who exhibit no response.[14] This result mirrors the findings related to posted wages, where older workers were more responsive. Second, the role of variable pay varies substantially with applicants' characteristics. For female, unemployed, young, and non-educated applicants, variable pay seems to attract applications. On the contrary, male, employed, older, more educated, and applicants reporting cognitive and manual skills, generally display small and noisy negative semi-elasticities. This result mimics findings discussed above for posted wages in high-skill vacancies

[14] Maestas et al. (2023) find that job amenities matter more for older workers. However, physical activity plays a role in Maestas et al. (2023) results and we do not consider this disamenity. Our sample of applicants is also relatively young, so the age dispersion that determines the groups is not comparable to the aforementioned paper.

Table 8: Applications and Individual Amenities: Heterogeneity by Applicants Characteristics

Panel (a): Gender, employment status, and age

	Female (1)	Male (2)	Emp. (3)	Unemp. (4)	Age≤25 (5)	Age>25 (6)
Bonuses and commissions	0.189	-0.057	-0.027	0.066	0.069	0.007
	(0.067)	(0.041)	(0.042)	(0.047)	(0.061)	(0.036)
Schedule flexibility	0.127	-0.116	-0.059	0.055	0.256	-0.219
	(0.031)	(0.040)	(0.026)	(0.027)	(0.030)	(0.030)
Work environment/Impact on society	-0.002	0.015	0.009	0.040	0.114	-0.036
	(0.055)	(0.028)	(0.036)	(0.036)	(0.038)	(0.033)
Working in teams	0.042	0.093	0.098	0.043	0.045	0.060
	(0.021)	(0.015)	(0.017)	(0.016)	(0.017)	(0.017)
Human capital development	-0.001	0.075	0.048	0.005	0.021	0.011
	(0.024)	(0.017)	(0.019)	(0.021)	(0.021)	(0.021)
No outliers	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,545	69,922	74,253	74,332	73,750	74,231
Adj. R^2	0.188	0.084	0.119	0.159	0.155	0.171

Panel (b): Education and skills

	No tert. (1)	Voc. trn. (2)	College (3)	Cogn. sk. (4)	Soc. sk. (5)	Man. sk. (6)
Bonuses and commissions	0.132	-0.054	-0.145	-0.145	0.037	-0.046
	(0.049)	(0.035)	(0.042)	(0.048)	(0.045)	(0.038)
Schedule flexibility	0.094	-0.106	-0.067	-0.136	-0.117	-0.241
	(0.027)	(0.032)	(0.032)	(0.031)	(0.027)	(0.031)
Work environment/Impact on society	0.081	0.007	-0.063	0.008	-0.002	-0.048
	(0.033)	(0.028)	(0.038)	(0.033)	(0.039)	(0.037)
Working in teams	0.021	0.052	0.149	0.154	0.095	0.068
	(0.016)	(0.018)	(0.022)	(0.022)	(0.020)	(0.019)
Human capital development	-0.030	0.026	0.128	0.101	0.069	0.029
	(0.020)	(0.022)	(0.021)	(0.021)	(0.021)	(0.018)
No outliers	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74,206	72,179	72,598	73,898	74,128	72,521
Adj. R^2	0.199	0.132	0.168	0.159	0.167	0.148

Notes: This table presents the estimated α coefficients from analogs of equation (1), using applications from specific applicant groups (specified in column titles) as the dependent variable and indicators of variable pay and individual amenities as key regressors. Panel (a) presents results by gender, employment status, and age. Panel (b) presents results by educational attainment (no tertiary education, vocational training, and college degree) and skill categories (cognitive, socio-emotional, and manual skills). Regressions exclude vacancies with over 1,000 applications and include 2-digit industry, year, and 1-digit occupation fixed effects. Standard errors (in parentheses) are clustered at the 2-digit industry level.

and, again, suggests that variable pay is conceived as a precarious job attribute in certain cases, associated with the application from workers with possibly worse outside options.

Table 8 includes separate indicators for each individual amenity and shows that different groups of applicants vary in their response to different amenities. Columns (1) and (2) of Panel (a) report gender differences. Female applicants are more responsive to vacancies that advertise schedule flexibility while male applicants are more responsive to vacancies that advertise working in teams and human capital development. This finding aligns with recent studies that highlight gender differences in the valuation of flexibility. Women disproportionately apply for jobs with flexible work arrangements and tend to avoid jobs requiring particular hours, even at the expense of lower wages (Goldin, 2014; Mas and Pallais, 2017; Wiswall and Zafar, 2018; Fluchtmann et al., 2024b). Columns (3) and (4) on Panel (a) show differences by employment status. Unemployed applicants exhibit a noisy positive response to all amenities except human capital development, while employed applicants mostly respond to working in teams and human capital development. Columns (5) and (6) of Panel (a) show that young applicants positively respond to all amenities, especially schedule flexibility and work environment/impact on society. On the contrary, older workers respond negatively to schedule flexibility and tend to react positively to the advertising of working in teams. Columns (1) to (3) of Panel (b) show that applicants without tertiary education respond positively to all amenities except human capital development, while more educated applicants, especially the ones with a college degree, apply less to vacancies advertising schedule flexibility and apply more often to vacancies that advertise working in teams and human capital development. This finding is in line with Maestas et al. (2023) who find that, the higher the level of education, the more workers are willing to pay for training opportunities. Finally, Columns (4) to (6) of Panel (b) show that applicants who report the various types of skills resemble the patterns of applicants with tertiary education. The implied heterogeneity in amenity valuation suggests that heterogeneous preferences for non-wage amenities may be a relevant source of monopsony power (Card et al., 2018).

4 The Causal Effect of Wages on Applications

The cross-sectional results support the existence of directed search based on posted wages as well as important occupational differences in this pattern. This section validates our central finding of occupational heterogeneity in directed search based on posted wages by estimating the causal effect of wages on applications using exogenous variation in minimum wages. The minimum wage variation is independent of the wage-posting decision and thus pertains to all vacancies.

4.1 Setting and data

Uruguay has a long tradition of unions that set industry-by-occupation minimum wages in collective bargaining agreements (CBAs) that coexist with a uniform national minimum wage (NMW).[15] The first law of wage councils in Uruguay dates back to 1943. The institution was eliminated in 1973 by the rising dictatorship and then restored in 1985 with the return to democracy, but in a much weaker version – de facto non-binding – than the pre-dictatorship scheme, especially after 1992. An economic crisis between 2000 and 2005, mainly driven by the economic downturn in Argentina and the exchange rate devaluation in Brazil, generated a substantial decrease in

[15] For details on Uruguay's labor market institutions and their history see Mazzuchi (2009) and ILO (2014).

real wages in Uruguay. In 2005, a new government took office that aimed at strengthening the existing labor market institutions to facilitate the recovery of real wages. As a result, the NMW increased considerably between 2005 and 2010, and the role of wage councils in wage determination was gradually restored, especially after Law 18566 was sanctioned in 2009, which expanded the coverage of the CBAs and established concrete rubrics for the bargaining rounds. Consequently, the collective bargaining coverage rate in Uruguay is very high, reaching 94.7% of all employees in 2018 (ILO, 2022). Minimum wage non-compliance plays a comparatively small role, estimated at 9.4% for all private-sector wage employees and 6.7% for those in urban areas (Marinakis, 2016).

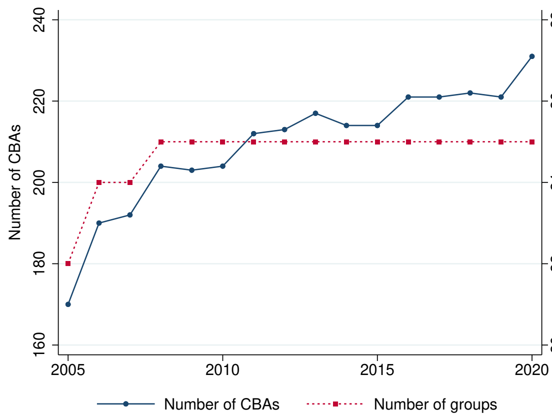
The NMW is determined by the central government, applies to all private-sector employees aged 18 and older, and sets a general wage floor. Wage councils determine sectoral CBAs through bargaining rounds, which give rise to industry-by-occupation minimum wages above the NMW. These negotiations are tripartite, as the wage councils involve representatives of the National Workers' Association (PIT-CNT), employers' organizations, and members of the central government. The mandate of the wage councils is to set wage floors and to negotiate working conditions considering expectations of future inflation, adjustments for past inflation not accounted for in previous negotiations, and additional increases aimed at restoring pre-crisis real wages.[16] From 2005 onwards, CBA bargaining rounds shifted from annual to biennial or triennial cycles, depending on the sector. In practice, however, almost all minimum wage adjustments take place once or twice per year on either January 1st and/or July 1st since each bargaining round sets a biannual sequence of wage adjustments (see Figure 3). The minimum wages specified in the CBAs automatically affect all workers and firms, as there is no affiliation requirement.

CBAs are negotiated at the *group* level. *Groups* correspond to broad economic industries. Each group bargains over one or more CBAs, depending on the number of *subgroups* considered. The objective of having different contracts within a group is to accommodate economic differences between sub-industries, although all CBAs within a group are jointly bargained and, in some cases, exhibit little within-group heterogeneity. Each group has discretion to define the occupations (i.e., *categories*) that will be subject to specific minimum wages in the bargained CBA.

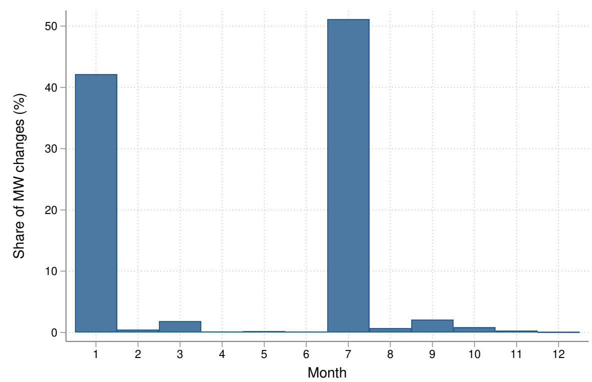
Figure 3 provides additional information about the CBAs. Panel (a) displays the number of groups and CBAs (subgroups) by year. In 2005, CBAs were negotiated in 20 groups. This increased to 24 groups in 2008 when CBAs became available for economic activities that were historically excluded from the wage councils, such as the domestic workers group and three groups representing activities of the rural economy. Within each group, the subgroups negotiate different CBAs. There were 172 subgroups negotiating CBAs in 2005, which reached 221 with the incorporation of the previously excluded groups in 2008, covering virtually all private sector employees. Since then, the increase in the number of subgroups is explained by a reorganization within groups rather than an

[16] Wage floor increases could be endogenous to labor market tightness. However, attempts to consider macroeconomic and sector-specific trends in CBAs failed, due to the difficulty of identifying appropriate indicators and reluctance of tripartite partners to use these. Therefore, only 20% of CBAs tried to explicitly incorporate such conditions in 2010 and 2012, and the initiative was no longer pursued in other years (Mazzuchi, 2022). Our controls, moreover, capture economic conditions at the sectoral and cell-level

Figure 3: CBAs: Number of Groups and Subgroups and Timing of Minimum Wage Adjustments



(a) Number of CBAs



(b) Month of adjustment

Notes: This figure presents key features of the CBA scheme. Panel (a) shows the number of sectoral groups and subgroups determining the CBAs yearly. Panel (b) shows the monthly distribution of minimum wage adjustments, pooling all changes observed in our period.

increase in coverage. Groups have autonomy to define the categories that will be affected by the sectoral minimum wages defined in the CBAs. There is substantial dispersion in the number of categories considered. In a typical year, a CBA in the 25th percentile defined 6 different minimum wages, while a CBA in the 75th percentile defined between 25 and 30 different minimum wages. Panel (b) shows that, among the 96,598 minimum wage changes that we identify in the raw CBA data, more than 90% happened either in January or July.

CBAs data. We rely on information of the industry-by-occupation minimum wages defined in each tripartite negotiation and recorded in the CBAs. After each bargaining round, each group defines nominal wages and biannual adjustments that are valid until the next bargaining round. CBAs and the corresponding list of industry-by-occupation minimum wages are public information. Therefore, we use digitized minimum wage data collected from each round's contract.

When merging the CBAs data with the BJ data, groups and categories that define industry-by-occupation minimum wages do not map one-to-one to the standardized codes available in the BJ data. Therefore, we manually assign 2-digit ISIC codes to each subgroup, and 1-digit ISCO occupation codes to each category within the contract. With this approach, the imputed codes can be broader or narrower than the standardized codes. For example, within the group "Commerce", there is a CBA for the subgroup "Stores", for which several 2-digit ISIC codes apply, and within the group "Food and beverages manufacturing", there are different CBAs for "Wheat Mills" and "Rice Mills", which can be associated to the same 2-digit industry. A similar issue occurs with the categories within each CBA. One minimum wage can be associated with several 1-digit occupation codes, and several minimum wages can be associated with the same 1-digit occupation code.

Since it is not possible to precisely attach specific minimum wages to vacancies because of this multiplicity problem, we build measures of exposure to minimum wage changes at the vacancy level by computing the average across all minimum wages that can be associated with a specific industry-occupation combination. Then, as an event, we code whether, on a given date, there is a change in the computed average. Under this strategy, non-exposed vacancies are vacancies whose industry-occupation combination either cannot be associated with a minimum wage in any CBA, or vacancies for which we can associate a minimum wage but it is not changing in the specific period. The resulting cells are defined at the 2-digit industry level and the 1-digit occupational level.

Our causal analysis aims to assess whether we can replicate the occupational heterogeneity in directed search patterns we found in the cross-section. This requires occupation-specific minimum wages to bind in all occupations. With only 20% of vacancies non-randomly posting a wage, we cannot estimate a first stage that directly links minimum wage increases and posted wages. To circumvent this limitation, we use survey data to explore whether minimum wages are binding across occupations. For 2011 and 2020, Table B.10 of Appendix B shows the occupational-level Kaitz index, defined as the ratio of the minimum wage (built from occupation-industry estimates) to the occupational monthly median wage (of full-time equivalent wages of employees). The average Kaitz equals between 0.76-0.79 for higher-skilled occupations and 0.91-0.94 for lower-skilled occupations. This suggests that the bite of the minimum wage is economically meaningful for both higher- and lower-skilled occupations, while being slightly stronger for the latter.[17]

4.2 Empirical strategy

Our empirical strategy exploits the frequent variation in minimum wages at the industry-by-occupation level provided by the CBAs. Each July and January, several industry-by-occupation cells (and, therefore, the vacancies within those cells) see their bargained wage floor adjusted (see Panel (b) of Figure 3). Other industry-by-occupation cells (and thus vacancies) see no change in their minimum wage, either because the contract is not adjusting wages in that adjustment window, or because some occupations do not have assigned minimum wages in certain sectoral contracts. These adjustments provide treatment and control groups for which we can estimate DID models around the time of adjustment. The empirical strategy uses an industry-by-occupation cell as the unit of observation, for which we build a balanced panel to estimate the DID specifications. As a robustness check, we also estimate a within-vacancy model, where the units of observation are vacancies that experience a minimum wage increase while being active (see Section 4.3).[18]

Our strategy may be interpreted as conservative for two reasons. First, since we use the industry and occupation attached to the vacancy to measure exposure to minimum wage changes, which do not match one-to-one with the definitions in the CBAs, our estimates should be interpreted as reduced-form intend-to-treat (ITT) estimations, possibly inducing attenuation bias. Second, we

[17] Consistent with the relevance of CBAs in Uruguay, the Kaitz values are relatively high. In comparison, the 2019 Kaitz index for the national minimum wage, which sets a general wage floor, was around 40.3 (ILO, 2020). We replicate this value with our 2020 survey data using occupation-level aggregates.

[18] Because vacancies are generally short-lived (see Section 2.2) we cannot implement the preferred DID strategy at the vacancy level. We acknowledge that the cell-level design may not control for within-cell unobserved heterogeneity. The within-vacancy design presented in Section 4.3 addresses this concern.

assume that job applicants are aware of the timing of the minimum wage adjustments and, therefore, can update their applications after minimum wages are increased. Inattention to minimum wages should work against finding application effects and, therefore, should also exert downward bias in our estimations.[19]

Estimating equation. In what follows, x_{it} denotes the variable x of cell i in calendar time (month) t, where a cell is a 2-digit industry-by-1-digit occupation combination. Cells included in the balanced panel are cells for which we observe at least one posted vacancy during the whole period. In the data, we observe vacancies spanning 70 2-digit industries and 8 1-digit occupations. In terms of our unit of observation, we observe vacancies in 506 different cells (of a potential of 560). Our period consists on 108 months between October 2011 to September 2020, giving form to a total sample size of 54,648.

Since treated cells potentially increase the minimum wage every six months, we implement a stacked event study as follows (Cengiz et al., 2019; Baker et al., 2022). We define event periods ranging from three months before a minimum wage increase to two months after. This modeling decision means that event periods run either from October to March, or from April to September, such that pre- and post-event indicators are defined relative to January or July. Each event is indexed by e. We consider data from October 2011 to September 2020, which translates into 18 different event windows where a subset of the cells experiences a minimum wage increase. In each event, the subset of control cells is composed of cells with no minimum wage increase. Then, we estimate standard event study specifications by allowing the cell fixed effects to vary by event. Since event periods do not overlap, time fixed effects automatically vary by event, and events are uniquely determined by calendar time, $e(t)$. To add more flexibility, we also allow time fixed effects to vary by 1-digit industries. Formally, the estimating equation is given by:

$$Y_{it} = \sum_{\tau=-3}^{2} \beta_\tau D_{i\tau e(t)} + \alpha_{ie(t)} + \gamma_{j(i)t} + X'_{it}\rho_{e(t)} + \epsilon_{it}. \tag{4}$$

Y_{it} is an outcome for cell i in time t. $D_{i\tau e(t)}$ are event indicators, where τ denotes the distance from the event (in months) meaning that $D_{i\tau e(t)}$ is equal to one if cell i was treated τ months ago in event $e(t)$. $\alpha_{ie(t)}$ are cell-by-event fixed effects. $\gamma_{j(i)t}$ are month-by-1-digit industry fixed effects. X_{it} are controls for the small share of minimum wage changes that occur in months different from January or July (see Panel (b) of Figure 3), whose effect is allowed to vary by event.[20] Under the parallel trends assumption, β_τ identifies causal effects from the minimum wage increase on Y_{it}. As it is standard in event studies, β_{-1} is normalized to 0. Since minimum wage changes may be

[19]If the BJ platform included many vacancies targeting self-employed workers, who are not covered by minimum wages, this would be another source of possible downward bias. In practice, the fraction of such vacancies is negligible. For example, when searching for the pertinent expression "independiente" in job titles, only 110 (0.14%) mention it.

[20]Following Cengiz et al. (2019), X_{it} is computed as follows. Let $\hat{t}$ be the month in which the rare minimum wage increase takes place. Then, define $Early_t = 1\{t \in \{\hat{t}-3, \hat{t}-2\}\}$, $Pre_t = 1\{t = \hat{t}-1\}$ and $Post_t = 1\{t \in \{\hat{t}, \hat{t}+1, \hat{t}+2\}\}$, and let $Rare_i$ be an indicator of cells that face rare minimum wage increases. Then X_{it} includes all the interactions between $\{Early_t, Pre_t, Post_t\} \times \{Rare_i\}$ for each event separately.

Table 9: Estimation Sample: Descriptive Statistics

	Obs.	Mean	Std. Dev.	p25	p50	p75
A. All occupations						
At least one opening	54,648	0.47	0.50	0	0	1
Total openings	54,648	4.62	14.95	0	0	2
Apps. per vac. (median)	54,648	35.33	90.39	0	0	34
Apps. per vac. (mean)	54,648	43.89	97.70	0	0	52
Treated	54,648	0.51	0.50	0	1	1
B. Lower-skill occupations						
At least one opening	27,432	0.47	0.50	0	0	1
Total openings	27,432	5.35	17.32	0	0	3
Apps. per vac. (median)	27,432	44.65	107.48	0	0	47
Apps. per vac. (mean)	27,432	55.92	116.29	0	0	70
Treated	27,432	0.60	0.49	0	1	1
C. Higher-skill occupations						
At least one opening	27,216	0.46	0.50	0	0	1
Total openings	27,216	3.89	12.05	0	0	2
Apps. per vac. (median)	27,216	25.95	67.72	0	0	25
Apps. per vac. (mean)	27,216	31.76	72.40	0	0	39
Treated	27,216	0.43	0.49	0	0	1

Notes: This table presents descriptive statistics for the estimation sample. The unit of observation is a 2-digit industry by 1-digit occupation cell by calendar month. Panel (a) shows statistics for all occupations, Panel (b) for the lower-skill occupational group, and Panel (c) for the higher-skill occupational group.

correlated within CBA across occupations, we cluster standard errors at the 2-digit industry level.

To provide a quasi-experimental test for the cross-sectional directed search patterns based on posted wages documented in Section 3, we define Y_{it}, our main outcome of interest, as the median number of applications received by vacancies of cell i posted in month t. We also consider a variation of equation (4) that interacts the event indicators with lower- and higher-skill occupation indicators. The sparsity of the balanced panel implies that $Y_{it} = 0$ is a frequent outcome, so we estimate the equation in levels and then compute back-of-the-envelope estimates of the implied elasticity using external data on average minimum wage increases. As a complement to our directed search test, we also estimate effects of other outcomes at the cell-by-time level such as number of posted vacancies, openings, share of vacancies advertising variable pay and non-wage amenities, and share of vacancies posting job requirements.

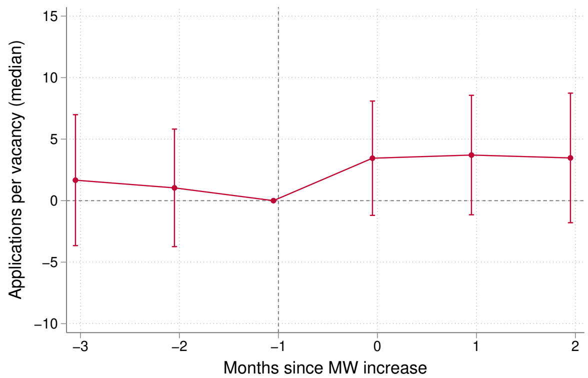
To provide summary results, we also report estimates from standard pooled DID regressions:

$$Y_{it} = \beta T_{ie(t)} \times \text{Post}_t + \alpha_{ie(t)} + \gamma_{j(i)t} + X'_{it}\rho_{e(t)} + \epsilon_{it}, \tag{5}$$

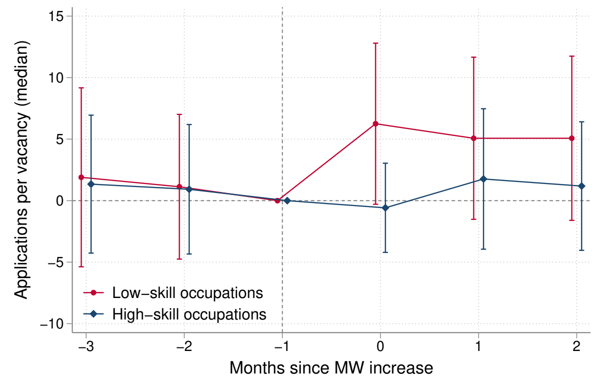
where $T_{ie(t)}$ is an indicator variable that takes value 1 if cell i is treated in event $e(t)$, Post_t is an indicator variable that takes value 1 if month t is equal to or larger than the treatment month (that is, if t corresponds to either January, February, March, July, August, or September), and all other variables are defined as in equation (4). The coefficient of interest in this specification is β.

Table 9 presents descriptive statistics of the estimation sample. 47% of the observations exhibit at least one vacancy opening. The mean number of openings, including the zeros, is 4.62. The

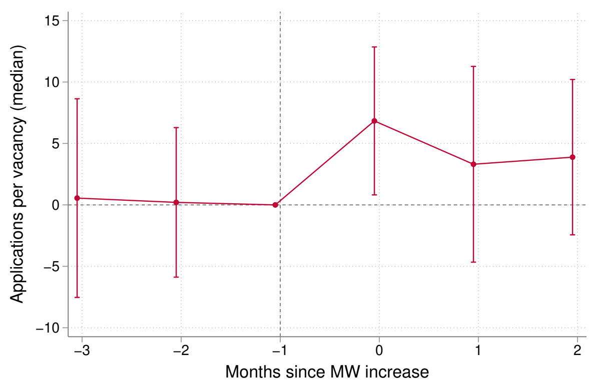
Figure 4: Event Studies: Median Number of Applications per Opening



(a) All vacancies



(b) By occupational group



(c) Triple differences

Notes: These figures plot the estimated β_τ coefficients for equation (4) with 95% confidence intervals, using the median number of applications per vacancy within industry-by-occupation cell as the dependent variable. Panel (a) pools all vacancies. Panel (b) considers interactions with lower- and higher-skill occupational indicators. Panel (c) plots the triple difference, capturing the differential effect between lower- and higher-skill vacancies. Regressions control for cell-by-event fixed effects, calendar month-by-1 digit-industry fixed effects, and minimum wage changes not occurring in January or July. Standard errors are clustered at the 2-digit industry level.

median and mean number of applications per opening is 35.33 and 43.89, respectively. 51% of the observations correspond to treated cell-by-event groups. Panels (b) and (c) break the statistics by low- and higher-skill occupations. The share of observations with at least one opening is remarkably similar across groups, although lower-skill vacancies usually exhibit more openings and more applications. Not surprisingly, lower-skill occupations are more likely to be treated than higher-skill occupations (60% versus 43%).

4.3 Application effects of the minimum wage

Our main results use the median number of applications per opening at the cell-level as dependent variable. Figure 4 shows the estimated β_τ coefficients of equation (4) with their corresponding 95% confidence intervals. Panel (a) shows the event study that pools all vacancies. The plot suggests that

Table 10: Difference-in-Differences Results: Applications per Opening, Vacancies, and Openings

Panel (a): All Occupations

	Main Results				Excluding Outliers				Excluding Zeros			
	Med. Apps. (1)	Mean Apps. (2)	Total Vacs. (3)	Total Ops. (4)	Med. Apps. (5)	Mean Apps. (6)	Total Vacs. (7)	Total Ops. (8)	Med. Apps. (9)	Mean Apps. (10)	Total Vacs. (11)	Total Ops. (12)
$\hat{\beta}$	2.641	2.213	0.009	0.008	2.266	1.847	0.007	0.007	2.494	1.663	0.004	-0.011
	(1.363)	(1.411)	(0.030)	(0.108)	(1.254)	(1.295)	(0.030)	(0.109)	(2.120)	(2.219)	(0.045)	(0.187)
Observations	54,648	54,648	54,648	54,648	53,892	53,892	53,892	53,892	34,464	34,464	34,464	34,464
$\Delta \log \mathrm{MW}$	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058
Pre-event outcome	39.519	50.808	1.567	5.480	36.189	47.561	1.584	5.543	56.575	72.934	2.267	7.921
Elasticity	1.147	0.747	0.096	0.025	1.073	0.665	0.081	0.021	0.756	0.391	0.029	-0.023

Panel (b): By Occupation Group

	Main Results				Excluding Outliers				Excluding Zeros			
	Med. Apps. (1)	Mean Apps. (2)	Total Vacs. (3)	Total Ops. (4)	Med. Apps. (5)	Mean Apps. (6)	Total Vacs. (7)	Total Ops. (8)	Med. Apps. (9)	Mean Apps. (10)	Total Vacs. (11)	Total Ops. (12)
$\hat{\beta}_{LS}$	4.451	4.182	0.021	-0.103	3.379	3.117	0.018	-0.109	4.774	4.187	0.019	-0.163
	(1.863)	(1.893)	(0.038)	(0.117)	(1.624)	(1.622)	(0.040)	(0.118)	(2.876)	(2.991)	(0.057)	(0.194)
$\hat{\beta}_{HS}$	0.031	-0.626	-0.008	0.168	0.698	0.056	-0.007	0.170	-0.709	-1.884	-0.017	0.203
	(1.316)	(1.450)	(0.027)	(0.161)	(1.288)	(1.462)	(0.027)	(0.162)	(2.011)	(2.183)	(0.041)	(0.260)
Observations	54,648	54,648	54,648	54,648	53,892	53,892	53,892	53,892	34,464	34,464	34,464	34,464
$\Delta \log \mathrm{MW}_{LS}$	0.059	0.059	0.059	0.059	0.060	0.060	0.060	0.060	0.059	0.059	0.059	0.059
Pre-event outcome (LS)	47.212	60.972	1.646	6.320	42.577	56.510	1.673	6.436	68.565	88.753	2.411	9.253
Elasticity (LS)	1.589	1.156	0.210	-0.273	1.333	0.927	0.178	-0.285	1.174	0.796	0.132	-0.297
$\Delta \log \mathrm{MW}_{HS}$	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057
Pre-event outcome (HS)	28.672	36.476	1.456	4.295	27.360	35.193	1.461	4.310	40.163	51.281	2.070	6.097
Elasticity (HS)	0.019	-0.303	-0.099	0.687	0.449	0.028	-0.083	0.696	-0.310	-0.644	-0.148	0.583

Notes: Panel (a) presents the estimated β coefficient of equation (5), while Panel (b) includes interactions with indicators for lower- and higher-skill occupational groups. Regressions include cell-by-event fixed effects, calendar month-by-1 digit-industry fixed effects, and control for non-January or July minimum wage changes. Dependent variables (in levels) include the median and mean number of applications, total number of vacancies, and total openings. Reported elasticities are computed by dividing the β-coefficient by the pre-event average outcome within treated cells, normalized by the log change in minimum wage among treated cells. Columns (1)-(4) present the main results, Columns (5)-(8) exclude bin-by-event window observations where the median number of applications exceeded 750, and Columns (9)-(12) exclude bin-by-event window observations with outcomes of 0 for more than 4 months in the event window. Standard errors (in parentheses) are clustered at the 2-digit industry level.

applications to vacancies in exposed cells increase after the minimum wage adjustments, although the increase is small and non-statistically significant at conventional levels. However, as shown in Panel (b), when interacting the event indicators with the low- and higher-skill occupation dummies, minimum wage increases tend to generate a significant increase in applications to exposed lower-skill vacancies with no effect on exposed higher-skill vacancies. Panel (c) plots the results from an analog triple difference regression, showing that the difference between lower- and higher-skill occupations is statistically significant, especially in the first month after the minimum wage adjustment. Table 10 shows the results of the pooled DID. Panel (a) shows results for the specification with no interactions, which estimates a noisy increase in 2.6 applications at the treated occupation-by-industry cell level, with an implied elasticity of 1.15 (Column (1)). Panel (b) shows the results for the specification with interactions for the occupational groups. The estimated effect for lower-skill vacancies is a significant average increase of 4.5 applications per cell, with an implied elasticity of 1.59. For higher-skill vacancies, the implied elasticity is only 0.02 (Column (1)).

Two remarks follow. First, the quasi-experimental exercise mirrors well the cross-sectional finding of heterogeneous patterns of directed search across occupations. Second, the magnitude of the implied wage-applications elasticity in lower-skill vacancies is similar in magnitude, albeit on the lower end of the distribution, to the labor supply elasticity estimates from the empirical monopsony literature.[21] This is reassuring given the reasons we expect attenuation bias in our regressions.

Robustness checks. Table 10 presents several robustness checks. For the sake of brevity, we focus on the specification including interactions by occupational group (Panel (b)). We also discuss below results from an alternative within-vacancy research design that yields similar results.

Column (2) of Panel (b) shows that using mean instead of median applications per cell-by-time generates similar, albeit slightly smaller, estimates. Yet, the fact that the panel is sparse and the distribution of applications per vacancy is skewed suggests that the median may be a better-behaved measure at the occupation-by-industry-by-month level. Since the equation is estimated in levels, outliers may play a significant role in driving the results. Columns (5) and (6) show that excluding the event window-by-cell units for which the median number of applications per opening per cell in at least one month exceeded 750 attenuates the results, but the qualitative conclusions do not change. Finally, Columns (9) and (10) show that restricting the event window-by-cell units for which the cell had openings in at least two months barely changes the point estimates, although it decreases precision.[22]

As an additional robustness check, we estimate the application effects of the minimum wage using a different research design that exploits within-vacancy variation. We consider the sample of vacancies that are open when a minimum wage change potentially occurs (that is, either between June and July or between December and January) and estimate DID regressions at the vacancy level, comparing exposed and non-exposed vacancies before and after the policy change. This design refines the previous analysis as it controls for vacancy fixed effects and thereby captures time-invariant unobserved heterogeneity at the vacancy level. Since vacancies are usually open during only one month or less (see Table 1), we cannot assess the parallel trends assumption. Moreover, the sample size decreases because vacancies posted in other months are not included in the sample and because most applications to vacancies are made in the first few days of the vacancy period (see Figure B.3 of Appendix B).[23] This pattern implies that we need to restrict to vacancies that have been open only for a few days when the minimum wage changes. On balance, we see the within-vacancy design as a complement to the previous analysis.

Our baseline sample used in the within-vacancy design consists of the 2,129 vacancies (2.7%

[21] Sokolova and Sorensen (2021) report a median labor supply elasticity across studies of 1.7 (with a larger mean). While our application elasticitity is conceptually distinct, this comparison to the literature provides a broad benchmark, since the labor supply elasticity can be approximated by the elasticity of recruitment multiplied by 2.

[22] We note that the implied elasticities are mechanically downward biased in the latter exercise because the exclusion of zeros distort the pre-event mean dependent variable by construction.

[23] 45% of applications happen in the first 2 days, 63% in the first 5 days, 72% in the first week. There are three explanations for this pattern. First, recent vacancies are more likely to appear first on the website. Second, when vacancies are filed, they may stop receiving applications. Third, applicants may opt for receiving emails with weekly updates of newly posted vacancies, which again may increase the salience of the recently posted ones.

of the total sample) that were posted between June 25 and June 30 or between December 26 and December 31 in any of the years considered. Since we estimate the regression in levels, we exclude vacancies that receive more than 1,000 applications. Table B.11 of Appendix B shows descriptive statistics. With this sample, we estimate the following regression:

$$Y_{jt} = \beta_{LS} T_j \times \text{Post}_t \times 1\{\text{Occ}_j \in LS\} + \beta_{HS} T_j \times \text{Post}_t \times 1\{\text{Occ}_j \in HS\} + \alpha_j + \gamma_t + \varepsilon_{jt}, \tag{6}$$

where Y_{jt} are the applications per opening to vacancy j in month t, T_j is an indicator that takes value 1 if the vacancy j is treated, Post_t is an indicator if month t is either January or July, α_j are vacancy fixed effects, and γ_t are months (calendar time) fixed effects. As above, treatment status is determined based on the industry-by-occupation-by-adjustment window attached to the vacancy.

Table B.12 of Appendix B shows the results. We estimate regression (6) for different subsamples based on the days the vacancy was open before the potential policy change. Columns (1), (2), (3), and (4) show results for vacancies that were open for 3 days or less, 4 days or less, 5 days or less, and 6 days or less, respectively. We note two findings. First, while they are noisy, results imply that treated lower-skill vacancies receive an increase in applications after the minimum wage increase, with no corresponding effect in higher-skill vacancies. That is, the within-vacancy exercise supports the patterns documented so far. Second, the magnitude of the effect is decreasing in the days open before the policy change. The implied elasticity for lower-skill vacancies is 5.1, 2.6, 1.4, and 0.4 in the corresponding columns. This is consistent with vacancies being more salient when they are recently posted.

Heterogeneity by applicant characteristics. Table 11 presents results of equation (5) with occupation interactions but using applications from particular groups of applicants as the dependent variable. All groups exhibit larger responses for lower-skill vacancies relative to higher-skill vacancies. Consistent with the cross-sectional analysis, we find larger and more significant application responses to wages for male and older applicants. The implied wage-application elasticity to lower-skill vacancies is 2.3 for male applicants, relative to a non-significant estimate of 1 for female applicants. Likewise, the lower-skill elasticity for older applicants is 1.7, compared to a 1.4 estimate for younger applicants. The implied elasticities, however, are not different between employed and unemployed applicants, and are stronger for job seekers with no tertiary education, which contrasts from what was found in the cross-sectional analysis. This difference may be driven by the fact that, within occupation and industry, less educated applicants may be more attached to minimum wage jobs than highly educated applicants.

4.4 Additional results

Vacancies and openings. The positive effect of minimum wages on applications may come at the expense of a decrease in vacancies or openings. We test this hypothesis by estimating similar models as above using the total number of vacancies and openings per cell as the dependent variable. Figure 5 and Table 10 show that we do not find any detectable effect on vacancies and openings.

Table 11: Differences-in-Difference Results on Applications: Applicant Heterogeneity

Panel (a): Gender, employment status, and age

	Female (1)	Male (2)	Emp. (3)	Unemp. (4)	Age≤25 (5)	Age>25 (6)
$\hat{\beta}_{LS}$	1.494	2.600	1.469	2.345	1.762	2.320
	(1.144)	(0.946)	(0.692)	(1.143)	(0.932)	(0.899)
$\hat{\beta}_{HS}$	0.336	-0.036	0.193	-0.023	0.654	-0.409
	(0.860)	(0.728)	(0.555)	(0.808)	(0.679)	(0.750)
Observations	54,648	54,648	54,648	54,648	54,648	54,648
$\Delta \log \text{MW}_{LS}$	0.059	0.059	0.059	0.059	0.059	0.059
Pre-event outcome (LS)	24.020	19.038	19.572	28.752	21.379	22.978
Elasticity (LS)	1.049	2.302	1.265	1.374	1.389	1.702
$\Delta \log \text{MW}_{HS}$	0.057	0.057	0.057	0.057	0.057	0.057
Pre-event outcome (HS)	11.336	14.573	13.283	16.146	9.893	16.694
Elasticity (HS)	0.522	-0.044	0.256	-0.025	1.165	-0.432

Panel (b): Education and skills

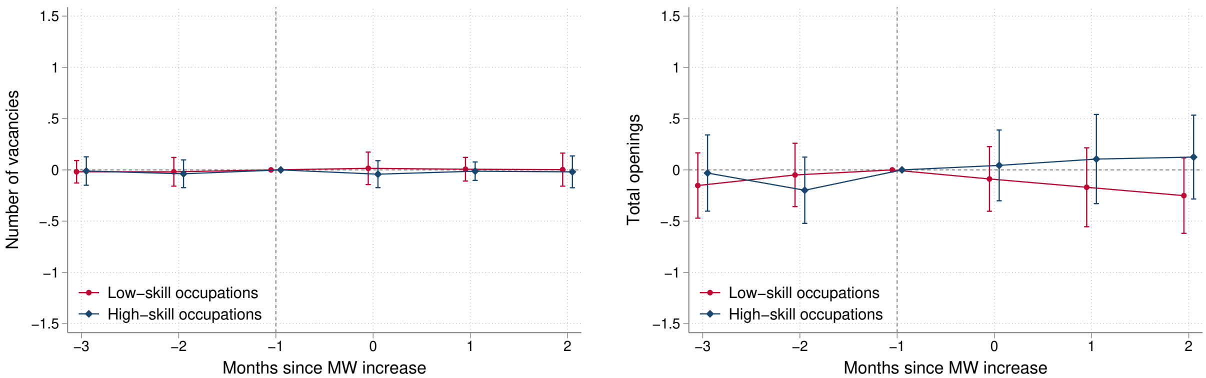
	No tert. (1)	Voc. trn. (2)	College (3)	Cogn. sk. (4)	Soc. sk. (5)	Man. sk. (6)
$\hat{\beta}_{LS}$	3.607	0.440	0.175	1.163	2.109	0.837
	(1.389)	(0.226)	(0.278)	(0.540)	(0.840)	(0.264)
$\hat{\beta}_{HS}$	0.095	-0.117	0.082	-0.081	-0.093	-0.144
	(0.938)	(0.200)	(0.306)	(0.484)	(0.659)	(0.222)
Observations	54,648	54,648	54,648	54,648	54,648	54,648
$\Delta \log \text{MW}_{LS}$	0.059	0.059	0.059	0.059	0.059	0.059
Pre-event outcome (LS)	32.696	6.201	6.441	14.272	21.791	6.565
Elasticity (LS)	1.859	1.196	0.459	1.373	1.631	2.148
$\Delta \log \text{MW}_{HS}$	0.057	0.057	0.057	0.057	0.057	0.057
Pre-event outcome (HS)	15.850	4.497	6.668	11.089	13.759	5.023’
Elasticity (HS)	0.105	-0.459	0.215	-0.129	-0.119	-0.504

Notes: This table presents the estimated β coefficient of equation (5) incorporating interactions with lower- and higher-skill occupational groups. The dependent variable is the number of applications made by applicants with the characteristic in column titles. Regressions include cell-by-event fixed effects, calendar month-by-1 digit-industry fixed effects, and controls for no-January or July minimum wage changes. Elasticities are computed by dividing the β-coefficient by the pre-event average outcome in treated cells, normalized by the log change in minimum wage among treated cells. Panel (a) presents results by gender, employment status, and age, and Panel (b) by educational attainment (no tertiary education, vocational training, and college degree) and skill category (cognitive, socio-emotional, and manual skills). Standard errors (in parentheses) are clustered at the 2-digit industry level.

This result suggests that the increase in applications may help firms buffer the increase in labor costs and/or that firms are adjusting other margins to pay for the increased minimum wage.

Advertised variable pay and non-wage amenities. If providing amenities is costly for firms, we might detect an effect of minimum wage changes on advertised variable pay and non-wage amenities (Clemens, 2021). We test this hypothesis by estimating similar models as above, using the share of vacancies that advertise variable pay and non-wage amenities as the dependent variable. Figure B.4 and Table B.13 of Appendix B suggest the absence of negative responses on advertised amenities. We note that CBAs may also determine amenities, as has been shown for example in studies for Brazil (Lagos, 2024; Corradini et al., Forthcoming). Then, the lack of incidence on non-wage amenities could come by design. However, while some Uruguayan CBAs

Figure 5: Event Studies: Total Vacancies and Total Openings



(a) Vacancies

(b) Openings

Notes: These figures plot the estimated β_τ coefficients of equation (4) with 95% confidence intervals, using different dependent variables. Coefficients are interacted with indicators for lower- and higher-skill occupational groups. Panel (a) uses total posted vacancies as a dependent variable, while Panel (b) uses total openings. Regressions control for cell-by-event fixed effects, calendar month-by-1 digit-industry fixed effects, and no-January or July minimum wage changes. Standard errors are clustered at the 2-digit industry level.

include provisions for amenities, the timing of their adoption is comparatively unstructured and not aligned with the schedule of minimum wage adjustments, and their implementation is weakly enforced (Urruty Rodríguez, 2024).

Vacancy requirements. Finally, firms could react to increased labor costs by becoming more selective in terms of education and skills requirements as shown by Butschek (2021) and Clemens et al. (2021). We test this hypothesis by estimating similar models as above using the share of vacancies that impose requirements as the dependent variable. Figure B.5 and Table B.14 of Appendix B suggest the absence of increases in education and skill requirements, although estimates are imprecise enough to make strong claims about these results. The only slightly significant positive estimate is an estimated increase in the share of higher-skill vacancies that require a college degree.

5 Conclusion

In this paper, we assess patterns of directed search in job applications, focusing on the role of posted wages and advertised variable pay and non-wage amenities. Using rich data from a prominent online job board in Uruguay, we provide a series of cross-sectional facts on job applications, some of which we then corroborate causally using plausibly exogenous minimum wage variation.

We find evidence of directed search based on posted wages driven by vacancies attached to lower-skill occupations, with applications to vacancies attached to higher-skill occupations showing no responsiveness. This heterogeneous response, which, to the best of our knowledge, has not been empirically documented before, is consistent with related evidence of the relative incidence of wage posting versus bargaining across occupations. The directed search pattern is found to be stronger for male, employed, older, college-educated, and for job applicants reporting different skills.

We also document that directed search patterns go beyond posted wages. We elicit advertised variable pay and non-wage amenities and find that they play a key role in the application process. Advertised amenities have a positive impact on applications, although their effect is attenuated when vacancies post a wage. We also document that the effect of advertised variable pay varies significantly across occupations: it deters applications to lower-skill vacancies while attracting applications to higher-skill vacancies.

The occupational heterogeneity in directed search based on posted wages is supported by a quasi-experimental exercise that uses minimum wage variation at the industry-by-occupation level to document positive application effects of minimum wage increases in lower-skill occupations. This analysis also suggests the absence of responses in the number of vacancies, openings, advertised amenities, or vacancy requirements after minimum wage increases.

For future research, while we conjecture that the differential incidence in wage posting and bargaining can explain the observed occupational patterns, it seems promising to explore the fundamental differences between occupations more deeply. In addition, we have been able to exploit plausibly exogenous variation in wages, but complementary analyses that rely on exogenous variation in variable pay and amenities would further enhance the understanding of the job application process. Finally, our results have theoretical implications, as they suggest that models of directed search could be extended to incorporate variable pay and amenities as additional features that applicants target in the application stage and to capture occupational differences in these preferences.

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Directed Search, Pay, and Non-Wage Amenities: Evidence from an Online Job Board

Online Appendix

A Methodology for Creating Variables from Free Text Entries

We provide an overview of the methods used to create variables from text entries based on Adamczyk et al. (2025) and Escudero et al. (2024). Additional details can be found in the references.

A.1 Skills

All skill-related variables are based on the methodology developed in Escudero et al. (2024). Their approach seeks to capture skills dynamics beyond formal qualification across diverse contexts, by covering the skills demanded by employers in vacancies and highlighted by workers in their online profiles. The authors propose a taxonomy that groups skills into three broad categories (cognitive, socio-emotional, and manual skills) and fourteen subcategories. See Table A.1 for a description of each category and subcategory and the sources each category was derived from.

The taxonomy is built upon literature from labor economics and psychology and has been adapted to individual contexts, with a focus on emerging and developing countries and online job board data. The starting point of the categorization is established taxonomies designed for classifying skills in U.S. online data, particularly Deming and Kahn (2018) but also Heckman and Kautz (2012) and Deming and Noray (2020). The first extension is to include manual skills, which are often omitted in U.S.-centered analyses. Second, the conceptual foundations relating to cognitive and socio-emotional skills are expanded to facilitate a more comprehensive analysis beyond individuals with high formal qualifications. Therefore, the taxonomy included additional keywords and expressions drawn from various studies (see Autor et al., 2003; Almlund et al., 2011; Heckman and Kautz, 2012; Hershbein and Kahn, 2018; Atalay et al., 2020; Deming and Noray, 2020), and the pilot for O-NET Uruguay.

To elicit the skill variables in the BJ data, the authors use a natural language processing (NLP) methodology that integrates pre-processing techniques with a rule-based classification approach, guided by the taxonomy and the specific list of keywords and phrases associated with each of the 14 subcategories. In a second step, this dictionary is enlarged by including synonyms of the original words obtained through scraping a thesaurus website (www.wordreference.com) and manually checking their applicability. This procedure leads to a total of 741 distinct skills, based on the unique keywords and expressions.

The skills-subcategory variables are then created using the unstructured text present in the vacancies posted by firms and the job spells of applicants available in their BJ profiles. The open-text descriptions offer the most viable approach for creating skills variables, as they contain detailed

Table A.1: Categorization of skills, definitions, and sources

Panel (a): Cognitive Skills

Subcategory	Definition	Sources
Cognitive skills (narrow sense)	Skills needed to perform tasks that require analysis and calculation, problem-solving, intuition, flexibility and creativity.	DK; ALM; DN
General computer skills Software skills and technical support Machine Learning and Artificial Intelligence Financial skills Writing skills Project management	These five subcategories relate closely to the cognitive skills described above. They correspond to skills that are needed in specific areas of work. They are listed as separate subcategories because they are often specifically mentioned in job adverts and in applicants' work experiences. They are mostly geared towards white-collar jobs, in line with the aim of the work by DK.	APST; DK; DN; O-NET Uruguay

Panel (b): Socio-Emotional Skills

Subcategory	Definition	Sources
Character skills	Character skills include three of the five categories of the five-factor personality model commonly used in the psychological literature. It includes conscientiousness, openness to experience, and emotional stability. In addition, this subcategory includes dimensions such as being relaxed, independent, self-confident, and the degree of vulnerability to stress.	DK; DN; HK
Social skills	Social skills include those character traits from the five-factor personality model that are less related to one's personal attributes and related more to how one interacts with other people, specifically agreeableness and extraversion. Other keywords that relate to the general ability to have personal interactions, such as working in teams or holding presentations, are included as well.	DK; DN; HK; APST; O-NET Uruguay
People management skills	Lastly, authors add two subcategories that refer to specific abilities within the broader realm of social interactions, and which are often listed as particular requirements in job adverts and applications.	DK; DN
Customer service skills		DK; ALM

Panel (c): Manual Skills

Subcategory	Definition	Sources
Finger-dexterity skills	This category focuses on manual skills that are usually classified as "routine" by ALM and which are common in machine operation and the production or handling of goods. Examples include picking and sorting in agriculture or working in an assembly line.	ALM; APST; O-NET Uruguay
Hand-foot-eye coordination skills	These manual skills are usually understood as "non-routine" by ALM. They are more commonly used in services-related occupations and include working in changing environments that necessitate adaptation. This category encompasses for example driving cars or repairing and cleaning items.	ALM; PST; O-NET Uruguay
Physical skills	This subcategory focuses on more innate bodily characteristics, such as physical strength, endurance, the ability to lift heavy objects or work while standing or walking.	O-NET Uruguay

Notes: This table describes the skills subcategories presented in Table 1 of Escudero et al. (2024), based on the concrete keywords used in the taxonomy. ALM stands for Autor et al. (2003), APST for Atalay et al. (2020), DK for Deming and Kahn (2018), DN for Deming and Noray (2020), HK for Hershbein and Kahn (2018), and HK for Heckman and Kautz (2012).

information on skills for all vacancies (99.9%) and a majority of applicants' job spells (68.5%). These open-text descriptions undergo a series of pre-processing steps using NLP techniques, including the translation of keywords and phrases from English to Spanish, tokenization, text normalization, lemmatization, n-gram creation in the skills taxonomy, and n-gram creation in the vacancy and applicants' data.

Finally, the skill variables are established by tallying keywords and phrases linked to each skill category and subcategory that are found within the text. A skill is considered present if at least one of the keywords/phrases from the dictionary is identified in the text.

A.2 Occupations

The raw data provided by BJ only classifies vacancies and applicants' job spells into ISCO-08 occupation codes for a subset of the data. Escudero et al. (2024) employed a similar methodology as above to elicit 1- and 2-digit occupational codes for the full sample of vacancies and applicants' job spells. To elicit the occupations vacancies seek to fill, the authors leveraged text from four open-text fields associated with each vacancy: job title, job description, required educational education, and hierarchical level of the position. To elicit the occupation associated with applicants' job spells, the authors used the same information, except for job titles, which are not available as a separate entry. This data undergoes NLP procedures similar to the ones used for eliciting skills variables. The resulting text is then categorized into ISCO-08 codes through a three-step process.

The first step is analogous to the rule-based model employed to create the skills variables. The authors employ a dictionary of keywords, selected based on the most frequently used words and phrases from the subset of vacancies and applicants' job spells already classified by BJ into ISCO-08 occupational codes. The dictionary originates from the ISCO-08 classification. This provided the set of rules to classify the remaining job titles into occupational categories at the 2-digit level. Additionally, the authors used information about the educational level to distinguish between levels 2 and 3, denoting individuals from the same field with either higher education (level 2) or any other education (level 3). Similarly, information about the hierarchical level is used to identify managers and directors, placing them in ISCO level 1.

To enhance the performance of the procedure, the authors introduced a machine learning algorithm (in the form of a predictive model) to assign codes to vacancies and job spells that were unclassified or for which the original BJ assignment significantly differs from the one that results from the algorithm: First, the model is trained using the already classified observations to assign 1-digit ISCO codes. Second, additional information from applicants and vacancies is incorporated into a second prediction model to refine the code assignment at the 2-digit level. Based on various tests and sensitivity analyses, the authors chose Gradient Boosting to code 1-digit and 2-digit occupations in the vacancy data, and Random Forest for the applicants' data. As a result, all vacancies have an assigned 1-digit occupation code, and 94.8% of also have an assigned 2-digit occupation. For applicants, all job spells with a text description were classified at the 1-digit level, and 97.8% were also classified at the 2-digit level.

A.3 Variable pay and amenities

The methodology for identifying advertised amenities in unstructured vacancy data is akin to the one used for the skills variables, and it is based on the procedure outlined in Adamczyk et al. (2025). To simplify the exposition in this appendix, we treat "variable pay" as an additional amenity.

We developed a taxonomy of amenities using the related empirical literature as a starting point and extended it to better suit the Uruguayan context and the nature of online job boards. As a first source, we follow Maestas et al. (2023), who provide a list of job attributes based on results from the American Worker Conditions Survey (AWCS). The survey collects workers' assessments of nine work characteristics: schedule flexibility, telecommuting opportunities, physical demands, pace of work, autonomy, paid time off, working with others, job-training opportunities, and impact on society. To broaden the scope of the categorization, we employ the comprehensive categorization proposed by Sockin (2024), which organizes non-wage amenities in 48 categories derived from the literature using a topic-modeling machine learning algorithm implemented in the text of amenities descriptions in U.S. employer-employee data. Table A.2 lists additional sources we use to refine the procedure for specific amenities.

We then undertook three steps to broaden the scope of the categorization. First, we reorganized these categories to align with vacancy data. The literature primarily relies on U.S. workers' reviews, but not all categories are pertinent to vacancy data because certain aspects of a job may not be appropriate to advertise in a posted vacancy. Second, we supplemented the list of keywords and expressions used in the literature to characterize different amenities, tailoring them to better fit the context of Uruguay. Third, we introduced an additional amenity category, "work equipment and allowances," to reflect the post-pandemic reality and to incorporate attributes of manual work that may hold greater importance in Uruguay and other global south countries relative to the U.S. economy.

The process results in a total of 16 amenity subcategories. In some cases, we adjusted specific subcategories to ensure there was no overlap among the keywords and expressions assigned to each subcategory. The process yielded a final set of 659 words and expressions, comprising 357 original terms and 302 different versions of the same expressions (for multi-word expressions). Table A.2 provides a list of these categories, along with their definitions and, where applicable, their sources in the literature.

To apply this dictionary to the BJ vacancy data, both the terms in the dictionary and the free text information from the job advertisements need to be formatted appropriately. The process is similar to the one used for creating the skills variables, albeit with some modifications. These steps encompass keyword detection, tokenization (dividing the text into single units or tokens), normalization (removing capitalization and special characters), removing stop words (including exceptions for words included in the dictionary, such as 'buen,' 'mucho,' 'gran,' etc.), and lemmatization (associating different versions of a word, such as conjugated verb forms, with a common root word, like unconjugated verbs). Once the text describing vacancies and the keywords and expressions from the dictionary are in the same format, they can be matched using an NLP rule-based classification approach to identify amenities in the vacancy data. Importantly, this process accommodates variation in word order within expressions and allow matches with up to one external word in between the words from the dictionary expression.

The algorithm then tallies the occurrences of words and expressions from the dictionary in the

Table A.2: Categorization of amenities, definitions, and sources

Panel (a): Variable Earnings

Subcategory	Definition	Sources
A01–Bonuses and commissions	Encompasses various forms of financial incentives and rewards aimed at motivating and compensating employees based on their performance, achievements, or specific goals within an organization.	S
A02–Hourly work and overtime	Encompasses aspects related to flexible earnings, reflecting the compensation and conditions associated with working beyond regular hours, in an hourly base or during specific periods within an employment arrangement.	BE

Panel (b): Fringe Benefits

Subcategory	Definition	Sources
A03–Paid time-off	Reflects provisions for employees to take time away from work while receiving compensation in specific circumstances, thereby promoting work-life balance and employee well-being.	M
A04–Health insurance	Includes provisions offered by employers to support employees' healthcare needs, ensuring access to medical services, and providing financial protection in cases of illness, accidents, or other health-related situations.	SK; S
A05–Retirement contributions	Encompasses provisions designed to assist employees in saving for their retirement and securing financial stability during their later years.	SK; S
A06–Food and services subsidies, and other employee discounts	Encompasses benefits related to food, housing, transportation, and various subsidies or discounts offered to employees.	G; L

Panel (c): Non-Wage Job Attributes

Subcategory	Definition	Sources
A07–Office space and other office amenities	Covers workplace-related benefits, including facilities and amenities provided by the employer such as on-site cafeterias, sports facilities, gyms, etc.	Q
A08–Location and commuting	Focuses on factors related to the workplace's geographical location and how employees commute to and from work.	WZ; LB
A09–Work equipment and allowances	Sheds light on how the organization assists employees in ensuring they have the necessary tools and technology, including in remote or home-based work setups.	The authors

Panel (d): Working Conditions

Subcategory	Definition	Sources
A10–Work schedule flexibility	Includes various aspects related to the flexibility of work schedules and arrangements, such as options for telecommuting, remote work, part-time employment, and flexible hours. Additionally, it covers practices that support a better work-life balance, including offering rest days or weekends off and promoting family-friendly work policies.	MP; M; S
A11–Workplace safety	Pertains to all aspects related to ensuring a safe working environment for employees. The focus is on creating a secure, hazard-free workplace that prioritizes the well-being of all employees.	PPB
A12–Job security	Encompasses all aspects related to ensuring job security, stability, and financial protection for employees in various employment scenarios.	Q

vacancy texts and aggregates them for each broader amenity category. To simplify the analysis, this number is transformed into an indicator variable for each amenity subcategory. The indicator takes the value of one if any of the keywords or expressions from that particular subcategory are identified in the job advert.

Table A.2: Categorization of amenities, keywords, and sources (continued)

Panel (e): Working Characteristics

Subcategory	Definition	Sources
A13–Work environment and impact on society	Provides insights into the organization's commitment to creating a positive workplace environment and contributing positively to the community and society as a whole.	BKS; S; M
A14–Physical effort and pace of work	This category evaluates the physical demands and pace of the job. It considers factors like short lunch breaks, quick restroom breaks, physically demanding tasks, extended periods of standing, and fast work pace.	HO; HA; NM; FP; M; HM; Q; LLC; MP; S
A15–Working in teams	Assesses the collaborative aspects of the job, providing insights into the team-oriented nature of the work environment.	M
A16–Human capital development	Assesses the opportunities for personal and professional growth and development within the organization, including aspects such as learning, training, mentoring, career advancement opportunities, etc.	AP; AAZ; PR; BBB; M; S

Notes: See Adamczyk et al. (2025) for additional details. S stands for Sockin (2024), BE for Beckers et al. (2008), M for Maestas et al. (2023), SK for Simon and Kaestner (2004), G for Glassdoor (2015), L for Libert (2016), Q for Quinn (1974), WZ for Wasmer and Zenou (2002); LB for Le Barbanchon et al. (2020), MP for Mas and Pallais (2017), PPB for Park et al. (2021), BKS for Breza et al. (2017), HO for Holmlund (1983), HA for Hayward et al. (1989), NM for Neumark and McLaughlin (2012), FP for Filer and Petri (1988), HM for Hamermesh (1990), LLC for Lopes et al. (2014), AAZ for Athey et al. (2000), AP for Acemoglu and Pischke (1999), PR for Parent (1999), and BBB for Barron et al. (1999).

Out of the 86,062 vacancies in the BJ data,[1] 50.6% were assigned at least one of the 16 amenities. While some vacancies list up to eight amenities, more than three-quarters of those with assigned amenities advertise only one or two. The most frequently matched subcategories are "human capital development" (22.6% of vacancies), "working in teams" (18.7%), and "work environment and impact on society" (17.9%). The lowest number of matches is found for "retirement contributions" (33 matches, or 0.04% of the observations) and "health insurance" (38 matches, 0.04% of the observations).

Regarding individual keywords, "trabajar en equipo (teamwork)", which belongs to the working in teams category, is the most frequently matched (with a total of 12,579 matches). Typically, in each subcategory, a few keywords dominate the majority of matches. Figure A.1 displays word clouds for all amenity subcategories, where the size of a word corresponds to its share of matches within that subcategory. The use of keywords and expressions underwent several rounds of manual verification to ensure that words and expressions were contextually accurate. This verification was manually conducted for a sample of vacancies for all words appearing at the top of the matches for each subcategory, and for a selection of other words deemed necessary by the authors of this study and Adamczyk et al. (2025). While the procedure was performed for the complete list of 16 amenities, in the analysis, we focus on the 5 amenities with the highest prevalence, namely, bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development. The rest of the amenities are found to be relatively infrequent and also, in some cases, offer additional interpretation challenges. Finally, in the context of our research

[1]The sample size mentioned here slightly deviates from sample sizes mentioned in Section 2. The filters to create our final analysis sample are not yet applied. Instead, the sample mentioned here excludes a few vacancies with blank or meaningless job text descriptions (see Atalay et al., 2020). In our main analysis, these vacancies are coded as having zero amenities.

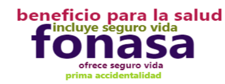
question we decided to treat “bonusses and commissions” as a separate category, since it captures variable pay rather than non-wage attributes.

Figure A.1: Word clouds for words matched in each amenity subcategory

(a) A01–Bonuses and commissions

(b) A02–Hours and overtime

(c) A03–Paid time off



(d) A04–Health insurance

(e) A05–Retirement contributions

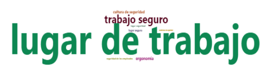
(f) A06–Food, subsidies & discounts

(g) A07–Office space & amenities

(h) A08–Location and commuting

(i) A09–Work equipment

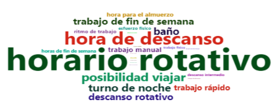
(j) A10–Work schedule flexibility



(k) A11–Workplace safety

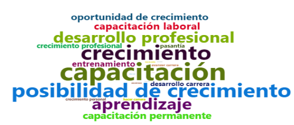
(l) A12–Job security

(m) A13–Work environment



(n) A14–Physical effort, pace of work

(o) A15–Working in teams

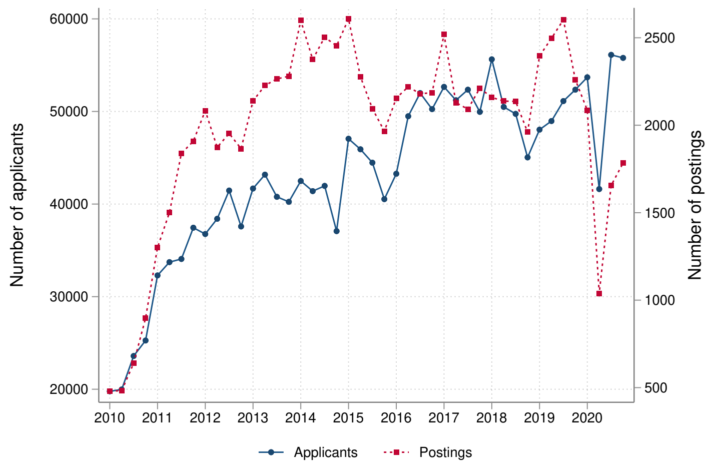


(p) A16–Human capital development

Notes: Authors’ elaboration based on Adamczyk et al. (2025). The analysis is based on the full sample of 86,062 vacancies. The words displayed in the word clouds represent the original words used to define amenities. For the matching process, these original words were lemmatized to facilitate the matching. The inclusion of original words in the figure is for clarity and ease of understanding.

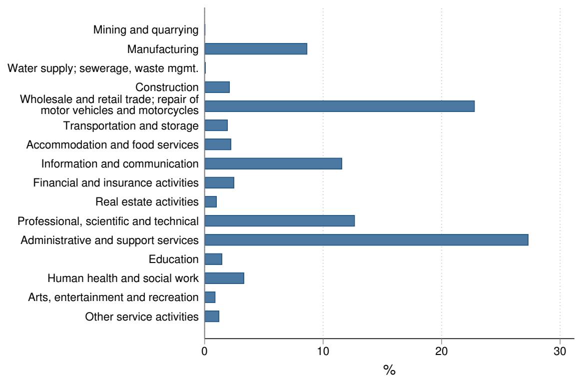
B Additional Figures and Tables

Figure B.1: Evolution of Applicants and Posted Vacancies in BJ

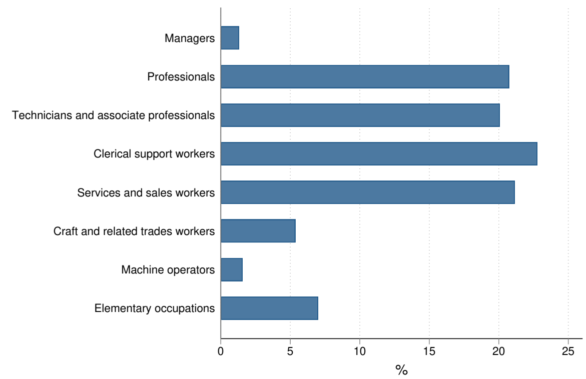


Notes: This figure shows, for each quarter between 2010 and 2020, the number of active applicants (i.e., IDs that made at least one application, left y-axis) and the number of posted vacancies in the BJ platform (right y-axis).

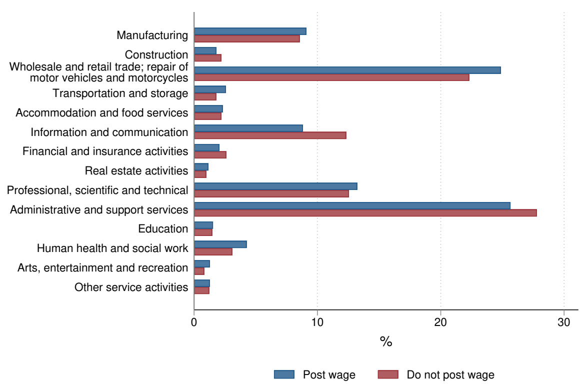
Figure B.2: Distribution of Vacancies: Industries and Occupations



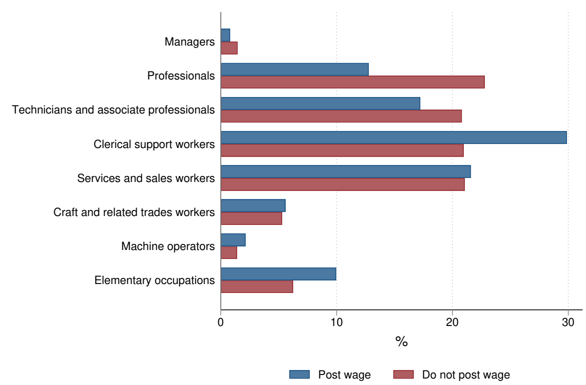
(a) Industry



(b) Occupation



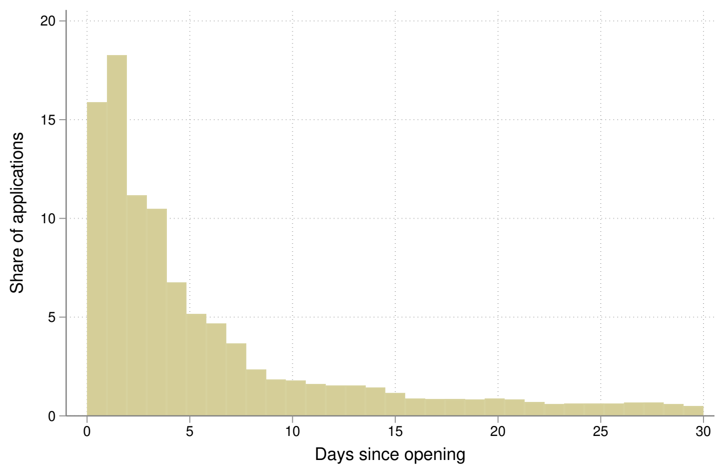
(c) Industry, by posting status



(d) Occupation, by posting status

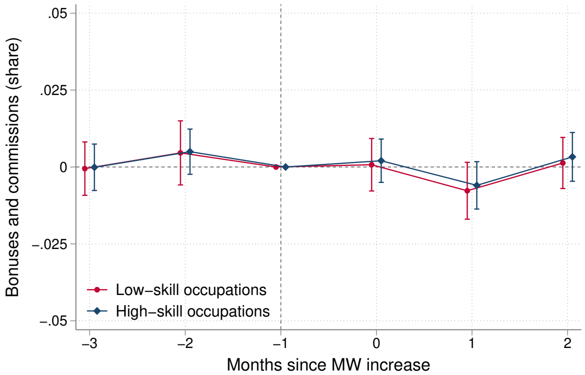
Notes: This figure plots the distribution of vacancies by industry and occupation. Panel (a) shows the distribution across one-digit industries (ISIC Rev.4), while Panel (b) does so for one-digit occupations (ISCO-08). Panels (c) and (d) replicate these distributions separately for vacancies with and without posted wages. Industries and occupations absent in the BJ vacancy data are omitted.

Figure B.3: Distribution of Applications by Distance to Opening Date

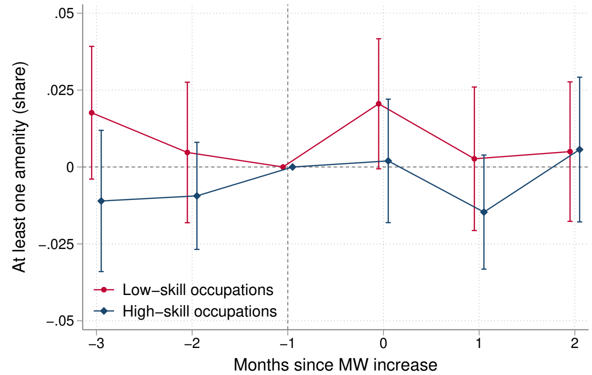


Notes: This figure plots the distribution of the timing of applications to vacancies relative to the opening date. “Distance” refers to the days elapsed since the opening of the vacancy.

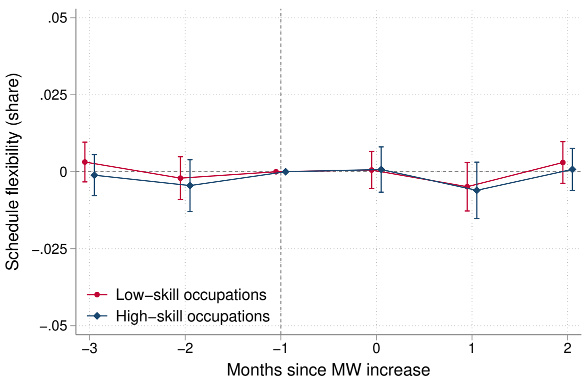
Figure B.4: Event Studies: Advertised Variable Pay and Non-Wage Amenities



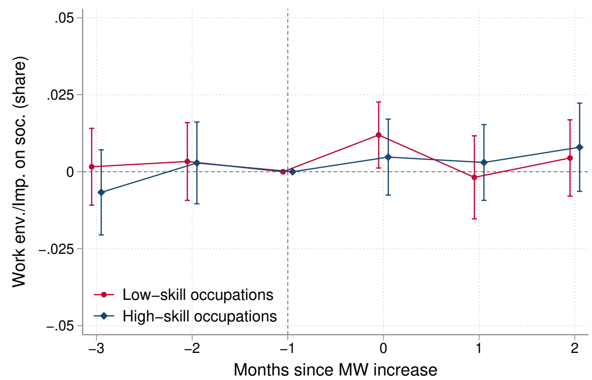
(a) Bonuses and commissions



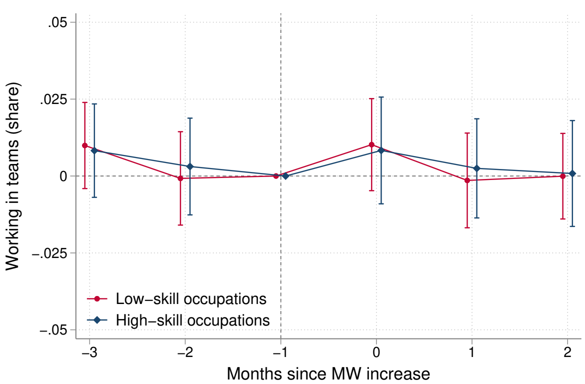
(b) At least one amenity



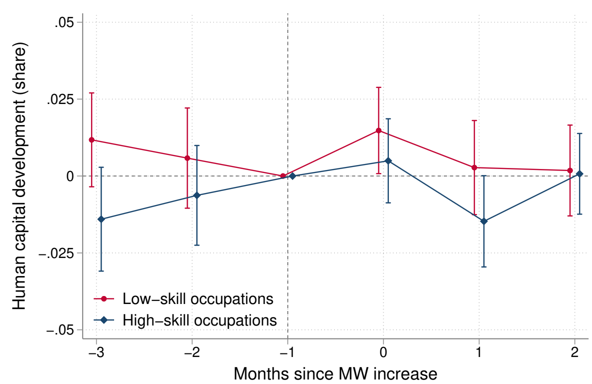
(c) Schedule flexibility



(d) Work environment/Impact on society



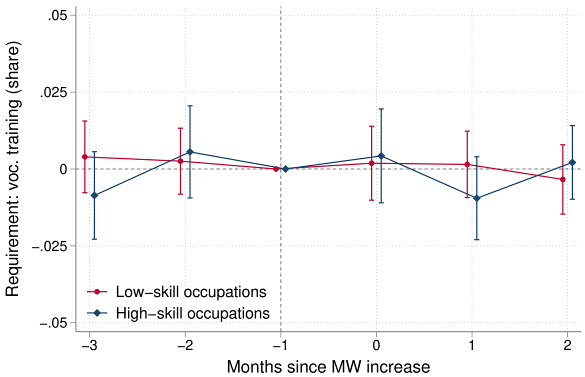
(e) Working in teams



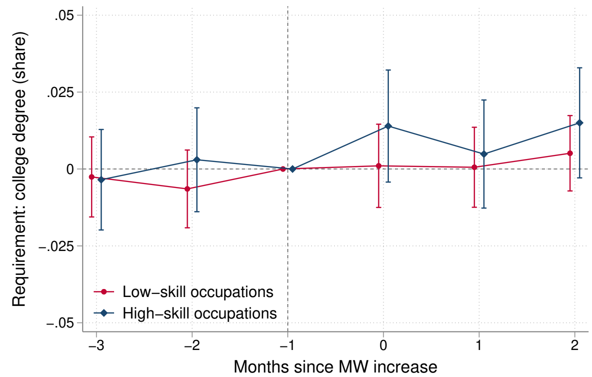
(f) Human capital development

Notes: These figures plot the estimated β_τ coefficients of equation (4) with their corresponding 95% confidence intervals using different dependent variables. Coefficients are interacted with indicators for lower- and higher-skill occupational groups. Panel (a) uses the share of vacancies that advertise bonuses and commissions. Panel (b) uses the share of vacancies that advertise at least one amenity. Panel (c) uses the share of vacancies that advertise schedule flexibility. Panel (d) uses the share of vacancies that advertise work environment/impact on society. Panel (e) uses the share of vacancies that advertise working in teams. Panel (f) uses the share of vacancies that advertise human capital development. Regressions control for cell-by-event fixed effects, calendar month-by-1 digit-industry fixed effects, and minimum wage changes not occurring in January or July. Standard errors are clustered at the 2-digit industry level.

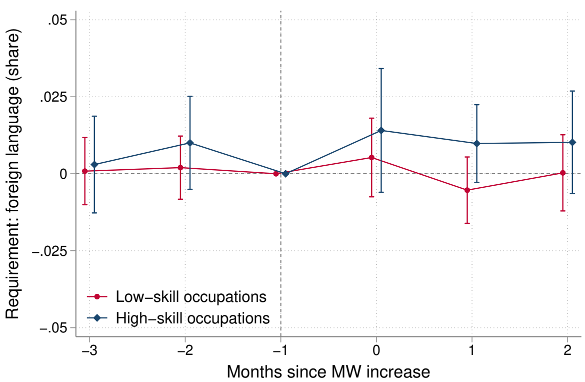
Figure B.5: Event Studies: Education and Skill Requirements



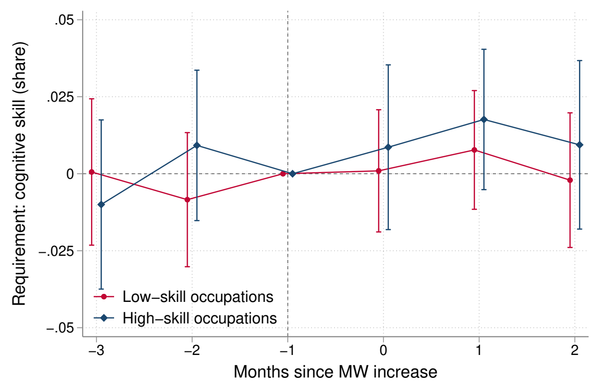
(a) Vocational training



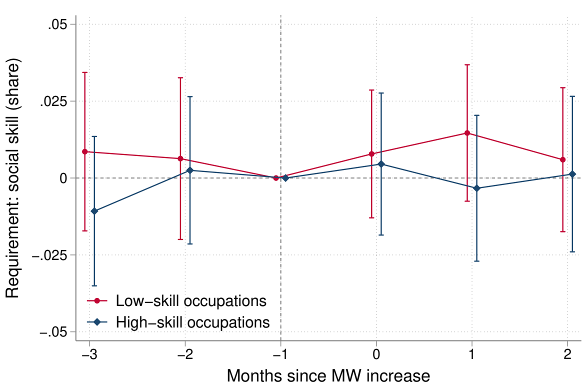
(b) College degree



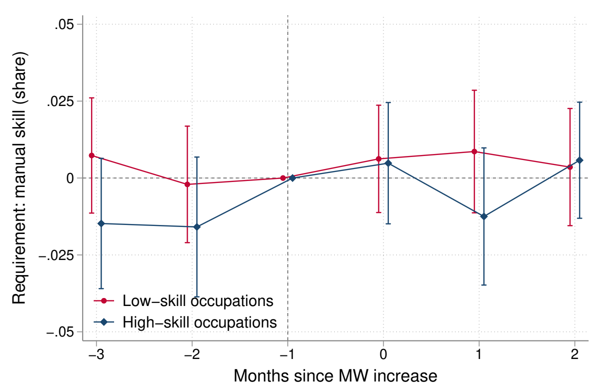
(c) Foreign language



(d) Cognitive skills



(e) Socio-emotional skills



(f) Manual skills

Notes: These figures plot the estimated β_τ coefficients of equation (4) with their corresponding 95% confidence intervals using different dependent variables. Coefficients are interacted with indicators for lower- and higher-skill occupational groups. Panel (a) uses the share of vacancies that require vocational training. Panel (b) uses the share of vacancies that require a college degree. Panel (c) uses the share of vacancies that require knowing a foreign language. Panel (d) uses the share of vacancies that require cognitive skills. Panel (e) uses the share of vacancies that require socio-emotional skills. Panel (f) uses the share of vacancies that require manual skills. Regressions control for cell-by-event fixed effects, calendar month-by-1 digit-industry fixed effects, and minimum wage changes not occurring in January or July. Standard errors are clustered at the 2-digit industry level.

Table B.1: Descriptive Statistics for Variable Pay and Amenities: All Amenities

	All vacancies (1)	Post wage (2)	Does not post wage (3)
Bonuses and commissions	0.07	0.07	0.06
Extra hours and overtime	0.01	0.02	0.01
Paid time off	0.00	0.00	0.00
Health insurance contributions	0.00	0.00	0.00
Retirement contributions	0.00	0.00	0.00
Food and services subsidies and discounts	0.02	0.03	0.01
Office space and other office amenities	0.01	0.00	0.01
Location and commuting	0.01	0.01	0.02
Work equipment and allowances	0.00	0.00	0.00
Schedule flexibility	0.05	0.04	0.06
Workplace safety	0.01	0.01	0.01
Job security	0.05	0.06	0.05
Work environment/Impact on society	0.16	0.14	0.16
Physical effort/Pace of work	0.03	0.03	0.03
Working in teams	0.19	0.14	0.20
Human capital development	0.23	0.18	0.24
Number of vacancies	77,874	15,835	62,039

Notes: This table shows summary statistics for the amenities advertised in our final sample of vacancies. The table details whereas vacancies advertise each individual amenity. This table considers the full list of amenities discussed in Appendix A. Statistics are also shown separately between vacancies that post a wage and vacancies that do not post a wage.

Table B.2: Cross-Sectional Patterns of Directed Search: Poisson Regression

Panel (a): All vacancies

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Posted wage)	-0.030	0.015	0.068	0.085	0.210	0.034
	(0.048)	(0.034)	(0.035)	(0.036)	(0.044)	(0.044)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	No	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	15,835	15,501	15,501	14,626	13,878	10,620
Pseudo R^2	0.000	0.064	0.139	0.172	0.174	0.415

Panel (b): Interactions with low- and higher-skill occupations

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Posted wage) (LS)	0.277	0.255	0.203	0.200	0.348	0.078
	(0.036)	(0.035)	(0.035)	(0.034)	(0.049)	(0.048)
Log(Posted wage) (HS)	-0.161	-0.101	-0.096	-0.093	-0.021	-0.046
	(0.045)	(0.037)	(0.036)	(0.037)	(0.033)	(0.055)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	No	Yes	Yes	Yes	Yes	Yes
Occupation group	Yes	Yes	No	No	No	No
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	15,835	15,501	15,501	14,626	13,878	10,620
Pseudo R^2	0.052	0.107	0.143	0.176	0.177	0.415

Notes: Panel (a) presents the α coefficient of equation (1) estimated using a Poisson model. If β denotes the point estimate, the elasticity is recovered as $\exp(\beta) - 1$. The standard error is estimated using the Delta method. Panel (b) presents the estimated $(\alpha_{LS}, \alpha_{HS})$ coefficients of equation (2), where LS and HS correspond to lower- and higher-skill occupations, respectively. The dependent variable is the log number of applications, and the key regressor is the log posted wage. Column (1) shows results with no controls in Panel (a) and includes a control for the broad occupational group in Panel (b). Column (2) excludes vacancies receiving more than 1,000 applications and includes 2-digit industry fixed effects, year fixed effects, and controls for advertised variable pay and amenities. Columns (3) and (4) add 1-digit and 2-digit occupation fixed effects, respectively. Column (5) excludes the vacancies at the top 5% of the posted wage distribution. Column (6) only considers vacancies that are posted by firms that post at least 10 vacancies in the BJ platform and includes firm fixed effects. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table B.3: Cross-Sectional Patterns of Directed Search: Different Posted Wage Definition

Panel (a): Midpoint of Salary Range

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Posted wage)	-0.048	-0.026	0.048	0.075	0.171	0.122
	(0.106)	(0.071)	(0.069)	(0.069)	(0.069)	(0.058)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	No	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	13,832	13,533	13,533	12,765	12,357	9,687
Adj. R^2	0.000	0.067	0.121	0.156	0.158	0.376

Panel (b): Midpoint of Salary Range, Excluding Ranges $\geq 50\%$ of Midpoint

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Posted wage)	-0.051	-0.018	0.055	0.088	0.208	0.162
	(0.116)	(0.081)	(0.078)	(0.076)	(0.076)	(0.063)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	No	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	13,004	12,720	12,720	11,994	11,565	9,143
Adj. R^2	0.000	0.069	0.124	0.159	0.162	0.369

Panel (c): Maximum of Salary Range

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Posted wage)	-0.084	-0.068	-0.006	0.018	0.061	0.060
	(0.085)	(0.052)	(0.050)	(0.048)	(0.053)	(0.042)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	No	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	14,082	13,778	13,778	12,995	12,551	9,839
Adj. R^2	0.001	0.068	0.122	0.157	0.155	0.374

Notes: This table presents the estimated α coefficient of equation (1) using different definitions of posted wage. The dependent variable is the log number of applications, and the key regressor is the log posted wage. Panel (a) considers the midpoint of the salary range. Panel (b) considers the midpoint of the salary range, excluding vacancies whose range exceeds the 50% of the midpoint. Panel (c) considers the maximum of the salary range. Column (1) shows results with no controls. Column (2) excludes vacancies receiving more than 1,000 applications and includes 2-digit industry fixed effects, year fixed effects, and controls for advertised variable pay and amenities. Columns (3) and (4) add 1-digit and 2-digit occupation fixed effects, respectively. Column (5) excludes the vacancies at the top 5% of the posted wage distribution. Column (6) only considers vacancies that are posted by firms that post at least 10 vacancies in the BJ platform and includes firm fixed effects. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table B.4: Cross-Sectional Patterns of Directed Search: Occupational Heterogeneity

Panel (a): Lower-Skill Occupations

	Clerical support (1)	Services and sales (2)	Machine operators (3)	Elem. occs. (4)	Low skill (5)	Low skill (6)	Low skill (7)
Log(Posted wage)	0.358	0.388	0.454	0.313	0.441	0.395	0.380
	(0.086)	(0.050)	(0.186)	(0.082)	(0.045)	(0.049)	(0.047)
No outliers	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	No	No	No	No	No	Yes	No
Occupation FE (2-digits)	No	No	No	No	No	No	Yes
Observations	4,491	3,300	331	1,539	9,661	9,661	9,661
Adjusted R^2	0.136	0.112	0.181	0.087	0.106	0.139	0.158

Panel (b): Higher-Skill Occupations

	Managers (1)	Profs. (2)	Techs. (3)	Craft (4)	High skill (5)	High skill (6)	High skill (7)
Log(Posted wage)	0.195	-0.183	0.037	-0.070	-0.047	-0.052	-0.024
	(0.152)	(0.053)	(0.091)	(0.060)	(0.047)	(0.047)	(0.053)
No outliers	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	No	No	No	No	No	Yes	No
Occupation FE (2-digits)	No	No	No	No	No	No	Yes
Observations	120	1,960	2,637	863	5,580	5,580	4,717
Adjusted R^2	0.128	0.047	0.072	0.074	0.058	0.067	0.124

Notes: Panel (a) presents the estimated α coefficient of equation (1) for lower-skill occupations. Panel (b) presents the estimated α coefficient of equation (1) for higher-skill occupations. The dependent variable is the log number of applications, and the key regressor is the log posted wage. Within each panel, Columns (1)-(4) show results for individual occupations in regressions that exclude vacancies receiving more than 1,000 applications and include 2-digit industry fixed effects, year fixed effects, and controls for advertised variable pay and amenities. Within each panel, Columns (5)-(7) show results for the broad occupation groups. Column (5) does not include occupation fixed effects, while Columns (6) and (7) include 1-digit and 2-digit occupation fixed effects, respectively. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table B.5: Requirements by Occupational Group

Panel (a): All Vacancies

	All	Lower-skill occupations	Higher-skill occupations
	(1)	(2)	(3)
Requires vocational training	0.14	0.13	0.15
Requires college degree	0.21	0.13	0.29
Requires foreign language	0.19	0.15	0.24
Requires cognitive skills	0.80	0.75	0.86
Requires social skills	0.83	0.84	0.82
Requires manual skills	0.38	0.37	0.40
Observations	77,874	40,881	36,993

Panel (b): Vacancies that Post a Wage

	All	Lower-skill occupations	Higher-skill occupations
	(1)	(2)	(3)
Requires vocational training	0.18	0.15	0.22
Requires college degree	0.15	0.10	0.24
Requires foreign language	0.18	0.14	0.24
Requires cognitive skills	0.74	0.70	0.80
Requires social skills	0.80	0.81	0.79
Requires manual skills	0.35	0.34	0.38
Observations	15,835	10,071	5,764

Notes: This table shows summary statistics for the presence of requirements (in terms of formal qualifications, foreign language, or skills) in our final sample of vacancies. Panel (a) considers all vacancies. Panel (b) restricts to vacancies that post a wage. Within each panel, statistics are shown for all vacancies, vacancies attached to lower-skill occupations, and vacancies attached to higher-skill occupations.

Table B.6: Cross-Sectional Patterns of Directed Search: Heterogeneity by Requirements

Panel (a): Formal Requirements

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Posted wage) (LS)	0.216	0.225	0.246	0.236	0.462	0.255
	(0.055)	(0.061)	(0.055)	(0.055)	(0.071)	(0.075)
Log(Posted wage) (HS)	-0.118	-0.079	-0.079	-0.069	0.044	0.025
	(0.058)	(0.055)	(0.054)	(0.055)	(0.053)	(0.120)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	No	Yes	Yes	Yes	Yes	Yes
Occupation group	Yes	Yes	No	No	No	No
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	6,248	6,149	6,149	5,805	5,312	4,095
Adj. R^2	0.084	0.139	0.167	0.219	0.225	0.426

Panel (b): Skill Requirements

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Posted wage) (LS)	0.494	0.464	0.418	0.406	0.546	0.328
	(0.049)	(0.050)	(0.055)	(0.051)	(0.058)	(0.048)
Log(Posted wage) (HS)	-0.133	-0.095	-0.091	-0.085	0.007	-0.001
	(0.053)	(0.042)	(0.042)	(0.046)	(0.047)	(0.070)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	No	Yes	Yes	Yes	Yes	Yes
Occupation group	Yes	Yes	No	No	No	No
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	14,430	14,112	14,112	13,309	12,631	9,868
Adj. R^2	0.050	0.102	0.130	0.166	0.170	0.374

Table B.6: Cross-Sectional Patterns of Directed Search: Heterogeneity by Requirements (continued)

Panel (c): No Formal Requirements

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Posted wage) (LS)	0.606	0.557	0.524	0.507	0.579	0.331
	(0.057)	(0.055)	(0.070)	(0.066)	(0.074)	(0.053)
Log(Posted wage) (HS)	0.007	0.002	0.018	0.027	0.122	0.019
	(0.074)	(0.061)	(0.066)	(0.070)	(0.067)	(0.076)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	No	Yes	Yes	Yes	Yes	Yes
Occupation group	Yes	Yes	No	No	No	No
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	9,327	9,092	9,092	8,573	8,365	6,530
Adj. R^2	0.036	0.096	0.123	0.147	0.152	0.383

Panel (d): No Skill Requirements

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Posted wage) (LS)	0.411	0.293	0.222	0.199	0.238	0.060
	(0.134)	(0.138)	(0.138)	(0.146)	(0.164)	(0.403)
Log(Posted wage) (HS)	0.026	-0.041	-0.036	0.098	0.152	-0.221
	(0.200)	(0.218)	(0.220)	(0.230)	(0.213)	(0.190)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	No	Yes	Yes	Yes	Yes	Yes
Occupation group	Yes	Yes	No	No	No	No
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	1,145	1,129	1,129	1,069	1,046	757
Adj. R^2	0.074	0.138	0.153	0.172	0.172	0.537

Notes: This table presents the estimated $(\alpha_{LS}, \alpha_{HS})$ coefficients of equation (2). The dependent variable is the log number of applications, and the key regressor is the log posted wage. LS and HS account for lower-skill and higher-skill, respectively. Panel (a) considers vacancies that post at least one formal qualification requirement (education and/or language). Panel (b) considers vacancies that post at least one skill requirement (cognitive, socio-emotional, and/or manual). Panels (c) and (d) present results without these requirements, respectively. Column (1) includes a control for the occupational group. Column (2) excludes vacancies receiving more than 1,000 applications and includes 2-digit industry fixed effects, year fixed effects, and controls for advertised variable pay and amenities. Columns (3) and (4) add 1-digit and 2-digit occupation fixed effects, respectively. Column (5) excludes the vacancies at the top 5% of the posted wage distribution. Column (6) only considers vacancies that are posted by firms that post at least 10 vacancies in the BJ platform and includes firm fixed effects. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table B.7: Cross-Sectional Patterns of Directed Search: Heterogeneity by Applicants Characteristics, Poisson Model

Panel (a): Gender, employment status, and age

	Female (1)	Male (2)	Emp. (3)	Unemp. (4)	Age$\leq$25 (5)	Age>25 (6)
Log(Posted wage) (LS)	0.018	0.446	0.450	0.070	-0.107	0.588
	(0.043)	(0.046)	(0.046)	(0.032)	(0.034)	(0.054)
Log(Posted wage) (HS)	-0.201	0.011	0.077	-0.180	-0.312	0.150
	(0.026)	(0.048)	(0.056)	(0.025)	(0.022)	(0.056)
No outliers	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,241	15,241	15,241	15,241	15,241	15,241
Pseudo R^2	0.191	0.118	0.150	0.150	0.142	0.237

Panel (b): Education and skills

	No tert. (1)	Voc. trn. (2)	College (3)	Cogn. sk. (4)	Soc. sk. (5)	Man. sk. (6)
Log(Posted wage) (LS)	0.028	0.518	0.890	0.725	0.471	0.571
	(0.031)	(0.052)	(0.084)	(0.068)	(0.047)	(0.051)
Log(Posted wage) (HS)	-0.239	-0.009	0.579	0.335	0.127	0.194
	(0.022)	(0.049)	(0.132)	(0.092)	(0.064)	(0.071)
No outliers	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Variable pay and amenities	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,241	15,241	15,241	15,241	15,241	15,241
Pseudo R^2	0.168	0.153	0.212	0.247	0.213	0.179

Notes: This table presents the $(\alpha_{LS}, \alpha_{HS})$ coefficients of equation (2) estimated using a Poisson model. If β denotes the point estimate, the elasticity is recovered as $\exp(\beta) - 1$. The standard error is estimated using the Delta method. The dependent variable is the log number of applications made by applicants with the characteristic depicted in the column title, and the key regressor is the log posted wage. LS and HS account for lower-skill and higher-skill, respectively. Panel (a) presents results by gender, employment status, and age. Panel (b) presents results by educational attainment (without tertiary education, vocational training, and college degree) and three categories of skills (cognitive, socio-emotional, and manual skills). Regressions exclude vacancies receiving more than 1,000 applications and include 2-digit industry fixed effects, year fixed effects, controls for advertised variable pay and amenities, and 1-digit occupation fixed effects. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table B.8: Correlation Between Variable Pay, Amenities, and Posted Wages

Panel (a): At Least One Amenity

	(1)	(2)	(3)	(4)	(5)	(6)
Bonuses and commissions	-0.148	-0.138	-0.106	-0.085	-0.067	-0.035
	(0.022)	(0.020)	(0.022)	(0.021)	(0.023)	(0.021)
At least one amenity	-0.013	-0.020	-0.028	-0.026	-0.028	-0.016
	(0.013)	(0.010)	(0.010)	(0.011)	(0.006)	(0.009)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	15,835	15,501	15,501	14,626	13,878	10,759
Adj. R^2	0.007	0.041	0.085	0.101	0.065	0.401

Panel (b): By Amenity (Multivariate)

	(1)	(2)	(3)	(4)	(5)	(6)
Bonuses and commissions	-0.134	-0.123	-0.093	-0.074	-0.058	-0.033
	(0.021)	(0.019)	(0.022)	(0.022)	(0.024)	(0.020)
Schedule flexibility	-0.288	-0.296	-0.299	-0.310	-0.266	-0.230
	(0.020)	(0.021)	(0.023)	(0.024)	(0.021)	(0.028)
Work environment/Impact on society	-0.071	-0.073	-0.065	-0.050	-0.028	-0.007
	(0.015)	(0.013)	(0.012)	(0.012)	(0.010)	(0.009)
Working in teams	0.079	0.069	0.055	0.050	0.039	0.029
	(0.017)	(0.015)	(0.016)	(0.018)	(0.017)	(0.009)
Human capital development	0.047	0.040	0.027	0.025	0.003	0.013
	(0.015)	(0.012)	(0.012)	(0.012)	(0.009)	(0.011)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	15,835	15,501	15,501	14,626	13,878	10,759
Adj. R^2	0.028	0.062	0.103	0.120	0.084	0.411

Notes: This table presents the estimated α^a coefficients of equation (B.8). The dependent variable is the log posted wage, and the key regressors are indicators for advertised amenities. Panel (a) presents results from regressions that include an indicator variable of advertising at least one amenity. Panel (b) presents results from regressions that include five indicators associated with variable pay and individual amenities (bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). Column (1) shows results with no controls. Column (2) excludes vacancies receiving more than 1,000 applications and includes 2-digit industry fixed effects, and year fixed effects. Columns (3) and (4) add 1-digit and 2-digit occupation fixed effects, respectively. Column (5) excludes the vacancies at the top 5% of the posted wage distribution. Column (6) only considers vacancies that are posted by firms that post at least 10 vacancies in the BJ platform and includes firm fixed effects. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table B.9: Correlation Between Variable Pay, Amenities, and Applications: By Occupation Group

	(1)	(2)	(3)	(4)	(5)	(6)
Bonuses and commissions (LS)	-0.113	-0.143	-0.051	-0.093	-0.094	-0.071
	(0.053)	(0.054)	(0.053)	(0.054)	(0.053)	(0.028)
Bonuses and commissions (HS)	0.421	0.287	0.250	0.159	0.141	0.083
	(0.084)	(0.065)	(0.067)	(0.064)	(0.067)	(0.072)
Schedule flexibility (LS)	0.056	0.008	-0.029	-0.024	-0.025	-0.059
	(0.043)	(0.042)	(0.046)	(0.045)	(0.045)	(0.039)
Schedule flexibility (HS)	0.028	0.030	0.043	0.085	0.085	0.043
	(0.039)	(0.030)	(0.030)	(0.028)	(0.028)	(0.042)
Work environment/Impact on society (LS)	0.113	0.113	0.105	0.104	0.103	0.066
	(0.031)	(0.031)	(0.031)	(0.032)	(0.032)	(0.020)
Work environment/Impact on society (HS)	-0.075	-0.045	-0.043	0.012	0.014	0.029
	(0.059)	(0.043)	(0.042)	(0.035)	(0.033)	(0.018)
Working in teams (LS)	0.138	0.100	0.071	0.072	0.073	0.041
	(0.034)	(0.027)	(0.025)	(0.023)	(0.023)	(0.021)
Working in teams (HS)	0.067	0.066	0.070	0.099	0.097	0.079
	(0.035)	(0.022)	(0.021)	(0.018)	(0.020)	(0.017)
Human capital development (LS)	0.003	0.012	0.014	0.014	0.012	-0.032
	(0.035)	(0.032)	(0.033)	(0.031)	(0.031)	(0.024)
Human capital development (HS)	-0.003	0.033	0.038	0.041	0.044	0.023
	(0.018)	(0.018)	(0.017)	(0.023)	(0.024)	(0.024)
No outliers	No	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digits)	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Occupation group	Yes	Yes	No	No	No	No
Occupation FE (1-digit)	No	No	Yes	No	No	No
Occupation FE (2-digits)	No	No	No	Yes	Yes	Yes
Winsorized wage	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Observations	75,928	74,533	74,533	70,592	69,891	58,758
Adj. R^2	0.072	0.114	0.138	0.185	0.184	0.352

Notes: This table presents the estimated $(\alpha^a_{LS}, \alpha^a_{HS})$ coefficients of equation (3). The dependent variable is the log number of applications, and the key regressors are indicators for advertised amenities. LS and HS account for lower-skill and higher-skill, respectively. Column (1) includes a control for the occupational group. Column (2) excludes vacancies receiving more than 1,000 applications and includes 2-digit industry fixed effects, and year fixed effects. Columns (3) and (4) add 1-digit and 2-digit occupation fixed effects, respectively, in exchange for the occupational group indicator. Column (5) excludes the vacancies at the top 5% of the posted wage distribution. Column (6) only considers vacancies that are posted by firms that post at least 10 vacancies in the BJ platform and includes firm fixed effects. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table B.10: Average Minimum Wages, Median Wages (Monthly, for Full-Time Equivalents), and Kaitz Indices, by Occupation in 2011 and 2020

	Year	Minimum Wage (Mean across more detailed Occupations)	Median Wage (Monthly, Full-Time Equivalents)	Kaitz Index: (2) over (3)
	(1)	(2)	(3)	(4)
Lower-skilled occupations:				
Clerical support workers	2011	16691.6	22335.9	0.75
	2020	32967.1	40898.6	0.81
Service & sales workers	2011	14665.8	14136.0	1.04
	2020	29982.2	28734.2	1.04
Plant & machine operators, & assemblers	2011	15920.9	17562.8	0.91
	2020	33125.3	34404.9	0.96
Elementary occupations	2011	11684.5	13221.0	0.88
	2020	27171.2	28087.1	0.97
Average Kaitz, lower-skilled occupations	2011			0.91
	2020			0.95
Higher-skilled occupations:				
Managers	2011	45944.3	58550.9	0.78
	2020	54997.5	85298.2	0.64
Professionals	2011	22870.9	38009.4	0.60
	2020	44621.9	70940.6	0.63
Technicians & assoc. professionals	2011	20820.7	25856.2	0.81
	2020	38370.3	50756.4	0.76
Craft & related trades workers	2011	17386.2	17571.4	0.99
	2020	40977.4	36557.8	1.12
Average Kaitz, higher-skilled occupations	2011			0.77
	2020			0.79

Notes: This table provides statistics assessing the minimum wage bite at the occupational level for 2011 and 2020, using the methodology of ILO (2020). The aggregated minimum wage figures in Column (2) are based on mean minimum wages within 2-digit industries, which were weighted depending on their share within the 1-digit occupations. They are defined in terms of monthly values for full-time workers. Median wages in Column (3) were computed using Uruguay's nationally representative household survey, the Encuesta Continua Hogares, restricted to employees, and expressed in full-time equivalents. For better comparability, those industries were excluded, which we also exclude in the paper's analysis. The wage and minimum wage data are shown in 2020 Uruguayan pesos. Following ILO (2020), in Column (4) the Kaitz index was then computed as the values shown in Column (2) over those in Column (3). In comparison, the national minimum wage - which provides a general wage floor and is distinct from the higher minimum wages set by collective bargaining agreements - amounted to 16,300 Uruguayan pesos in 2020, implying an average Kaitz index of 0.5102 for lower-skilled occupations and 0.3079 for higher-skilled occupations, for the national minimum wage. Lower-skilled occupations have an employment share of 0.6022 and higher-skilled of 0.3978. This yields an average Kaitz index of 0.43 in 2020 for the national minimum wage. Reassuringly, this replicates the value reported by ILO (2020).

Table B.11: Estimation Sample: Descriptive Statistics (Within-Vacancy Design)

	Obs.	Mean	Std. Dev.	p25	p50	p75
A. All occupations						
Apps. per vac.	4288	88.22	149.66	15	40	101
Days open $t-1$	4288	3.86	1.64	2	4	5
Treated	4288	0.56	0.50	0	1	1
B. Lower-skill occupations						
Apps. per vac.	2220	114.96	185.42	21	56	135
Days open $t-1$	2220	3.86	1.65	2	4	5
Treated	2220	0.67	0.47	0	1	1
C. Higher-skill occupations						
Apps. per vac.	2068	59.52	89.18	11	28	72
Days open $t-1$	2068	3.85	1.63	2	4	5
Treated	2068	0.45	0.50	0	0	1

Notes: This table presents descriptive statistics of the estimation sample used in the within-vacancy design (see equation (6)). The unit of observation is a vacancy by calendar month. Panel (a) shows summary statistics for all occupations combined. Panel (b) shows summary statistics for the lower-skill occupational group. Panel (c) shows summary statistics for the higher-skill occupational group. "Days open in $t-1$ refers to the days the vacancy is active in the BJ before the minimum wage change takes place. The sample includes vacancies that were posted between June 25 and 30 as well as December 26 and 31 during the years 2011 through 2020. We exclude vacancies receiving more than 1,000 applications.

Table B.12: Within-Vacancy Design

Days open:	3	4	5	6
	(1)	(2)	(3)	(4)
$\hat{\beta}_{LS}$	25.439	16.344	10.554	3.104
	(7.829)	(6.515)	(5.558)	(5.019)
$\hat{\beta}_{HS}$	1.068	-2.390	-4.476	-0.292
	(7.376)	(5.787)	(5.194)	(4.609)
Obs.	1,730	2,498	3,370	4,258
$\Delta \log \text{MW}_{LS}$	0.077	0.084	0.082	0.082
Pre-event outcome (LS)	64.411	74.497	91.111	99.952
Elast. LS	5.111	2.624	1.405	0.379
$\Delta \log \text{MW}_{HS}$	0.114	0.103	0.095	0.091
Pre-event outcome (HS)	32.448	41.823	58.165	62.112
Elast. HS	0.290	-0.553	-0.810	-0.052

Notes: This table presents the estimated (β_{LS}, β_{HS}) coefficients of equation (6). Regressions include vacancy and calendar month fixed effects. The dependent variable is the number of applications (in levels). Each column considers a different sample of vacancies that vary on the days they were open before the minimum wage took place, ranging from 3 (Column (1)) to 6 (Column (4)). Reported elasticities are computed by dividing the β-coefficient by the pre-event average outcome within treated cells, normalized by the log change in minimum wage among treated cells. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table B.13: Difference-in-Differences Results: Variable Pay and Non-Wage Amenities

	Bon. and Comm. (1)	At least one (2)	Sch. Flex (3)	Work. Env. (4)	Work. Teams (5)	HK Dev. (6)
$\hat{\beta}_{LS}$	-0.003	0.002	-0.001	0.003	-0.000	0.001
	(0.002)	(0.005)	(0.002)	(0.003)	(0.004)	(0.004)
$\hat{\beta}_{HS}$	-0.002	0.004	0.000	0.007	0.000	0.004
	(0.002)	(0.006)	(0.002)	(0.004)	(0.005)	(0.005)
Observations	54,648	54,648	54,648	54,648	54,648	54,648
$\Delta \log \text{MW}_{LS}$	0.059	0.059	0.059	0.059	0.059	0.059
Pre-event outcome (LS)	0.322	0.073	0.042	0.122	0.132	0.160
Elasticity (LS)	-0.171	0.450	-0.319	0.440	-0.019	0.064
$\Delta \log \text{MW}_{HS}$	0.057	0.057	0.057	0.057	0.057	0.057
Pre-event outcome (HS)	0.340	0.027	0.038	0.111	0.152	0.186
Elasticity (HS)	-0.096	2.972	0.171	1.032	0.013	0.358

Notes: This table presents the estimated β coefficient of equation (5) in a model that considers interactions with indicators for lower- and higher-skill occupational groups. Regressions include cell-by-event fixed effects, calendar month-by-1 digit-industry fixed effects, and minimum wage changes not occurring in January or July. The dependent variables, as depicted in the column titles, include (in levels) the share of vacancies advertising bonuses and commissions, the share of vacancies advertising at least one amenity, the share of vacancies advertising schedule flexibility, the share of vacancies advertising work environment/impact on society, the share of vacancies advertising working in teams, and the share of vacancies advertising human capital development. Reported elasticities are computed by dividing the β-coefficient by the pre-event average outcome within treated cells, normalized by the log change in minimum wage among treated cells. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table B.14: Difference-in-Differences Results: Vacancy Requirements

	Voc trn. (1)	College (2)	Language (3)	Cogn. (4)	Social (5)	Manual (6)
$\hat{\beta}_{LS}$	-0.002	0.005	-0.001	0.005	0.005	0.004
	(0.004)	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)
$\hat{\beta}_{HS}$	-0.000	0.011	0.007	0.012	0.004	0.010
	(0.004)	(0.005)	(0.004)	(0.007)	(0.007)	(0.005)
Observations	54,648	54,648	54,648	54,648	54,648	54,648
$\Delta \log \text{MW}_{LS}$	0.059	0.059	0.059	0.059	0.059	0.059
Pre-event outcome (LS)	0.104	0.091	0.114	0.573	0.649	0.298
Elasticity (LS)	-0.354	0.965	-0.133	0.142	0.118	0.250
$\Delta \log \text{MW}_{HS}$	0.057	0.057	0.057	0.057	0.057	0.057
Pre-event outcome (HS)	0.130	0.196	0.158	0.637	0.635	0.317
Elasticity (HS)	-0.004	1.027	0.781	0.335	0.100	0.535

Notes: This table presents the estimated β coefficient of equation (5) in a model that considers interactions with indicators for lower- and higher-skill occupational groups. Regressions include cell-by-event fixed effects, calendar month-by-1 digit-industry fixed effects, and minimum wage changes not occurring in January or July. The dependent variables, as depicted in the column titles, include (in levels) the share of vacancies requiring vocational training, the share of vacancies requiring a college degree, the share of vacancies requiring foreign language knowledge, the share of vacancies requiring cognitive skills, the share of vacancies requiring socio-emotional skills, and the share of vacancies requiring manual skills. Reported elasticities are computed by dividing the β-coefficient by the pre-event average outcome within treated cells, normalized by the log change in minimum wage among treated cells. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

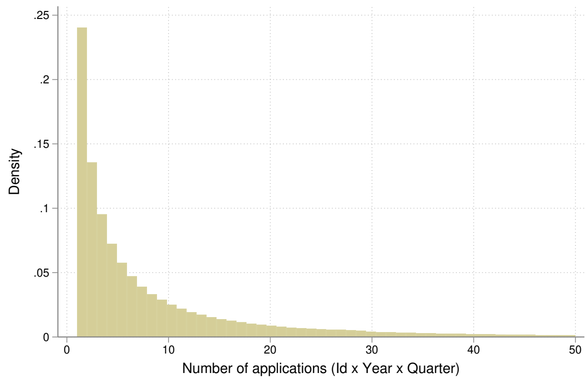
C Application Portfolios

To proxy groups of applications made in the same job search spell (applicants may search for jobs at multiple stages in their careers, thus applying to jobs in different job search spells), we consider an applicant ID-by-quarter-by-year as a unit of observation and focus on "active spells", i.e., applicant ID-by-quarter-by-year combinations where job seekers make at least one application. This strategy leads to 1,668,348 applicant-by-spell observations with at least one application.

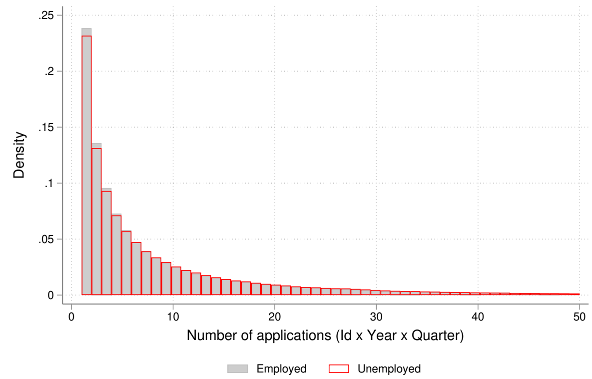
Number of applications. Figure C.1 shows the distribution of the number of applications at the applicant-by-spell level. Panel (a) shows wide variation in the number of applications across applicants. While 23% of applicants with positive applications make a unique application, 51% of applicants submit between 2 and 10 applications in a given spell, and 13% submit between 11 and 20 applications. Only 3% of applicants submit more than 50 applications in a given spell (not shown in the histogram). Panels (b), (c), and (d) show the distributions separately by employment status, gender, and educational attainment. Distributions look remarkably similar across demographic groups, especially with respect to gender.

Diversity in applications. We then explore whether applications made by a given applicant in a given quarter tend to target vacancies in specific industries or occupations. We explore diversification in application portfolios using the following statistic. Let i index observations (active applicant ID-spell combinations) with N_i the total applications made by the applicant in the spell. Each application goes to a vacancy attached to a group $g \in G$, with $\#G$ the number of different possible groups. For example, G may be the set of 2-digit industry codes, g a particular 2-digit industry, and $\#G$ the number of different 2-digit industries. Let $\#g_i \in \{1, ..., \min\{\#G, N_i\}\}$ be

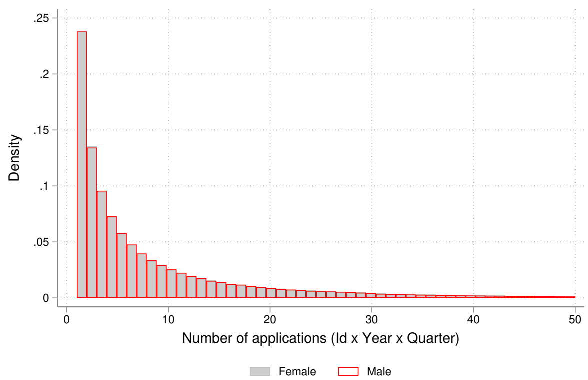
Figure C.1: Distribution of Number of Applications at the Applicant-by-Spell Level



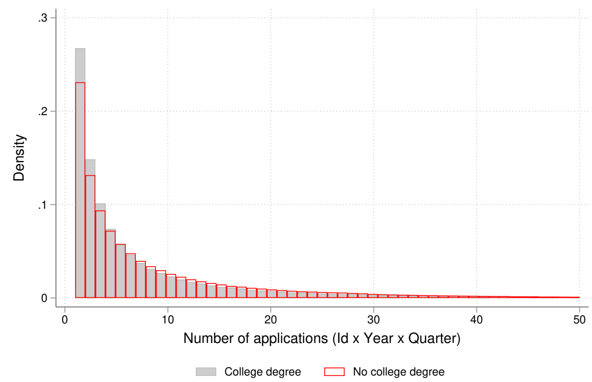
(a) All applicants



(b) By employment status



(c) By gender



(d) By education

Notes: This figure shows histograms for the number of applications made by applicants in a quarter-by-year to our final sample of posted vacancies. Panel (a) considers all applicants. Panel (b) distinguishes applicants by employment status. Panel (c) distinguishes applicants by gender. Panel (d) distinguishes applicants by educational attainment. These plots only consider applicant-quarter-year combinations with a positive number of applications. For readability, we censor the histograms at 50 applications.

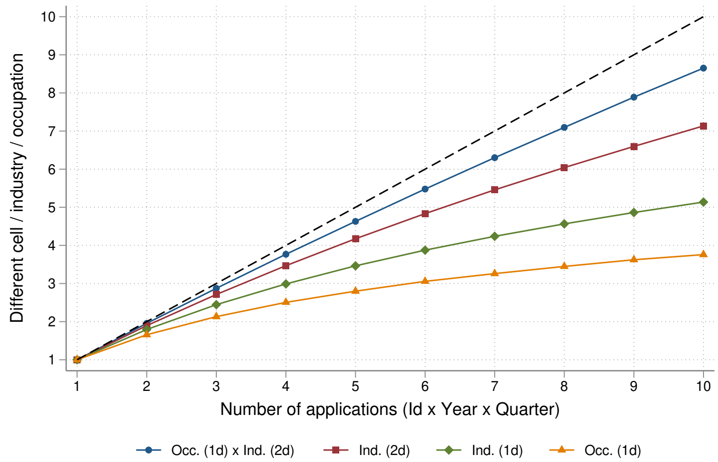
the number of groups spanned by the N_i applications of applicant i. For example, if $N_i = 10$, $\#g_i = 5$ means that the 10 applications span 5 different 2-digit industries. When $N_i = 1$, $\#g_i$ is mechanically 1. When $N_i > 1$, the upper bound of g_i is given by $\min\{\#G, N_i\}$. We measure diversification with the quantity:

$$\mathcal{D}(N) = \mathbb{E}_i \left[\#g_i | N_i = N \right]. \tag{C.1}$$

When $\mathcal{D}(N) = 1$, applications are not diversified: all are made to the same group of vacancies. When $\mathcal{D}(N) = N$, applications are completely diversified: all are made to vacancies that belong to different groups. This implies that the distance between $(N, \mathcal{D}(N))$ and the 45-degree line can be used to visually diagnose the extent of diversification in application portfolios.

We focus on four different groups of vacancies. We first consider a narrow definition of vacancies

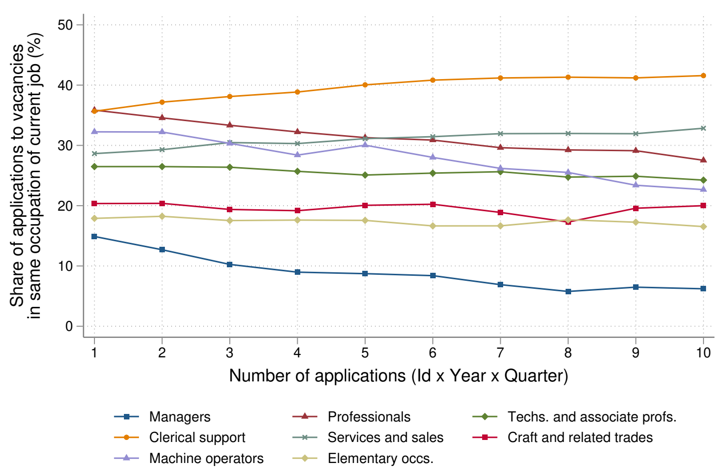
Figure C.2: Portfolio Diversification: Different Groups



Notes: This figure plots the statistic described in equation (C.1), the average number of "groups" individuals apply to in each quarter-by-year, as a function of the total number of applications made in the quarter-by-year to our final sample of posted vacancies (see Section 2 for details on the sample restrictions). "Groups" refer to 2-digit industries by 1-digit occupation cells (blue curve, which considers 504 categories), 2-digit industries (red curve, 70 categories), 1-digit industries (green curve, 14 categories), and 1-digit occupations (yellow curve, 8 categories). For readability, we censor the figure at 10 applications.

that share their 2-digit (ISIC Rev. 4) industry code and their 1-digit (ISCO 08) occupation code. We also consider broader group definitions: 2-digit industry codes alone, 1-digit industry codes alone, and 1-digit occupation codes alone.

Figure C.3: Share of Applications to Vacancies in Same Occupation of Current Job



Notes: This figure plots the share of applications made to vacancies attached to the same 1-digit occupation of the current employment as a function of the total number of applications made in the quarter-by-year to our final sample of posted vacancies (see Section 2 for details on the sample restrictions). By construction, this figure only considers applicants who are employed in the quarter-year of the application. As an example, around 15% of applications from job seekers employed as managers, who make 1 application in a given quarter-by-year, target managerial jobs (with the remaining applications targeting jobs in other 1-digit occupations); and around 8% of applications from job seekers employed as managers, who make 10 applications in a given quarter-by-year, target managerial jobs.

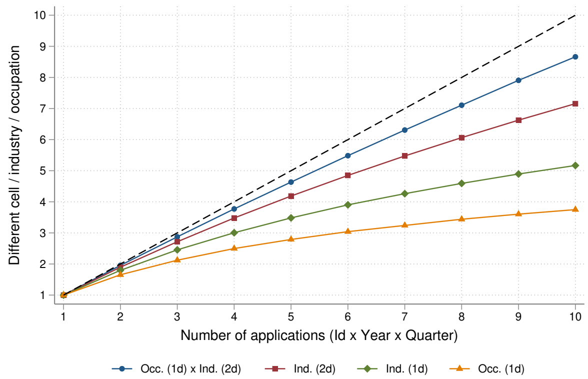
Figure C.2 shows the results. We focus on applicant-spell observations making 10 or fewer applications ($N_i \in \{1, ..., 10\}$). The black dotted curve is the 45-degree line. When considering the narrower group definition (blue curve, 2-digit industry by 1-digit occupation cell), the levels of diversification are substantial. For example, $\mathcal{D}(2) = 1.96$, which means that almost everyone who applies to 2 vacancies applies to vacancies in 2 different industry-by-occupation cells. While $\mathcal{D}(N)/N$ decreases with the number of applications, it remains large across the distribution of N. Individuals making 5 and 10 applications span 4.6 and 8.7 industry-by-occupation cells, respectively. While mechanically smaller, diversification remains large when considering broader groups (2-digit industries, 1-digit industries, and 1-digit occupations alone). Applicants who make 2 applications span, on average, 1.90 2-digit industries, 1.79 1-digit industries, and 1.66 1-digit occupations. Applicants who make 5 applications span, on average, 4.2 2-digit industries, 3.5 1-digit industries, and 2.8 1-digit occupations. Applicants who make 10 applications span, on average, 7.1 2-digit industries, 5.1 1-digit industries, and 3.8 1-digit occupations.[2]

A possible caveat of these results is that, conditional on making several applications, the vacancy offer distribution at a given point in time may be limited, thus preventing job seekers from implementing "non-diversified" application portfolios. For example, at a given point in time, there may be few vacancies (maybe one or none) associated with a particular industry-by-occupation cell. In that sense, the spike at 1 in Figure C.1 may partially reflect an aversion to diversification for a subset of applicants. Yet, the fact that we observe a non-trivial share of job seekers making multiple applications and that, conditional on making multiple applications, job seekers apply to a wide range of vacancies in terms of industries and occupations, shows that significant numbers of applicants are, in fact, diversifying their applications. Figure C.4 explores for heterogeneities by applicant characteristics (employment status, gender, education, and job search spell length). The figures suggest that all subgroups of applicants are diversifying their applications.

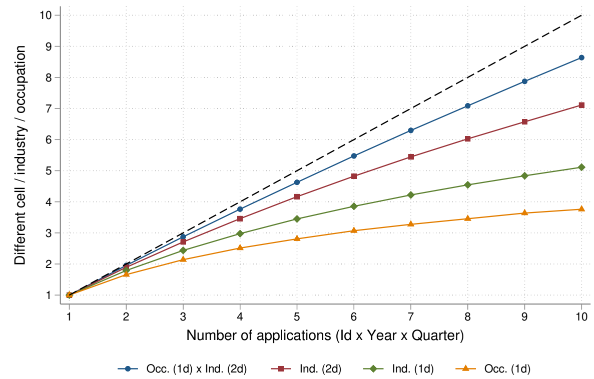
As a final test for "willingness to diversify," we leverage the fact that, for the majority of employed job seekers, we observe the 1-digit occupation of their current job and the occupation attached to the vacancies they apply to. Then, we can observe the share of on-the-job applications that are made to vacancies attached to the same occupation as the current job. Figure C.3 shows the results split by occupation of the current job and number of applications made in the job search spell. The figure reveals that job seekers who apply for jobs while employed are also willing to apply to vacancies attached to other occupations, suggesting that diversification is plausible.

[2]This result is not exclusively explained by differences in $\#G$, since $\mathcal{D}(N)$ remains far below the upper bounds. The number of 2-digit industry by 1-digit occupation cells observed in the vacancy data is 504. The number is 70, 14, and 8 for 2-digit industries, 1-digit industries, and 1-digit occupations, respectively.

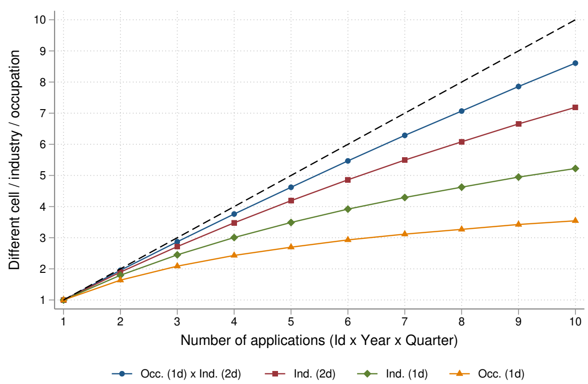
Figure C.4: Portfolio Diversification: Heterogeneity



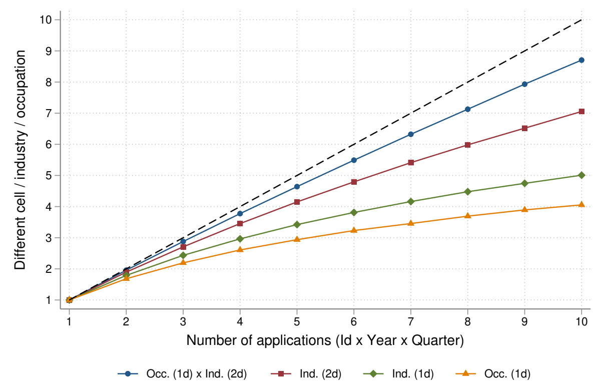
(a) Employed



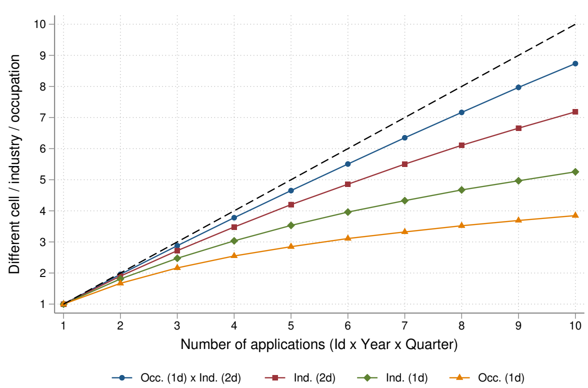
(b) Unemployed



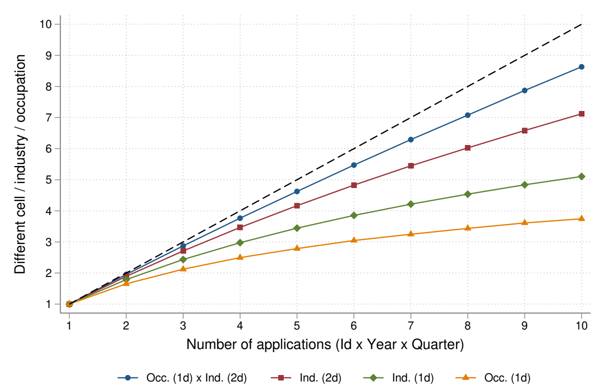
(c) Female



(d) Male



(e) College degree



(f) No college degree

Notes: This figure plots the statistic described in equation (C.1), the average number of "groups" individuals apply to in each quarter-by-year, separately for applicants with different characteristics as a function of the total number of applications made in the quarter-by-year to our final sample of posted vacancies (see Section 2 for details on the sample restrictions). Panel (a) considers employed applicants. Panel (b) considers unemployed applicants. Panel (c) considers female applicants. Panel (d) considers male applicants. Panel (e) considers applicants with a college degree. Panel (f) considers applicants without a college degree. "Groups" refer to 2-digit industries by 1-digit occupation cells (blue curve, which considers 504 categories), 2-digit industries (red curve, 70 categories), 1-digit industries (green curve, 14 categories), and 1-digit occupations (yellow curve, 8 categories). For readability, we censor the figure at 10 applications.

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