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

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Abstract

We leverage rich data from a prominent online job board in Uruguay to assess directed search patterns in job applications, focusing on posted wages and advertised non-wage amenities. We document three sets of cross-sectional facts about the job application process. First, we observe substantial heterogeneity across applicants in the number of applications they send within an application spell, and find a large degree of diversification in the occupations and industries of the vacancies they apply to within job seekers that send multiple applications. Second, we find robust evidence of directed search based on posted wages, especially for male, employed, older, college-educated, and skilled job applicants. Importantly, we show that the wage-application correlation is driven by vacancies attached to lower-skill occupations, with applications to vacancies attached to higher-skill occupations showing no responsiveness to posted wages. Third, by applying text analysis to the job ads, we elicit advertised non-wage amenities and explore their role in the application process. We find evidence of directed search based on amenities and show that applications to lower-skill vacancies are consistent with lexicographic job preferences: amenities predict applications only when wages are not posted. We also find substantial heterogeneity in the role of non-wage amenities by amenity, occupation, and applicant characteristics, thus rejecting homogeneous preferences and the existence of a scalar (rather than vector-valued) index of job amenities. Finally, we leverage industry-by-occupation minimum wage variation to show that the occupational heterogeneity in directed search patterns documented in the cross-section is supported by quasi-experimental difference-in-differences estimates of the effects of wages on applications.

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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

Unpacking the "black box" of job applications and recruitment is an active area of research in economics. Evidence about the job application process informs about the presence of 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. Moreover, as argued by Holzer et al. (1991), job queuing behavior suggests the existence of ex-ante rents in the labor market. In this spirit, 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 constitutes evidence of rents in the labor market, even if compensating differentials partially rationalize cross-sectional wage dispersion.[1]

Despite its importance, the empirical study of job applications is challenging because most datasets record equilibrium outcomes, which, by definition, are only observed after the job application process has finished. 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. More recently, economists have started using vacancy-level data from private online job boards to understand 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; Arnold et al., 2023; Batra et al., 2023). Given the increasing role that online job platforms are playing (Smith, 2015; Faberman and Kudlyak, 2016) and the unique information they can provide on pre-matching behavior, this strand of work is increasingly attracting interest from applied researchers seeking to better understand the subtleties of the search and matching process.

This paper builds on this literature and uses data from a large online job board in Uruguay to study directed search patterns in job applications, focusing on the role of posted wages and advertised non-wage amenities. The data comes from BuscoJobs (BJ), a prominent online job search platform that operates in more than 30 countries.[2] 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., Forthcoming). 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. On top of the complete application portfolio, applicant profiles contain information on gender, age, employment status,

[1]See Slichter (1950), Krueger and Summers (1988), and Card et al. (2024) on industry wage differentials. See Card et al. (2013, 2018) and Song et al. (2019) on firm wage differentials. See Bonhomme and Jolivet (2009), Sorkin (2018), Taber and Vejlin (2020), Lamadon et al. (2022), Lavetti (2023), Maestas et al. (2023), Morchio and Moser (2023), Roussille and Scuderi (2024), and Sockin (2024) on the role of non-wage amenities for rationalizing wage dispersion.

[2]In some English-speaking countries, BJ is known as FindoJobs.

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., Forthcoming); and the non-wage amenities advertised in the job post (Adamczyk et al., Forthcoming).

We use the data to develop an analysis of directed search patterns in the labor market, that is, on the extent to which job seekers direct their search toward vacancies with specific attributes (as opposed to applying to vacancies at random). The analysis proceeds in two parts. The first part develops a cross-sectional analysis that confirms and extends the main findings of Banfi and Villena-Roldan (2019) and Marinescu and Wolthoff (2020). The second part makes use of the fact that the Uruguayan setting is characterized by Collective Bargaining Agreements (CBAs) that dictate and frequently adjust minimum wages which vary at the industry-by-occupation level to complement our cross-sectional analysis with differences-in-differences estimates of wage effects on job applications. While the main focus of this exercise is to test whether the cross-sectional results are supported by a quasi-experimental framework, we note below that the findings in this section are also novel to the minimum wage literature.

In the first cross-sectional exercise, we characterize application portfolios at the applicant level and explore to what extent they are diversified or concentrated in a few industries or occupations. We find that there is substantial heterogeneity in the number of applications per job search spell across applicants. 23% of job seekers with positive applications make a unique application in a given spell, 51% of applicants submit between 2 and 10 applications in a given spell, and 13% submit between 11 and 20 applications in a given spell. Only 3% of applicants submit more than 50 applications in a given spell. The distributions of the number of applications are relatively stable across different types of applicants, although job seekers who are unemployed and/or don't have a college degree submit, on average, slightly more applications.

We also document that application portfolios are diversified. Job seekers who submit multiple applications in a given quarter rarely concentrate their applications within a specific industry and/or occupation. Instead, workers tend to apply for vacancies that span a wide range of industries and occupations. For example, when applicants submit 5 applications in a given quarter, their applications span, on average, 4.2 2-digit industries, 3.5 1-digit industries, and 2.8 1-digit occupations. This qualitative pattern remains consistent regardless of the number of applications made. We also find that while on-the-job searchers partially direct their search to vacancies attached to the same occupation as their current job, they also apply to several vacancies attached to other occupations. This set of findings suggests that workers do not exhibit strong attachments to an occupation and, especially, an industry at the time of application, implying that they possibly consider other job attributes when choosing the vacancies they apply for, making directed search patterns feasible. The fact that industries seem to be more diversified than occupations also suggests that industry wage differentials possibly reflect rents.

The second cross-sectional exercise explicitly explores directed search based on posted wages. We first replicate Banfi and Villena-Roldan (2019) and Marinescu and Wolthoff (2020) main finding of a positive and significant correlation between posted wages and vacancy-level applications once appropriate skill controls (in our case, occupations) 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 a subset of occupations (clerical support, services and sales, plant and machine operators, and elementary occupations), which we refer to as *lower-skill 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 remaining occupations (managers, professionals, technicians and associate professionals, and craft workers), which we refer to as *higher-skill occupations*, the relationship between applications and posted wages is completely absent. This finding is consistent with wage posting being more prevalent in lower-skill occupations and wage bargaining being more prevalent in higher-skill occupations (e.g., Hall and Krueger, 2012; Caldwell and Harmon, 2019; Lachowska et al., 2022) since posted wages may provide different information for applicants depending on their occupation, thus mediating the application responsiveness.

In this exercise, we also take advantage of the applicant-level data and explore whether the responsiveness of applications to posted wages varies with applicant characteristics. Both a vacancy-level analysis and an application-level analysis show that applications made by male, employed, older, college-educated, and skilled job seekers are significantly more responsive to wages than applications made by female, unemployed, young, non-college-educated, and unskilled job seekers, respectively. We also find that applicants with presumably worse labor market prospects (female, unemployed, young, non-educated, and unskilled) display negative elasticities with respect to higher-skill vacancies even conditional on industry and occupation. This finding is consistent with models of directed search where workers trade-off wages with job search spell length (e.g., Moen, 1997) and 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 transitions (e.g., Burdett and Mortensen, 1998; Postel-Vinay and Robin, 2002a,b).

Finally, the third cross-sectional exercise assesses the role of non-wage amenities in the job application process. We provide a battery of correlational exercises that consistently show that advertised amenities matter for job seekers. First, we explore correlations between amenities and posted wages. Advertising at least one amenity is, in our preferred specification, associated with 4% lower posted wages, but the average effect masks substantial heterogeneity by amenity. While advertising bonuses and commissions, schedule flexibility, and a good work environment negatively correlate with posted wages, advertising working in teams and possibilities for human capital development positively correlate with posted wages. Second, we explore whether amenities correlate with applications. We find that, on average, advertising amenities increase the volume of applications; however, the effect is, again, very heterogeneous in size and sign across amenities, occupations (conditional on amenity), and applicant characteristics.

One novel result that emanates from this exercise is that we find robust evidence of "lexicographic" preferences for jobs in lower-skill vacancies. Amenities only increase applications to lower-skill vacancies when vacancies do not offer a posted wage but the effect of the amenity index vanishes when posting a wage. On the contrary, higher-skill vacancies show a positive effect regardless of the wage-posting status. This finding can also be interpreted as a consequence of the heterogeneous incidence of wage posting versus wage bargaining across skills. Under wage posting, the wage may be interpreted as a "sufficient statistic" for job attributes, giving job ads a secondary role conditional on the wage. For higher-skill vacancies, however, the lack of information implicit in posted wages may provide a bigger role to the advertised amenities. This result is consistent with Banfi and Villena-Roldan (2019), who show that applicants direct their search toward high-paying vacancies even when wages are not posted, and 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 note that the substantial heterogeneity we find across amenities, occupations, and applicant characteristics seems to reject the existence of homogeneous preferences for amenities and, more importantly, a scalar (rather than vector-valued) amenity index at the job level. In this sense, we see our results as consistent with Lindenlaub and Postel-Vinay (2022), Maestas et al. (2023), and Sockin (2024).

While informative, the cross-sectional patterns may be biased by omitted variables and selection on unobservables. The correlations between applications, wages, and amenities could be driven by vacancy (or firm) characteristics that are valued by workers but are unobserved by the econometrician. Importantly, as suggested by Skoda (2022), Arnold et al. (2023), and Batra et al. (2023), the sample of vacancies that decide to post a wage is possibly selected. In our setting, the distribution of industries and occupations is similar between vacancies that post and do not post wage. Still, the extent to which wage posting correlates with latent wages can affect the interpretation of the cross-sectional elasticities.

In this context, the second part of the paper provides causal estimates of the effect of wages on applications by leveraging plausibly exogenous variation in minimum wages at the industry-by-occupation level. The objective of this exercise is to test whether the occupational heterogeneity in directed search documented in the cross-section is confirmed in a quasi-experimental framework, thus providing stronger grounds for its causal interpretation. On a high level, the institutional setting is organized as follows. In response to an economic crisis that deteriorated real wages, Uruguay implemented a set of labor market institutions in 2005, including wage councils that carried out periodic 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 sectoral CBAs.[3] These CBAs were gradually expanded,

[3]Wage councils were central actors in the Uruguayan economy until 1973 – when a dictatorship eliminated them – and, while they operated between 1985 and 1992 after the return to democracy, they were not binding between 1992 and 2005.

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 specific 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 observed 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) 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 lower-skill vacancies in industry-by-occupation cells exposed to minimum wage increases face a significant increase in applications, while exposed higher-skill vacancies show no response to the policy change. That is, the quasi-experimental DID results that rely on exogenous minimum wage variation confirm our cross-sectional finding of occupational heterogenitiy in directed search, providing stronger grounds for a causal interpretation. The implied wage-application elasticity in lower-skill vacancies is around 1.5, which aligns with 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 no change in other margins suggests the presence of rents in the Uruguayan lower-skill labor market. Then, these results speculate that the minimum wage policy has contributed to increased rent-sharing in Uruguay, thus helping make "bad jobs better" (Acemoglu, 2001; Rodrik and Stantcheva, 2021).

Related literature This paper contributes to the growing empirical literature that uses online job board data to characterize empirical patterns in job applications, in particular, related to directed search behavior.[4] The closest papers to ours are Banfi and Villena-Roldan (2019) and Marinescu and Wolthoff (2020) who use data from Chile and the United States, respectively, to document that, conditional on

[4]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; Arnold et al., 2023; Batra et al., 2023), job-specific skill requirements (Deming and Kahn, 2018; Hershbein and Kahn, 2018), and the role of information in job applications (Belot et al., 2019).

appropriate vacancy-level skill controls, vacancies that post higher wages receive more applications. We replicate this finding in the cross-section, document novel heterogeneities by vacancies' occupation and applicants' characteristics, and confirm the directed search pattern using quasi-experimental variation in minimum wages. Both papers also 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 non-wage amenities from job ad texts and showing directed search based on amenities. Also, the fact that application portfolios are diversified is, to the best of our knowledge, novel to this literature. While the aforementioned papers exclusively rely on cross-sectional variation in wages, another strand of literature has causally established 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.[5]

This paper also contributes to the literature on non-wage amenities and compensating differentials. Recent structural analyses of the role of non-wage amenities in wage determination proceed by adding structure to a wage residual, usually giving form to a scalar "amenity index" estimated from equilibrium data (e.g., Sorkin, 2018; Taber and Vejlin, 2020; Lamadon et al., 2022; Morchio and Moser, 2023; Roussille and Scuderi, 2024). While useful for understanding the aggregate role of compensating differentials on cross-sectional wage dispersion, these papers do not open the "black box" of amenities. Different papers have tried to explicitly elicit willingness to pay for specific non-wage job attributes, either using survey data, quasi-experimental designs, structural work, or controlled experiments, sometimes rejecting the existence of a scalar amenity index (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 advertised amenities from job ad texts, using the methodology outlined in Adamczyk et al. (Forthcoming). Our estimated effects of advertised amenities on applications are consistent with estimates of willingness to pay for non-wage job attributes. Importantly, our analysis also suggests substantial heterogeneity by occupation, applicant, and amenity, hinting at the existence of heterogeneous preferences for non-wage amenities and the rejection of a scalar (rather than vector-valued) amenity index.

Finally, this paper contributes to the vast empirical 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, papers have studied the effects of minimum wages on other margins of adjustment including, for example, prices (Allegretto and Reich, 2018; Harasztosi and Lindner, 2019; Leung, 2021; Ashenfelter and Jurajda, 2022; Renkin et al., 2022), productivity (Riley and Bondibene,

[5]A related literature studies the link between vacancy duration and wages (Bassier et al., 2023; Mueller et al., 2023).

2017; Mayneris et al., 2018; Coviello et al., 2022; Dustmann et al., 2022; Emanuel and Harrington, 2022; Ku, 2022; Ruffini, Forthcoming), and profits (Draca et al., 2011; Harasztosi and Lindner, 2019; Drucker et al., 2021; Vergara, 2023). We provide evidence on a complementary margin that can help firms buffer minimum wage shocks: the effect on job applications (Holzer et al., 1991; 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. (2023), and with recent evidence on positive effects of minimum wages on search effort (Piqueras, 2023). Contrary to the discussion in Clemens (2021), we estimate null effects on advertised amenities. Finally, the fact that the estimated additional applicants are relatively unskilled together with the lack of estimated effects on vacancy requirements does not align with previous findings on skill upgrading (Butschek, 2021; Clemens et al., 2021).[6]

Structure of the paper Section 2 describes the institutional setting and the data. Section 3 provides cross-sectional (descriptive) evidence on application patterns. Section 4 presents the results of the causal analysis that exploits variation in minimum wages. Finally, Section 5 concludes.

2 Institutional Setting and Data

This section describes the institutional setting studied in this paper and the data used in the empirical analysis. It also provides descriptive statistics of our sample of interest.

2.1 Institutional setting

Uruguay is located in South America and its population reached 3.5 million in 2020. The country performs above the Latin American average for a range of socio-economic indicators (UNDP, 2022) and has been classified since 2012 as a high-income country according to the World Bank (World Bank, 2022). A large majority of the Uruguayan population lives in urban areas. In 2020, 73.5% of employment took place in the services sector, followed by manufacturing (18.2%) and agriculture (8.3%). The public sector represents around 15% of employment. Informal employment in Uruguay is comparatively low relative to the Latin American region, and the share of the population covered by at least one type of social protection benefit is 93.8% (ILO, 2022). Especially 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.

[6]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).

2.2 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 during the period 2010 to 2020. BJ operates in more than 30 countries around the world and is a leading online job board in Uruguay. Its effective coverage is estimated to capture around 60% of total online vacancies in the country (Escudero et al., Forthcoming).

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 posted, 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 need to include in their profile their personal information, employment histories, employment status, educational attainment (including degrees and certifications), 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 additional variables derived through NLP models as described by Adamczyk et al. (Forthcoming) and Escudero et al. (Forthcoming). 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. Descriptive statistics for the variables created are presented in Section 2.3.

First, we estimate whether job ads advertise non-wage amenities by looking at keywords and expressions that are unique to specific amenity categories. We predefine a list of categories by adapting the definitions of Maestas et al. (2023) and Sockin (2024) to vacancy data and the Uruguayan context. We start with a list of 16 amenities but, throughout the paper, we focus on the 5 amenities that are estimated to be advertised on at least 5% of the vacancies in our sample[7]: "bonuses and commissions" (including various forms of financial incentives and rewards aimed at compensating employees based on their achievements), "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

[7]The other amenities are rarely advertised (see Table B.1 of Appendix B), with only 5% of vacancies advertising at least one of the remaining 9 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.

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). The NLP procedure requires job ads' texts to have at least 15 words (Atalay et al., 2020). Only 1.1% of the vacancies in our sample have descriptions that do not meet this requirement. We code these vacancies as not advertising any amenity. For the remaining 98.9% of vacancies in our sample, 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 forms of expressions), 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 classification 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 also 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. (Forthcoming), 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–which 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. 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 (ML) techniques such as Gradient Boosting models were also used to identify the vacancy-level and applicant-job-spell level occupation (Escudero et al., Forthcoming). Vacancy-level occupations were recovered using both job ads and job 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.

2.3 Descriptive statistics

In the remaining of the section, we provide descriptive statistics to depict a more comprehensive picture of the BJ platform and the vacancy and applicants' samples used in the subsequent empirical exercises.

Vacancies For the period 2010-2020, 87,030 vacancies were posted in BJ. 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. This leaves us with 86,896 vacancies. As shown in Figure B.1 of Appendix B, 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.[8] This restriction leads us to drop 8,916 additional vacancies, so our final sample consists of 77,980 posted vacancies.

Figure 1 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., Forthcoming). 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 additional 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 that are looking to hire several workers, 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. We also note that some vacancies attach a minimum value that is essentially non-informative (i.e., close to zero), so we impute the wage reference as missing whenever the advertised

[8] As it is shown in Figure B.1 of Appendix B, in this period, more than 1,500 vacancies were posted during each quarter (with the exception of early 2020), and the number of different applicant profiles making positive applications grew from more than 30,000 in 2011 to around 50,000 in 2016 and subsequent years.

wage is lower than 1,000 Uruguayan pesos (as of 2020).[9]

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. Meanwhile, other requirements are specified in the open text of job ads, which are elicited using NLP and ML techniques as described in Section 2.2. We observe that 80% of vacancies require at least one cognitive skill. Likewise, 83% of vacancies require at least one socio-emotional skill, and 38% require at least one manual skill.

Applicants Panel (b) of Table 1 presents descriptive statistics of the applicants registered in the BJ platform. We identify 698,880 profiles in the 2010-2020 period, of which 410,955 are denoted as "active" profiles, i.e., individuals who made at least one application in the period October 2011 to September 2020.[10] To get a sense of the order of magnitude, the total population in Uruguay was estimated to be 3,530,912 in 2020, of which 2,067,384 (59%) was between 20 and 64 years old (INE, 2021). This implies that the total number of profiles created represents approximately 34% of the working-age population in Uruguay in 2020. 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% have completed a college degree. The median applicant was born in 1990. While the overall educational structure resembles that of the national labor force, BJ applicants tend to have higher educational attainment levels on average. They also include a disproportionate number of younger workers (Escudero et al., Forthcoming).

Applications 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.

Amenities Table 2 shows descriptive statistics for the amenities advertised in our sample of vacancies. 45% of the vacancies in our sample advertise at least one of the 5 amenities described in Section 2.2. The average number of amenities advertised is 0.7, which can be decomposed as 55% of vacancies advertising zero amenities, 27% advertising one, 12% advertising two, 4% advertising three, and less than 2% ad-

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

[10] 244,960 profiles report no application in the 2010-2020 period, while 42,965 only made applications between January 2010 and September 2011 and/or October 2020 and December 2020.

vertising four or five amenities. The share of vacancies advertising amenities is larger among vacancies that do not post wages (46% versus 39%). Table 2 also shows that the three most commonly advertised amenities are "human capital development", "working in teams", and "work environment/impact on society", which are featured in 23%, 19%, and 16% of vacancies, respectively. "Bonuses and commissions" and "schedule flexibility" are advertised in 7% and 5% of the vacancies, respectively.

3 Cross-Sectional Facts on Job Applications

Having described the setting and the data, we proceed with the cross-sectional analysis. We perform three exercises. First, we explore how diverse application portfolios are in terms of industries and occupations. Second, we explore whether posted wages affect applications. Third, we explore the role of advertised non-wage amenities in the application process. We pay particular attention to heterogeneity analyses at the applicant, vacancy, and amenity levels during the analysis.

3.1 How diverse are application portfolios?

To study application portfolios, we analyze the universe of applications made to the vacancies considered in our analysis. To proxy groups of applications made in the same job search spell, we consider an applicant ID-by-quarter-by-year as a unit of observation (applicants may have their profiles active for several years, thus applying to jobs in different job search spells). If application spells are longer than a quarter, our measure will underestimate the number of applications by search spell. This strategy leads to 1,668,348 applicant-by-spell observations with at least one application. Through the lens of the statistics reported in Table 1, this number implies that, on average, an active profile makes applications in 4.1 different quarters between 2011 and 2020. There is, however, substantial heterogeneity. 34.4% of the applicant profiles are active only in one quarter, 37.4% between 2 and 4 different quarters, 16.0% between 5 and 8 quarters, 6.4% between 9 and 12 quarters, and 5.8% in 13 or more different quarters.[11]

Number of applications Figure 2 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. Dis-

[11] Applicants who are active only for one quarter may be different than the average applicant. For example, they may enter the BJ website but then use it less actively as they quickly find employment. In Figure B.2 of Appendix B, we show that the distributions of the number of applications are indeed slightly different between applicants who are active only during one quarter compared to the applicants who are observed for several quarters. However, in Figure B.4 of Appendix B, we also show that the results of this subsection are robust to excluding the applicant IDs that are observed only for one quarter.

tributions look remarkably similar across demographic groups, especially with respect to gender. While employed and college-educated applicants tend to make fewer applications on average than unemployed and non-college-educated applicants, they still show wide dispersion in the number of applications.

Diversity in applications Having established that applicants are heterogeneous in the number of applications made by spell, we then explore whether applications made by a given applicant in a given quarter tend to target vacancies in specific industries or occupations or if, instead, their applications are diversified across industries and occupations. This analysis can inform about the extent of directed search in the labor market: if workers are strongly attached to particular industries and occupations and, therefore, their behavior is less responsive to wage differentials across industries and occupations, we would expect to see their job applications concentrated within narrow categories of vacancies.

We explore diversification in application portfolios using the following statistic. Let i index observations (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 the number of groups spanned by the N_i applications of applicant i.[12] 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:

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

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, taking into account the heterogeneity in the number of applications documented above.

We study diversification focusing on four different groups of vacancies. We first consider a narrow definition of vacancy groups that share their 2-digit industry code and their 1-digit occupation code, thus employing a stricter definition of a possibly relevant labor market.[13] If industry-by-occupation cells constitute an accurate definition of the relevant local labor market of the applicant, we should expect job seekers to make the majority of their applications to vacancies in the same industry-by-occupation cell.[14] We also consider broader group definitions of relevant labor markets: 2-digit industry codes alone,

[12] Formally, $\#g_i$ can be thought of as the cardinality of the partition of N_i in the space of G.

[13] We follow the categorizations of ISCO 08 for occupations and ISIC Rev. 4 for industries.

[14] The usual definition of a local labor market also considers a geographical dimension (e.g., Manning and Petrongolo, 2017). We disregard this dimension since more than 50% of the country lives in the metropolitan area of Montevideo, the

1-digit industry codes alone, and 1-digit occupation codes alone.

Figure 3 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. Figure B.3 of Appendix B shows results for $N_i \in \{1, ..., 50\}$, which displays a similar pattern.[15] Two aspects of the figure are worth highlighting. First, 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. This result implies that job seekers rarely target industry-by-occupation cells when making applications. Second, 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.[16]

The fact that industries seem to be more diversified than occupations is worth highlighting. It implies that it is more accurate to think that, when applying, workers fix occupations and arbitrage industries than the other way around, suggesting that directed search is plausible. For the very least, the analysis rejects the hypothesis that applicants target labor markets defined by narrow industry-by-occupation cells, which would limit their sensitivity to wage differentials across industries. In that spirit, the analysis suggests that industry-wage differentials (Krueger and Summers, 1988; Card et al., 2024) cannot be rationalized by workers having strong attachment to particular industries. On the contrary, it suggests that industry wage differentials may give form to a job ladder.

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 2 may partially reflect an aversion to diversification for a subset of applicants. However, 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

capital city, and the data does not allow us to do a more granular analysis within the city.

[15] When applicants make too many applications, $\mathcal{D}(N)$ is more likely to be mechanically affected by $\#G$, affecting the interpretability of $\mathcal{D}(N)$ in the tail of the distribution.

[16] 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.

and occupations, shows that significant numbers of applicants are, in fact, diversifying their applications. Diversification seems indeed substantial even conditional on only making 2 applications. Then, if this concern is driving the results, we should observe all applicants making a unique application, a pattern that is strongly rejected in Figure 2.[17]

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 4 shows the results split by occupation of the current job and number of applications made in the job search spell. As a benchmark, if applications were made randomly, the share of applications targeted to vacancies attached to the same occupation would match the distribution of posted vacancies displayed in Panel (b) of Figure 1. Figure 4 shows that job seekers in all occupations display shares larger than the benchmark suggested by Figure 1, which implies that workers apply more often to vacancies attached to their current occupations. However, 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.[18] This pattern is observed even for applicants who make only 1 application in a given job search spell. This result is consistent with recent findings in Altmann and Sebald (2024) and Fluchtmann et al. (Forthcoming).

3.2 Cross-sectional patterns of directed search

The fact that job seekers have diversified application portfolios suggests they may direct their search based on characteristics other than occupation and industry. This subsection explores directed search patterns based on posted wages. As mentioned previously, among our sample of 77,874 vacancies, 15,835 (20.3%) include a salary range in the posted ad. On average, vacancies that post a wage receive 21% more applications (with a median of 29%) relative to those that do not include wage information. While the distribution of industries and occupations is similar between vacancies that post and do not post wages (see Figure 1), the difference in applications suggests that the decision to post a wage may be endogenous. In Section 4, we therefore complement the analysis below with quasi-experimental results to provide further ground for a causal interpretation of the effects of wages on applications.

[17] Figure B.5 of Appendix B 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. Per the concern described above, differences in diversification by applicant characteristics may be partially reflected by the differential distributions in the number of applications observed in Figure 2.

[18] Figure 4 displays no clear differential pattern by number of applications.

Applications and wages We start by non-parametrically exploring the relationship between log applications and log posted wages, pooling all vacancies that post a wage in our dataset.[19] Figure 5 shows different binscatter 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 by 2-digit industry fixed effects, year fixed effects, and the advertised non-wage amenities in the vacancy. 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 suggest 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 in terms of cross-sectional wage-application elasticities, we run OLS regressions of the following type:

$$\log \text{App}_j = \alpha \log w_j + X_j'\beta + \epsilon_j, \tag{2}$$

where App_j is the number of applications per opening for vacancy j, w_j is the posted wage of vacancy j, and X_j are vacancy-level controls. We cluster standard errors at the 2-digit industry level.

Panel (a) of Table 3 shows the estimate of α under different sets of controls, resembling the analysis in Figure 5. 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 amenities. Including this set of 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 5, omitting the upper tail increases the elasticity to 0.33. Finally, as a robustness check, Column (6) leverages the fact that several firms in the platform post multiple vacancies and, therefore, considers only vacancies posted by firms with 10 or more posted vacancies and includes firm fixed effects. 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.[20] We note that our analysis

[19] 1.6% (260) of vacancies advertising a wage had zero applications and are, therefore, excluded from the analysis. Replicating the exercise in levels to include the vacancies with zero applications yields equivalent results.

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

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 the aforementioned papers, possibly because they use job titles as the skill control which are substantially narrower than 1-digit or 2-digit occupational codes. The sensibility of the estimated elasticity to the included controls, however, provides a similar narrative in qualitative terms.[21]

In most of the exercises that follow, we report results for the same different sets of controls and sample refinements. Given the lessons from related literature and the results of Panel (a) in Table 3, however, we designate the specification of Column (3) (no outliers, 2-digit industry fixed effects, year fixed effects, advertised 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 One caveat of the analysis above is that it pools all vacancies when estimating the cross-sectional wage-application relationship. It could be the case, however, that different occupations react differently to posted wages. For example, findings in Hall and Krueger (2012), Caldwell and Harmon (2019), and Lachowska et al. (2022) suggest that wage posting is more prevalent in low-wage occupations relative to wage bargaining, a feature that could mediate how job seekers attached to different occupations interpret and react to posted wages in online job ads. To explore for occupational heterogeneities, we replicate the analysis separately by 1-digit occupation categories.

Figure 6 presents binscatter 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 amenities. The data reveals the existence of two groups of occupations that display opposite patterns. Panel (a) shows results for clerical support, services and sales, plant and machine operators, and elementary occupations. We denote this group of occupations as *lower-skill*. Vacancies in this group exhibit a monotone and positive relationship between applications and posted wages. Panel (b) shows results for managers, professionals, technicians and associate professionals, and craft workers. We denote this group of occupations as *higher-skill*. 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

[21] Table B.2 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 presumably more relevant to job seekers to decide on applications relative to the maximum.

clear positive correlation between applications and posted wages, whereas the higher-skill group displays no such relationship.[22]

Table B.3 in Appendix B presents estimates of equation (2) separate by 1-digit occupation group, confirming the patterns displayed in Figure 6. Panel (b) of Table 3 summarizes the results by replicating Panel (a) of Table 3 using a model with interactions:

$$\log \text{App}_j = \alpha_{LS} \log w_j \times 1\{\text{Occ}_j \in LS\} + \alpha_{HS} \log w_j \times 1\{\text{Occ}_j \in HS\} + X_j'\beta + \epsilon_j, \tag{3}$$

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 6. 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). On the contrary, 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 regression with no interactions.

One possible explanation for this pattern is that higher-skill vacancies impose more requirements on applicants in terms of formal qualifications or skills, which could prevent job seekers to apply to high-wage higher-skill vacancies. In fact, Table B.4 of Appendix B shows that requirements are generally more prevalent in higher-skill vacancies. Table B.5 of Appendix B, however, shows that the heterogeneous pattern across occupation groups holds after restricting the sample to vacancies that post requirements, either in terms of formal qualifications (Panel (a)) or skills (Panel (b)). That is, even conditional on posting a requirement, directed search appears to be prevalent in lower-skill vacancies and absent in higher-skill vacancies.

[22] We refer to the two data-driven occupational groups as lower- and higher-skilled for the sake of exposition clarity and consistency with existing economic literature (e.g., Kunst et al., 2022; Montobbio et al., 2023) while acknowledging the limitations of skill-based categories based on broad occupation codes. At a high level, this categorization is aligned with the ISCO-08 guidelines (ILO, 2012), which classifies the four 1-digit occupations in our lower-skilled group at the lowest skill levels 1 and 2, and three of the four 1-digit occupations in our higher-skilled group (managers, professionals, and technicians and associate professionals) at the highest skill levels 3 and 4. In the ISCO-08 guidelines, skill levels are determined based on the complexity and range of tasks and duties typically associated with an occupation, as well as the level of formal education required to perform those tasks. This classification system relies on a broad generalization of tasks and duties typically performed within an occupation without accounting 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 (Konings and Vanormelingen, 2015; Attanasio et al., 2011; Alfonsi et al., 2020). It is worth noting that our higher-skill group includes craft and related trades workers which ISCO-08 classifies at skill level 2. One possible explanation for why craft and trades workers exhibit similar application patterns to the rest of occupations in the higher-skill group is the level of wages. This occupation typically commands a higher average salary compared to other occupations classified at a similar ISCO skill level 2 (see Table B.12 of Appendix B).

Applicant-level heterogeneity Finally, we leverage our applicant-level data and test whether directed search patterns are heterogeneous by applicant characteristics. We proceed in two ways. First, we estimate equation (3) 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, amenity controls, and 1-digit occupation fixed effects. While the larger responsiveness in vacancies attached to lower-skill occupations relative to 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 ($\widehat{\alpha}_{LS} = 0.61$) 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 and skill level. Columns (1) to (3) of Panel (b) reveals larger responsiveness for applicants with tertiary education, especially for job seekers with a college degree ($\widehat{\alpha}_{LS} = 0.83$). Columns (4) to (6) show that applicants with cognitive, socio-emotional, and manual skills, are also more responsive to posted wages, both in low- and higher-skill occupation vacancies.[23]

It is noteworthy that the groups of applicants with presumably worse labor market prospects exhibit negative higher-skill elasticities. This finding is consistent both with models of directed search where workers trade-off wages with job search spell length (e.g., Moen, 1997) and with models with on-the-job search where the lack of outside options may encourage workers to apply to low-wage jobs to climb the job ladder in future 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 the importance of labor market experience to access higher paying jobs.

As a second exploration for applicant-level heterogeneity in directed search behavior, we use application-level data to test whether applicant demographics predict the log posted wage of the vacancy they are applying to conditional on being a vacancy that posts wage. Let i index applicants and j index vacancies.

[23] One caveat of this exercise is that not all vacancies receive applications that span the complete distribution of applicants observables. As a consequence, the number of vacancies considered in each regression is not constant. We opt to report these results since standard fixes such as using $\log(1 + \text{App}_j)$ or the inverse hyperbolic sine transformation of applications as dependent variables may induce bias in the implied elasticity (Chen and Roth, 2024).

Then, for all applications made to vacancies that post a wage, we estimate:

$$\begin{aligned}\log w_{ij} &= \alpha_F \text{Female}_i + \alpha_E \text{Employed}_{ij} + \alpha_A \text{Age}_{ij} + \alpha_V \text{Voc.Trn.}_i + \alpha_C \text{College}_i \\ &\quad + \alpha_{CS} \text{Cogn.Sk.}_{ij} + \alpha_{SK} \text{Soc.Sk.}_{ij} + \alpha_{MS} \text{Man.Sk.}_{ij} + X_j'\beta + \epsilon_{ij}, \qquad (4)\end{aligned}$$

where Age_{ij} is applicant i's age when applying to vacancy j; and Female_i, Employed_{ij}, Voc.Trn._i, College_i, Cogn.Sk._{ij}, Soc.Sk._{ij}, and Man.Sk._{ij} are indicator variables taking the value of 1 if applicant i is, respectively, female, employed when applying to the vacancy, has a vocational training degree, has a college degree, and reports having cognitive, socio-emotional, and manual skills when applying.[24] As above, X_j contains vacancy-level controls which may include industry fixed effects, year fixed effects, advertised amenities, and occupation fixed effects. Standard errors are clustered at the applicant level. One advantage of this approach relative to the vacancy-level exercise reported in Table 4 is that, by controlling simultaneously for all applicant characteristics, it can better isolate the partial correlation of a specific attribute. If applicant characteristics are correlated with each other, the exercise above may be picking similar variation across columns, spuriously attributing results to particular characteristics.

Table B.6 of Appendix B shows the results. The analysis is consistent with the results of the vacancy-level analysis of Table 4. Estimates are all significant and remarkably stable across specifications, suggesting that applicant-level heterogeneity is not driven by differential sorting to vacancies. The preferred specification (Column (3)) suggests the following point estimates, with little variation across columns. Relative to male job seekers, female job seekers apply to vacancies that post 5.7% lower wages. Relative to the unemployed, employed applicants apply to vacancies that post 5.2% higher wages. Being one year older predicts a 0.6% higher posted wage. Relative to applicants with no tertiary education, applicants with vocational training and a college degree apply to vacancies that post, on average, 3.9% and 10.8% higher wages, respectively. Likewise, applicants with cognitive skills, socio-emotional skills, and manual skills, apply to vacancies with 5.3%, 0.7%, and 1.5% higher posted wages, respectively.

3.3 The role of non-wage amenities

The analysis above focused on the relationship between applications and wages, in some cases controlling for the amenities advertised in the vacancy. It does not, however, explore the concrete role amenities play for job seekers, which may yield a deeper understanding of the previously shown heterogeneities in the results on wages. Then, in this third exercise, we explore correlations that inform the role of non-wage amenities in the application process. We start by exploring correlations between posted wages and amenities. We then analyze how amenities correlate with applications and show heterogeneities by amenity, vacancy characteristics, and applicants' characteristics.

[24] In our data, formal education indicators are time-invariant. However, skills variables are time-variant since they are built from current employment and, in the case of unemployed individuals, employment histories.

Posted wages and amenities To document correlations between advertised amenities and posted wages, we estimate OLS regressions of the form:

$$\log w_j = \sum_{a \in \mathcal{A}} \alpha^a \mathrm{Am}_j^a + X_j' \beta + \epsilon_j, \tag{5}$$

where $\mathcal{A}$ includes bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development, and $\mathrm{Am}_j^a = 1\{\text{Vacancy } j \text{ advertises amenity } a\}$. We also consider regressions that only include $\mathrm{Am}_j = 1\{\text{Vacancy } j \text{ advertises at least 1 of the 5 amenities}\}$. The potential set of controls is the same as in the previous subsection, and we keep clustering standard errors at the 2-digit industry level. We also consider the natural extension of equation (3) where we test whether the correlation vary with occupational group:

$$\log w_j = \sum_{a \in \mathcal{A}} \alpha_{LS}^a \mathrm{Am}_j^a \times 1\{\mathrm{Occ}_j \in LS\} + \sum_{a \in \mathcal{A}} \alpha_{HS}^a \mathrm{Am}_j^a \times 1\{\mathrm{Occ}_j \in HS\} + X_j' \beta + \epsilon_j. \tag{6}$$

Table 5 presents the estimates of equation (5). Panel (a) shows that advertising at least one amenity is negatively correlated with posted wages. In our preferred specification, vacancies that advertise at least one amenity post, on average, 4% lower wages. If the amenities considered are valued by job seekers, this result suggests that amenities play a role in rationalizing wage dispersion, as suggested by Sorkin (2018), Lamadon et al. (2022), and Morchio and Moser (2023). A quantitative assessment of the degree of compensating differentials, however, is beyond the scope of this paper since it would require estimating willingness to pay for amenities to interpret the magnitude of the coefficients in terms of job utility (Maestas et al., 2023). By looking at Column (6), we note that the inclusion of firm fixed effects tend to both substantially attenuate the estimated elasticity and increase the R^2, suggesting that an important part of the variation in the wage-amenity bundle (conditional on occupation) is between firms.

Panel (b) of Table 5 shows that there is important heterogeneity by amenity in its correlation with posted wages, both in terms of signs and magnitudes. Advertising bonuses and commissions is associated with lower posted wages ($\widehat{\alpha}^a = -0.093$ in our preferred specification). Advertising schedule flexibility exhibits a more sizable relationship with posted wages ($\widehat{\alpha}^a = -0.299$). Work environment/impact on society also shows a negative semi-elasticity ($\widehat{\alpha}^a = -0.065$). Conversely, working in teams is positively associated with posted wages ($\widehat{\alpha}^a = 0.055$). The same pattern is true, albeit noisier, for human capital development ($\widehat{\alpha}^a = 0.027$).[25] The heterogeneity in sign and magnitude across amenities makes even more difficult the translation from these cross-sectional correlations to their implications for inequality in job rents, as different amenities may be valued differently (Maestas et al., 2023; Sockin, 2024).

Table 6 presents the estimates of equation (6) using the "at least one amenity" indicator, where

[25] Interestingly, work environment/impact on society shows a precisely estimated null relationship conditional on firm indicators, which suggests that it is a purely firm-level rather than job-level non-wage attribute.

we test whether these correlations vary between lower- and higher-skill occupations. We find that the negative correlation is concentrated in lower-skill occupations, with a semi-elasticity of -5.7% in our preferred specification. For higher-skill occupations, the correlation between advertising at least one amenity and the posted wage is a precisely estimated zero. Table B.7 of Appendix B, however, shows that this average effect masks substantial heterogeneity by amenity. When compared to the results of Panel (b) in Table 5, the zero average effect on higher-skill occupations seems to be driven by a more negative correlation between posted wages and bonuses and commissions and work environment/impact on society, and especially by a much larger positive correlation with working in teams and human capital development. Semi-elasticities for lower-skill occupations are generally more nuanced and aligned with the aggregate results displayed in Table 5. Interestingly, and in contrast to what is observed for higher-skill occupations, lower-skill occupations show no relationship between posted wages and advertised possibilities of human capital development.

Applications and amenities While providing estimates of willingness to pay for each amenity is beyond the scope of this paper, the following exercise indirectly explores, through a revealed preference logic, the value workers put on amenities by assessing their effect on job seekers' applications. To document correlations between amenities and applications, we estimate analogs of equations (2) and (3) but using the amenity indicators as the main right-hand-side variables of interest:

$$\log \mathrm{App}_j = \sum_{a \in \mathcal{A}} \alpha^a \mathrm{Am}_j + X_j' \beta + \epsilon_j, \tag{7}$$

$$\log \mathrm{App}_j = \sum_{a \in \mathcal{A}} \alpha^a_{LS} \mathrm{Am}_j \times 1\{\mathrm{Occ}_j \in LS\} + \sum_{a \in \mathcal{A}} \alpha^a_{HS} \mathrm{Am}_j \times 1\{\mathrm{Occ}_j \in HS\} + X_j' \beta + \epsilon_j. \tag{8}$$

We also explore whether the relationship between amenities and applications is mediated by the wage-posting status of the vacancy, by estimating the following modified version of equation (3):

$$\log \mathrm{App}_j = \sum_{a \in \mathcal{A}} \alpha^a_W \mathrm{Am}^a_j \times \mathrm{Post}_j + \sum_{a \in \mathcal{A}} \alpha^a_N \mathrm{Am}^a_j \times (1 - \mathrm{Post}_j) + X_j' \beta + \epsilon_j, \tag{9}$$

where $\mathrm{Post}_j = 1\{\text{Vacancy } j \text{ posts a wage}\}$. Finally, we provide estimates of a "saturated model" where we explore all the cross-interactions between lower- and higher-skill occupation indicators and Post_j. All regressions that allow for heterogeneous effects of amenities by wage-posting status control for Post_j.

Table 7 shows the estimates of equation (7). Panel (a) shows that vacancies that advertise at least one amenity receive more applications. Our preferred specification suggests a semi-elasticity of 6.9%. Panel (b) shows that the application effect vary with amenity, although estimates become smaller, noisier, and sensitive to the inclusion of controls. The only amenity that systematically exhibits a positive and significant semi-elasticity is working in teams, with a semi-elasticity of 7% in the preferred specification.

The attenuation observed after the introduction of industry and, especially, occupation fixed effects may be explained by either amenities being idiosyncratic to industry-occupation cells, thus experiencing little variation within cell, or by substantial heterogeneity across vacancies in the role of specific amenities that, if working in opposite directions, may lead to small and noisy average effects.

To explore the latter hypothesis, we proceed with the estimation of equations (8), (9), and the saturated model. Estimates for the indicator of advertising at least one amenity are shown in Table 8. Separate estimates by amenity are reported in Tables B.8, B.9, and B.10 of Appendix B.

We first discuss heterogeneities by occupational group. Panel (a) of Table 8 shows that advertising at least one amenity has a positive effect on applications in both occupational groups, however, the effect seems larger for higher-skill occupations ($\widehat{\alpha}^a_{LS} = 0.047$ and $\widehat{\alpha}^a_{HS} = 0.093$ in the preferred specification). Table B.8 of Appendix B shows starker differences between lower- and higher-skill occupations when looking at individuals amenities. Bonuses and commissions negatively affect applications to lower-skill vacancies ($\widehat{\alpha}^a_{LS} = -0.051$), while having a large positive relationship with applications to higher-skill vacancies ($\widehat{\alpha}^a_{HS} = 0.25$). A similar pattern is observed regarding schedule flexibility (negative effect on lower-skill occupations and vice versa), although the semi-elasticities are small in magnitude and non-statistically significant in most of the specifications. These results suggest that variable pay and flexibility may have different implications for utility depending on the occupation. For example, in lower-skill occupations, bonuses and commissions may constitute the primary source of earnings, potentially introducing income volatility and uncertainty. On the contrary, in higher-skill occupations, bonuses and commissions often form part of incentive schemes that supplement (rather than replace) base salary. Similarly, schedule flexibility in lower-skill occupations 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. On the contrary, work environment/impact on society shows a large and significant positive effect on lower-skill occupations ($\widehat{\alpha}^a_{LS} = 0.105$) and a small, unstable, and non-significant effect on higher-skill occupations. 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.

We turn next to explore heterogeneities by wage-posting status. Panel (b) of Table 8 shows that the application effect of posting at least one amenity is driven by vacancies that do not post a wage. When posting a wage, the estimated semi-elasticity is a precisely estimated zero. On the contrary, the estimated semi-elasticity is 8.7% for vacancies that do not post a wage. This result suggests that job seekers may implement a lexicographic application strategy: they base their application on posted wages and, when absent, they predict job characteristics based on the vacancy description. There are two pieces of evidence in related literature that are consistent with this pattern. 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 posted 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. Then, information contained in job ads may be secondary to the posted wage, which could rationalize lexicographic job search preferences. In Panel (c) of Table 8 we show that the lexicographic pattern is driven by lower-skill occupations. Advertising at least one amenity has a negative and significant effect on applications in lower-skill vacancies with posted wage (-7.2%), while the effect of amenities is positive in lower-skill vacancies with no posted wage (8.5%) and higher-skill vacancies regardless of the wage posting status (14.5% and 8.9%).

Tables B.9 and B.10 of Appendix B report similar results for the individual amenities. Similar patterns emerge. Bonuses and commissions are negatively related with applications to lower-skill vacancies with posted wages, do not affect applications to lower-skill vacancies with no posted wage, and increase applications to higher-skill vacancies regardless of the wage-posting status. Schedule flexibility also exhibits negative effects for lower-skill vacancies with posted wage but positive effects for the rest of the groups, especially for higher-skill vacancies with posted wage. Working environment/impact on society does not affect applications to vacancies with posted wages, but positively affect applications to lower-skill vacancies with no posted wage. Working in teams seems to significantly affect applications in all groups of vacancies, and the effect of human capital development seems positive but small and usually non-significant.

Applicant-level heterogeneity Finally, as in the previous subsection, we explore for heterogeneities by applicants' characteristics using both the vacancy-level strategy previously illustrated in Table 4 and the application-level strategy previously illustrated in Table B.6 of Appendix B, but using the amenity indicators as the main variables of interest.

Table 9 shows the results of the vacancy-level analysis focusing on the indicator of advertising at least one amenity, where we estimate equation (7) using applications from specific groups of applicants as the dependent variable. There is little heterogeneity across applicants on the relationship between applications and advertising at least one amenity. The notable exception is age, where young workers show large responsiveness (semi-elasticity of 9.5%), contrary to older workers who exhibit no response.[26] This result mirrors the findings related to posted wages, where older workers were more responsive, thus suggesting a life-cycle evolution of the relative valuation of wages and amenities. Alternatively, this result

[26] This finding seems to contradict Maestas et al. (2023), who argues that job amenities matter more for workers at older ages. This comparison comes with two caveats. First, physical activity plays a role in Maestas et al. (2023) result. This disamenity is not considered in our analysis. Second, our sample of applicants is relatively young, so the dispersion in age that determines the groups is not comparable to the aforementioned paper.

may reflect cohort effects, with recent cohorts caring more about amenities. Workers with cognitive and socio-emotional skills also display larger effects relative to the aggregate effect displayed in Table 7.

Table 10, however, shows that different groups of applicants react differently to specific amenities. Columns (1) and (2) of Panel (a) report substantial gender differences. Female applicants are more responsive to vacancies that advertise bonuses and commissions and 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. Specifically, 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., 2024). 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 with bonuses and commissions and 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 skilled applicants resemble the patterns of applicants with tertiary education.

Finally, Table B.11 of Appendix B provides application-level estimates of applicant-level heterogeneity in the relationship between applications and amenities. Regressions are analogs of equation (4) that use different indicators of advertised amenities as dependent variables, thus testing whether applicant demographics predict the amenities of the vacancy they are applying to. This exercise confirms the result discussed above. Relative to male, female applications are more frequently targeting vacancies that advertise bonuses and commissions, schedule flexibility, and work environment/impact on society, and less frequently vacancies that advertise working in teams and human capital development. Similarly, relative to the unemployed, applications from employed job seekers are more likely to target vacancies that advertise working in teams and human capital development, and less likely to target vacancies that advertise bonuses and commissions, schedule flexibility, and work environment/impact on society. Tertiary education and cognitive skills yield a similar prediction, with particularly large point estimates for job seekers with a college degree. Job seekers with socio-emotional skills positively predict all amenities (except schedule flexibility), while job seekers with manual skills negatively predict all amenities. Finally, age at the time of application has a negative effect on all amenities.

3.4 Summary of findings and discussion

In this section, we documented several cross-sectional facts on job applications that suggest heterogeneous patterns of directed search across applicants and jobs.

First, we reject that applicants concentrate applications in narrow groups of vacancies and, instead, show that some job seekers apply to several vacancies and generally diversify applications in terms of occupations and, especially, industries. This descriptive fact, which, to the best of our knowledge, has not been documented before, suggests that job seekers consider a broad set of jobs when making applications, thus directing their search based on job attributes that go beyond the industry-occupation tag.

Building from that finding, and consistent with previous literature (Banfi and Villena-Roldan, 2019; Marinescu and Wolthoff, 2020), we show that applications react to posted wages once we condition on the occupation of the vacancy. Novel to the literature, we find a stark and robust heterogeneity in directed search patterns between lower-skill (clerical support, services and sales, plant and machine operators, and elementary occupations) and higher-skill (managers, professionals, technicians, and craft workers) vacancies. Within lower-skill vacancies, applicants systematically direct their search toward vacancies that pay higher wages. The contrary is observed for higher-skill vacancies, where no relationship is found between posted wages and applications. This heterogeneity is consistent with recent evidence of heterogeneous incidence of wage posting and wage bargaining across occupations (e.g., Hall and Krueger, 2012; Caldwell and Harmon, 2019; Lachowska et al., 2022) if those findings imply that posted wages in higher-skill occupations provide less information to applicants than posted wages in lower-skill occupations. Also novel to the literature, we find that the directed search pattern for lower-skill occupations is stronger for male, employed, older, educated, and skilled applicants.

Finally, when looking at the role of non-wage amenities, we also find evidence supporting directed search behavior based on advertised amenities. We present a battery of novel correlations that, with several subtleties, give form to two main high-level takeaways that deserve further exploration.

First, we find that application patterns in lower-skill vacancies are consistent with "lexicographic" preferences for jobs. That is, while amenities tend to attract applicants in higher-skill vacancies, they only attract applicants in lower-skill vacancies when the vacancy does not post a job. This finding is also consistent with the incidence of wage posting in lower-skill occupations, where the posted wage is more likely to be interpreted as a "sufficient statistic" for the job attributes relative to higher-skill occupations. Second, we provide evidence of substantial heterogeneity in the role of non-wage amenities for rationalizing posted wages and applications across amenities, occupations, wage posting status, and applicant characteristics. Consistent with related literature (e.g., Lindenlaub and Postel-Vinay, 2022; Maestas et al., 2023; Sockin, 2024), these results reject the existence of a single amenity index that affects the application process. While some models allow for preference heterogeneity and, therefore, allow for multiple job rankings based on individual preferences (e.g., Morchio and Moser, 2023; Roussille and Scuderi, 2024), the modeled preference is exercised over a scalar (rather than vector-valued) measure of amenities that our results suggest may be misspecified.

4 The Causal Effect of Wages on Applications

The results presented in the previous section support the existence of directed search patterns within the labor market for vacancies associated with lower-skill occupations. The cross-sectional nature of the analysis, however, prevents us from ruling out alternative narratives related to selection bias into posting and unobserved heterogeneity. This section validates our central finding of occupational heterogeneity in directed search by estimating the causal effect of wages on applications using exogenous variation in minimum wages.

4.1 Setting and data

Collective Bargaining Agreements Uruguay has a long tradition of strong unions that set industry-by-occupation minimum wages in collective bargaining agreements (CBAs) that coexist with a uniform national minimum wage (NMW).[27] 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 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 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).

The NMW is determined by the central government, applies to all private-sector employees aged 18 and older, and sets a general wage floor. In addition, wage councils determine sectoral CBAs through bargaining rounds, which give rise to industry-by-occupation minimum wages above the NMW (Marinakis, 2016). 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

[27] For a detailed description of Uruguay's labor market institutions and their history see Mazzuchi (2009) and ILO (2014).

expectations of future inflation, adjustments for past inflation not accounted for in previous negotiations, and additional increases aimed at restoring pre-crisis real wages, particularly for occupations with a large share of low-wage workers. 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 7 below). Importantly, 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 7 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, there are the above-mentioned subgroups that 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 increase in coverage. Panel (b) shows the distribution and evolution of the number of wage floors defined within CBAs. As explained before, groups have autonomy to define the categories that will be affected by the sectoral minimum wages defined in the CBAs. The number of categories corresponds to the number of occupations with a fixed minimum wage in the CBA. 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. Some groups defined more than a hundred categories, which explains the distance between the median and the average. The number of categories within CBAs is very stable over time. Finally, Panel (c) 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. This feature will be important for our empirical strategy below.

CBAs data As our last data source, we rely on information on 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.

One caveat when merging the CBAs data with the BJ data is that 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 4-digit ISIC codes to each subgroup, and 2-digit ISCO occupation codes to each category within the contract. One problem with this approach is that 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 4-digit ISIC codes apply. Likewise, within the group "Food and beverages manufacturing", there are different CBAs for "Wheat Mills" and "Rice Mills", which can be associated to the same 4-digit industry code. A similar issue occurs with the categories within each CBA: one minimum wage can be associated with several 2-digit occupation codes, and several minimum wages can be associated with the same 2-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 summary statistics (such as the average, the minimum, or different quantiles) of all minimum wages that can be associated to a specific industry-occupation combination. Then, we code whether, on a given date, there is a change in the computed statistic.[28] 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 (according to the ISIC Rev. 4 classification) and the 1-digit occupational level (according to the ISCO 08 classification).

Economic significance of the minimum wage across occupations Our causal analysis aims to assess whether we can replicate the occupational heterogeneity in directed search patterns we found earlier in the cross-section. This exercise requires occupation-specific minimum wages to bind in all occupations. To validate this assumption, we use survey data to explore whether minimum wages are differentially binding across occupations. Table B.12 of Appendix B shows that higher-skill occupations exhibit higher average wages than lower-skill occupations but also higher minimum wages. The ratio between average hourly minimum wages and median hourly wages compares well across the different occupations, ranging from 6% to 18%. This suggests that the economic significance of the minimum wage is indeed comparable for the two occupational groups.

[28]Since CBAs change in a coordinated fashion, the measure of exposure does not depend on the choice of the statistic.

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 (c) of Figure 7). 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. This pattern of adjustments gives rise to natural 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 standard event-study specifications. As a robustness check, we also estimate models using a within-vacancy design where the units of observation are vacancies that experience a minimum wage increase while active (see Section 4.3).

Our strategy may be interpreted as conservative for two reasons. First, as discussed above, we do not observe the exact minimum wage that is attached to each vacancy. 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 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.

Estimating equations 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; Gardner, 2021; Baker et al., 2022; Dube et al., 2023). 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 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:

$$Y_{it} = \sum_{\tau=-3}^{2} \beta_\tau D_{i\tau e(t)} + \alpha_{ie(t)} + \gamma_{j(i)t} + X_{it}'\rho_{e(t)} + \epsilon_{it}. \tag{10}$$

Y_{it} is an outcome of interest 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 (c) of Figure 7), whose effect is allowed to vary by event.[29] 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 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 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 (10) 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 non-wage amenities, and share of vacancies posting job requirements.

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

$$Y_{it} = \beta T_{ie(t)} \times \text{Post}_t + \alpha_{ie(t)} + \gamma_{j(i)t} + X_{it}'\rho_{e(t)} + \epsilon_{it}, \tag{11}$$

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 (10). The coefficient of interest in this specification is β.

[29] Following Cengiz et al. (2019, 2021), 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 11 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 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 8 shows the estimated β_τ coefficients of equation (10) with their corresponding 95% confidence intervals. Panel (a) shows the event study that pools all vacancies. The plot suggests that 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 12 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 aspects of this result are worth discussing. First, it is remarkable how the quasi-experimental exercise, despite yielding conservative estimates, mirrors the cross-sectional finding of heterogeneous patterns of directed search across occupations. This is especially true given the differences between the used variation, design, and set of vacancies. 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 documented in the empirical monopsony literature (Sokolova and Sorensen, 2021). This benchmark is reassuring given the reasons for which we expect attenuation bias in our regressions.

Robustness checks and within-vacancy design Table 12 provides some robustness checks to our main estimates. For the sake of brevity, we focus the discussion 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.[30]

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 allows us to refine the previous analysis as it controls for vacancy fixed effects and thereby captures time-invariant unobserved heterogeneity at the vacancy level. At the same time, since vacancies are usually open during only one month or less (see Table 1), we are not able to transparently assess the parallel trends assumption. The sample size, moreover, 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.8 of Appendix B).[31] This pattern implies that we need to restrict to vacancies that have been open for a few days when the minimum wage change kicks in. Given these advantages and limitations, we see the within-vacancy design as a complement to the previous analysis, where we are interested in whether the main conclusions hold across the two empirical strategies.

Our baseline sample of vacancies used in the within-vacancy design consists of the 2,129 vacancies (2.7% 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.13 of Appendix B shows descriptive statistics.

[30]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.

[31]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.

With this sample, we estimate the following regression:

$$Y_{jt} = \beta_{LS} T_j \times \text{Post}_t \times 1\{\text{Occ}_j \in LS\} + \beta_{HS} T_j \times \text{Post}_t \times 1\{\text{Occ}_j \in HS\} + \alpha_j + \gamma_t + \varepsilon_{jt}, \tag{12}$$

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.14 of Appendix B shows the results. We estimate regression (12) for different sub-samples 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 were recently posted.

Heterogeneity by applicant characteristics Table 13 presents results of equation (11) 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

In the remainder of the section, we discuss results for complementary dependent variables.

Vacancies and openings The positive effect of minimum wages on applications may come at the expense of a contraction in labor demand in terms of 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. Analog to the elusive employment effect estimated in related literature (Manning, 2021a), Figure 9 and Table 12 show that we do not find any detectable effect on vacancies and openings. 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 non-wage amenities If providing amenities is costly for firms, advertised non-wage amenities could decrease after the minimum wage increase (Clemens, 2021). We test this hypothesis by estimating similar models as above using the share of vacancies that advertise non-wage amenities as the dependent variable. Figure B.6 and Table B.15 of Appendix B suggest the absence of negative responses on advertised amenities. The only advertised amenity that exhibits a non trivial negative implied elasticity is bonuses and commissions, however, the event studies suggest that the negative effect is possibly driven by differential pre-trends.

Vacancy requirements Finally, firms could react to increased labor costs by becoming more selective in terms of education and skills requirements. Evidence of this narrative has been presented by Butschek (2021) and Clemens et al. (2021). We test for this hypothesis by estimating similar models as above using the share of vacancies that impose requirements as the dependent variable. Figure B.7 and Table B.16 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 Conclusions

In this paper, we assess patterns of directed search in job applications, focusing on the role of posted wages and advertised non-wage amenities. Using rich data from a prominent online job board in Uruguay, we are able to provide a series of empirical facts on job applications.

First, we document substantial heterogeneity across applicants in the number of applications they send within an application spell, and find a large degree of diversification in terms of the occupations and industries of the vacancies they apply to within job seekers that send multiple applications. Second, we find robust evidence of directed search based on posted wages that is driven by vacancies attached to lower-skill occupations, with applications to vacancies attached to higher-skill occupations showing no responsiveness to posted wages. The directed search pattern is found to be stronger for male, employed, older, college-educated, and skilled job applicants. Finally, by applying text analysis to the job ads, we elicit advertised non-wage amenities and find they play a key role in the application process. We find evidence of directed search based on amenities and show that applications to lower-skill vacancies are consistent with lexicographic job preferences where amenities affect applications only when wages are not posted. We also find substantial heterogeneity on the role of non-wage amenities by amenity, occupation, and applicant characteristics, thus rejecting the existence of a scalar (rather than vector-valued) relevant index of job-specific amenities.

The occupational heterogeneity in directed search 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 exercise also suggests the absence of responses in the number of vacancies, openings, advertised amenities, or vacancy requirements after minimum wage increases.

Our findings help inform several mechanisms behind the search-and-matching process in the labor market. They are consistent with models of directed search and suggest that industry- and firm-wage differentials can be rationalized by the existence of rents rather than by strong worker attachment to industries. They moreover unveil important occupational heterogeneities, which are consistent with the larger incidence of wage posting (rather than bargaining) in lower-skill occupations that has been documented in related literature.

Based on our findings, several avenues of future research may be worth pursuing. First, it seems promising to explore the fundamental differences between occupations more deeply. While we conjecture that the differential incidence in wage posting can explain these differences, further research is needed to depict a clearer picture of that pattern. Second, we have been able to exploit plausibly exogenous variation in wages, but additional causal analyses that rely on exogenous variation in amenities would further enhance the understanding of the job application process. Beyond their potential for informing economic theory, such analyses have practical value in that they shed light on how certain governmental interventions and firms' recruitment strategies may affect the applicant pool.

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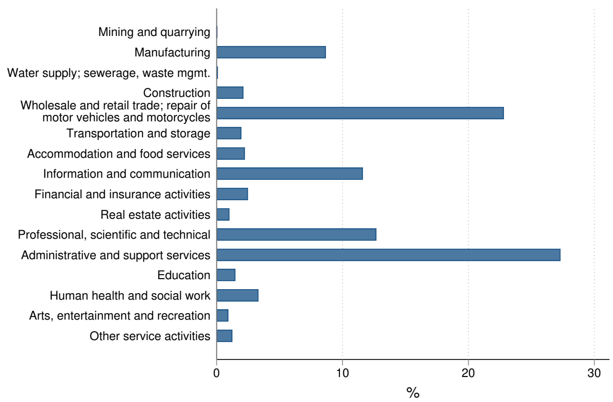
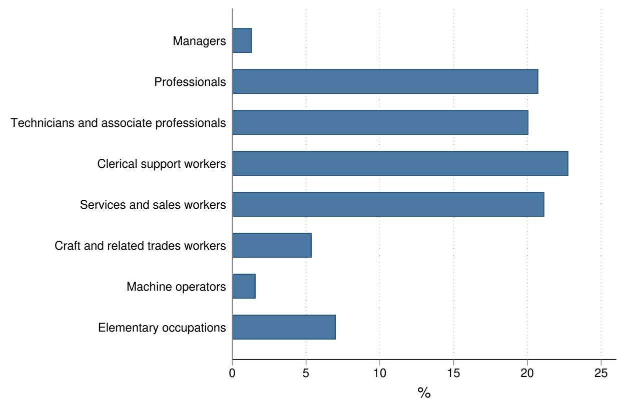
Figures and Tables

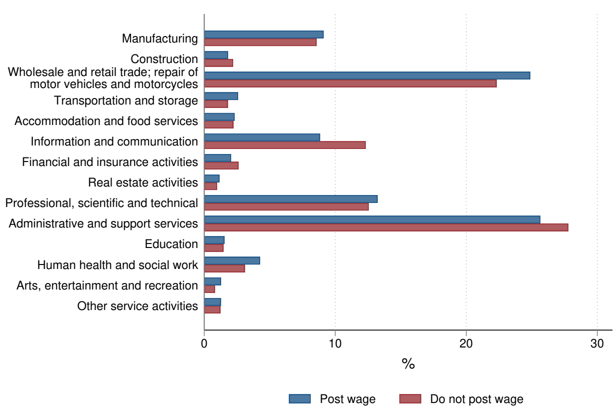
Figure 1: Distribution of BJ Vacancies: Industries and Occupations



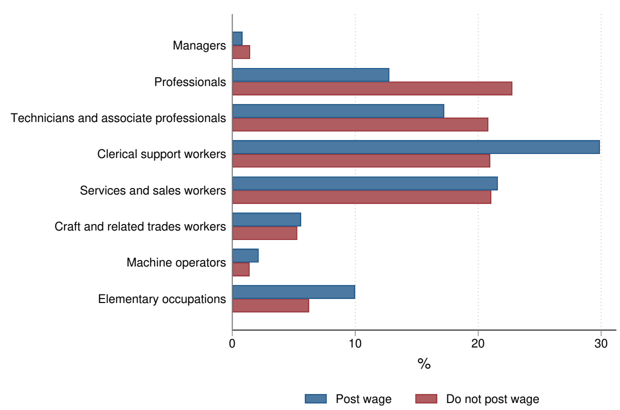
(a) Industry



(b) Occupation



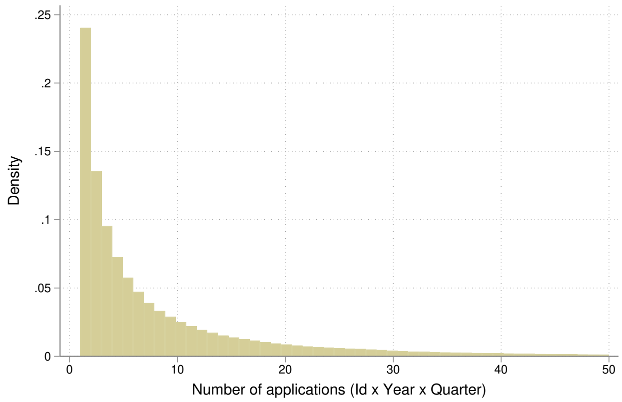
(c) Industry, by posting status



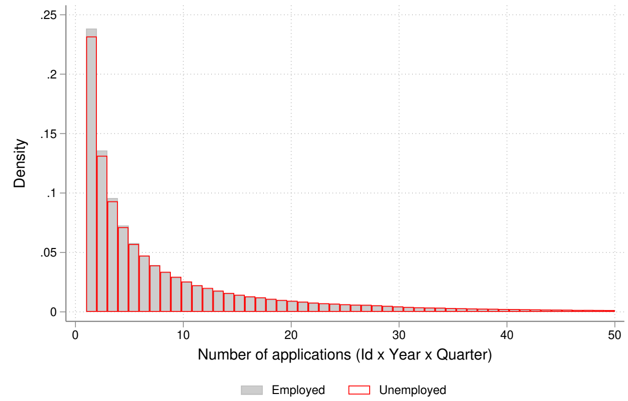
(d) Occupation, by posting status

Notes: This figure plots the distribution of industries and occupations of our sample of vacancies. Panel (a) shows the distribution of vacancies over one-digit industries (ISIC Rev. 4). Panel (b) shows the distribution of vacancies over one-digit occupations (ISCO-08). Panels (c) and (d) replicate Panels (a) and (b) by showing these distributions separately for vacancies that post and do not post a wage. Industries and occupations for which there are no vacancies in the BJ data are omitted from the figures.

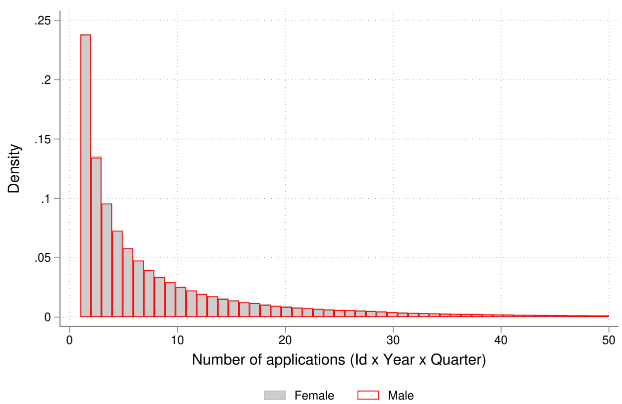
Figure 2: Distribution of Number of Applications at the Applicant-by-Spell Level



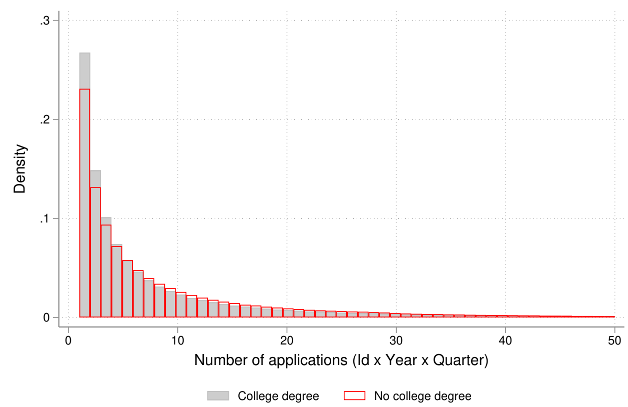
(a) All applicants



(b) By employment status



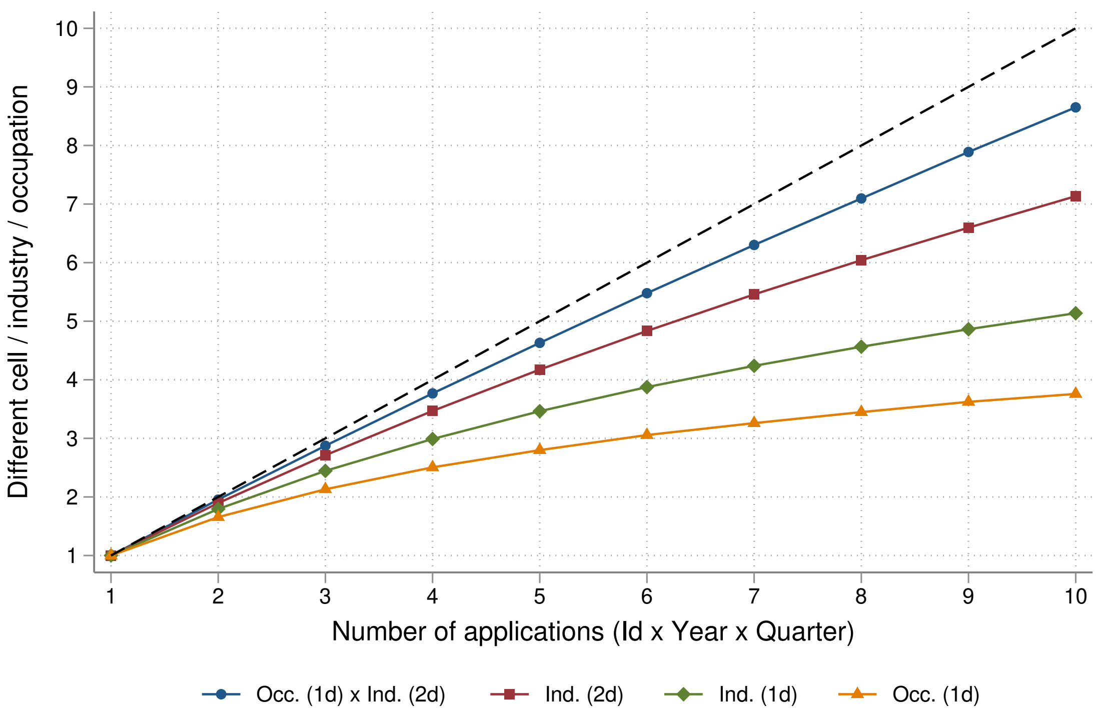
(c) By gender



(d) By education

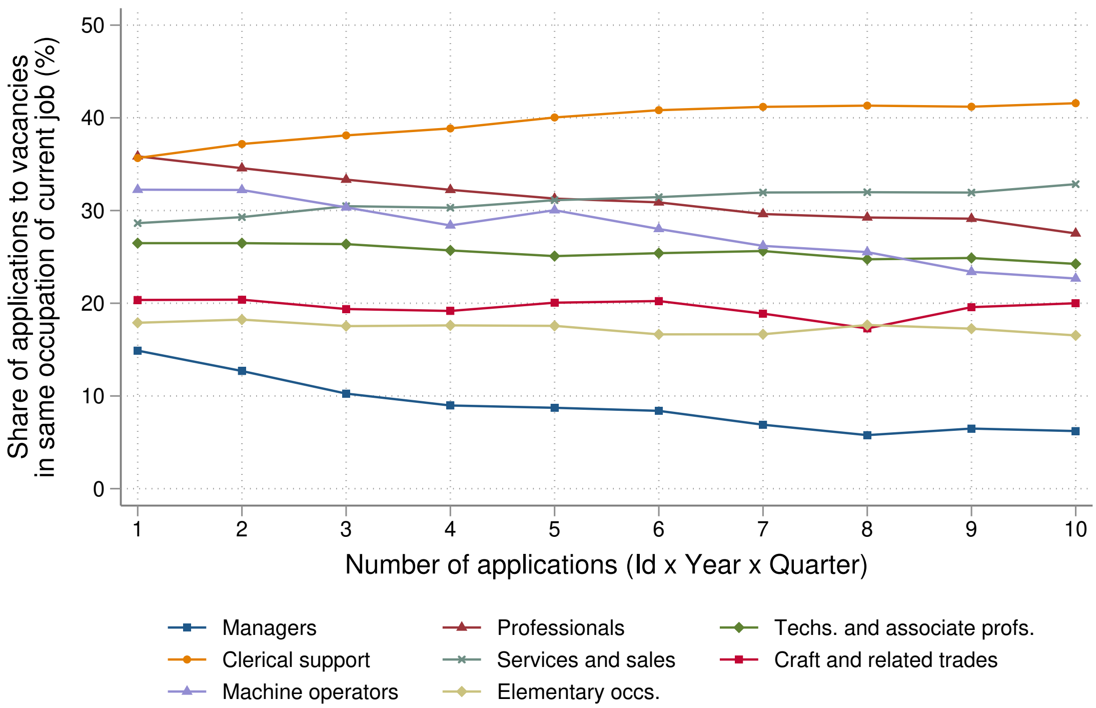
Notes: This figure shows histograms for the number of applications made by applicants in a quarter-by-year to our final sample of posted vacancies (see Section 2 for details on the sample restrictions). Panel (a) considers all applicants. Panel (b) distinguishes applicants by employment status. Panel (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.

Figure 3: Portfolio Diversification: Different Groups



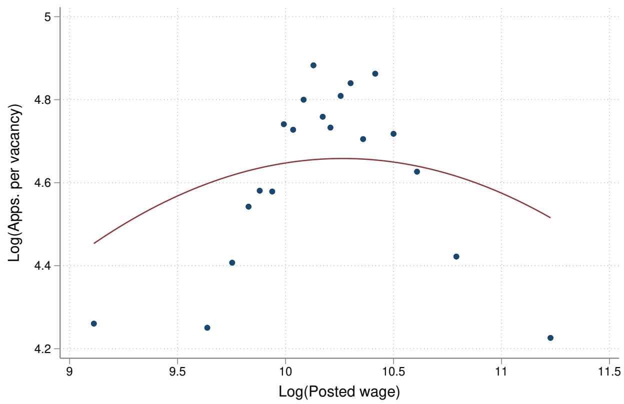
Notes: This figure plots the statistic described in equation (1), the average number of "groups" individuals apply to in each quarter-by-year, as a function of the total number of applications made in the quarter-by-year to our final sample of posted vacancies (see Section 2 for details on the sample 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.

Figure 4: Share of Applications to Vacancies in Same Occupation of Current Job

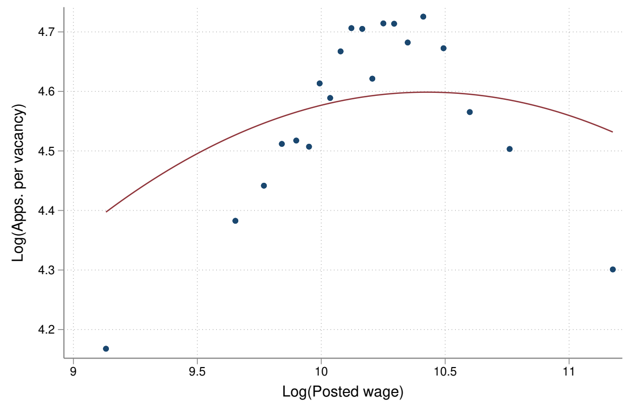


Notes: This figure plots the share of applications made to vacancies attached to the same 1-digit occupation of the current employment as a function of the total number of applications made in the quarter-by-year to our final sample of posted vacancies (see Section 2 for details on the sample restrictions). By construction, this figure only considers applicants who report being employed in the quarter-year of the application.

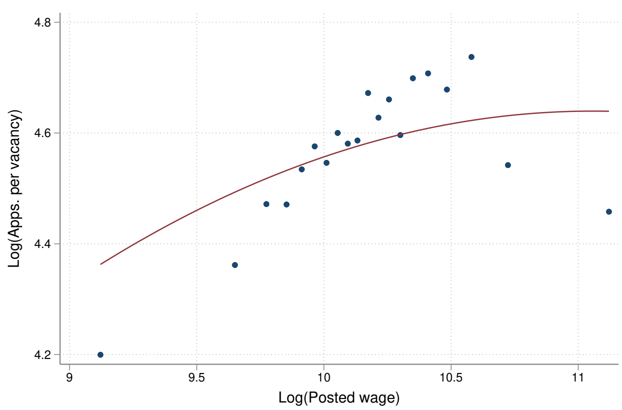
Figure 5: Cross-Sectional Relationship Between Applications and Posted Wages (All Vacancies)



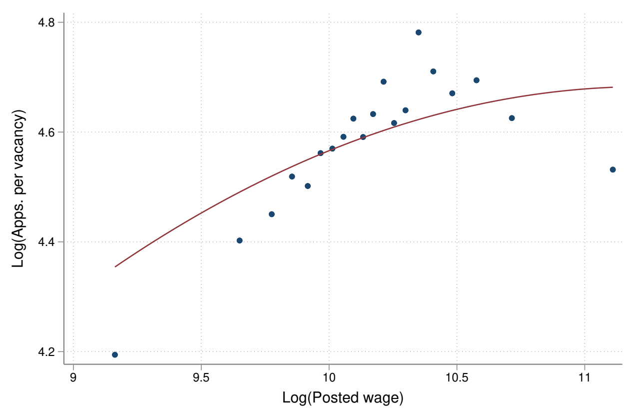
(a) No controls



(b) Industry FEs, year FEs, amenities, and no outliers



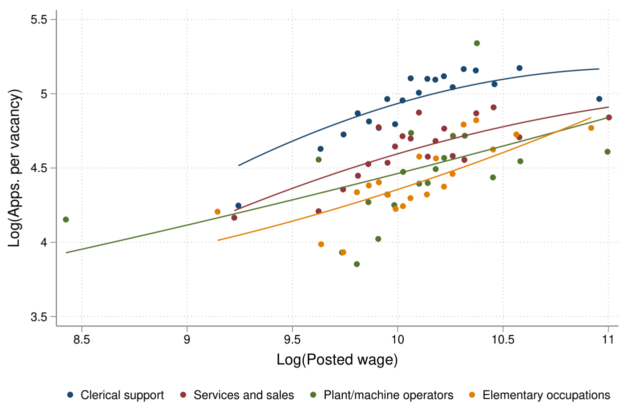
(c) Panel (b) + 1-digit occupation FEs



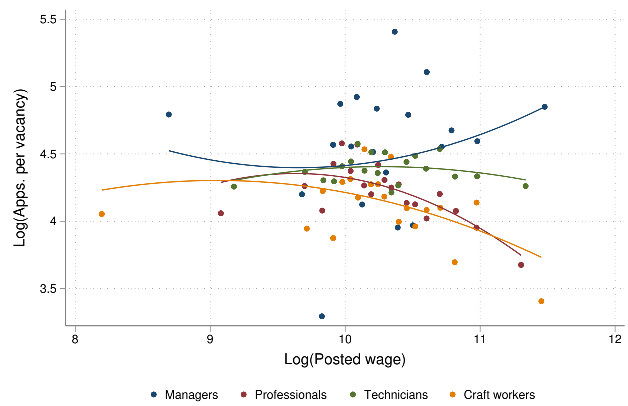
(d) Panel (b) + 2-digit occupation FEs

Notes: This figure shows binned scatterplots and corresponding quadratic fits for the relationship between the log number of applications per vacancy and the log posted wage. The analysis considers all vacancies in our final sample that post a wage (see Section 2 for details on the sample restrictions). Panel (a) does not include controls. Panel (b) excludes vacancies receiving more than 1,000 applications and includes 2-digit industry fixed effects, year fixed effects, and controls for advertised amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). Panels (c) and (d) augment Panel (b) specification by including 1-digit and 2-digit occupational fixed effects, respectively.

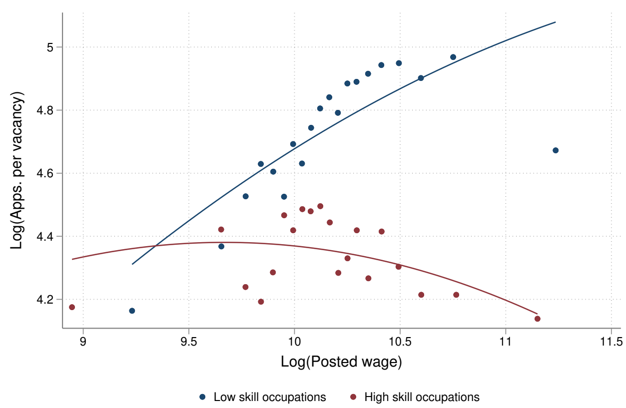
Figure 6: Cross-Sectional Relationship Between Applications and Posted Wages (By Broadly Defined Occupations)



(a) Lower-skill occupations



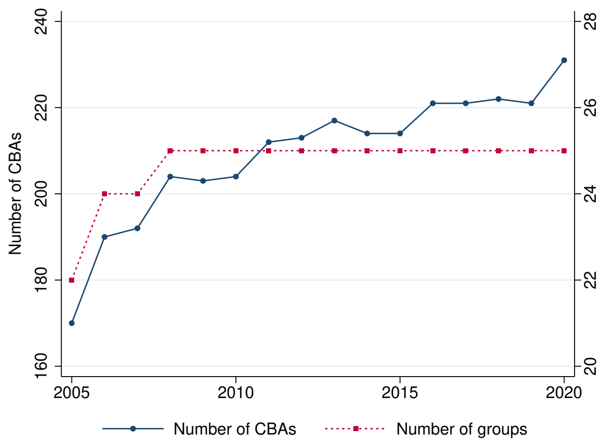
(b) Higher-skill occupations



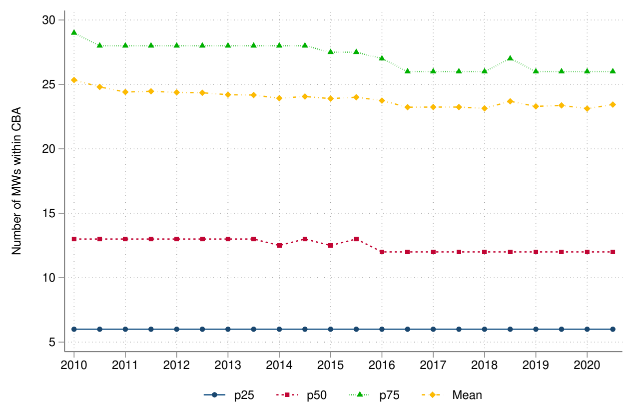
(c) By broad group

Notes: This figure shows binned scatterplots and corresponding quadratic fits for the relationship between the log number of applications per vacancy and the log posted wage separately by occupation. The analysis considers all vacancies in our final sample that post a wage (see Section 2 for details on the sample restrictions). All plots exclude vacancies receiving more than 1,000 applications and include 2-digit industry fixed effects, year fixed effects, and controls for advertised amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). Panel (a) plots the aforementioned relationship for lower-skilled occupations (clerical support, services and sales, plant and machine operators, and elementary occupations). Panel (b) plots the aforementioned relationship for higher-skilled occupations (managers, professionals, technicians and associate professionals, and craft workers). Panel (c) plots the aforementioned relationship separately for the two aggregate occupational groups.

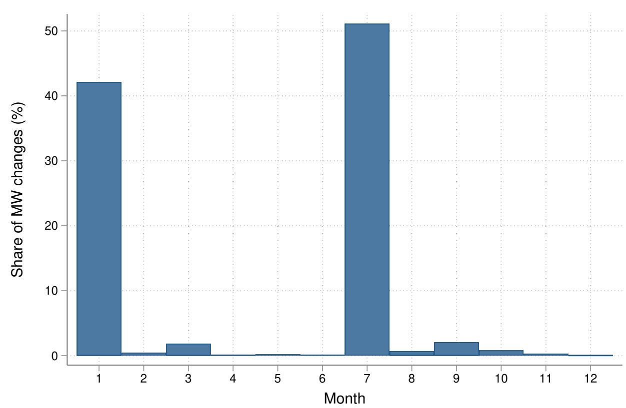
Figure 7: Collective Bargaining Agreements (CBAs): Number of Groups and Subgroups, Minimum Wages within CBAs, and Timing of Minimum Wage Adjustments



(a) Number of CBAs



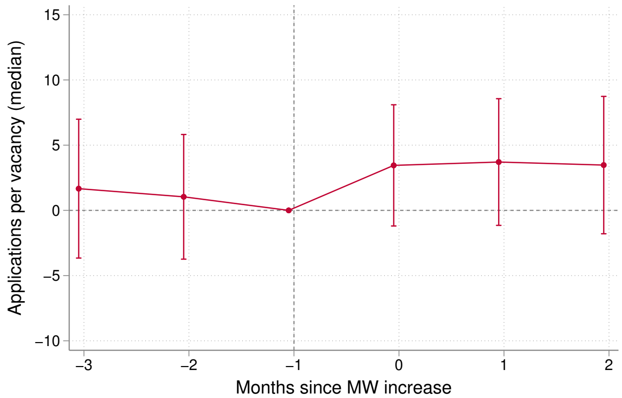
(b) Number of minimum wages within each CBA



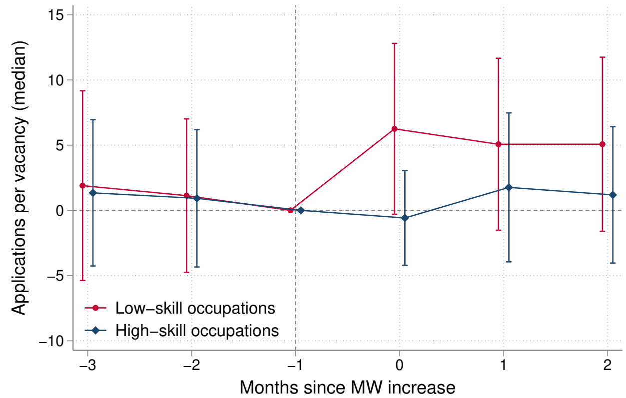
(c) Month of adjustment

Notes: This figure presents descriptive facts on the scheme of CBAs. Panel (a) shows the number of sectoral groups and related subgroups that determine the CBAs by year. Panel (b) shows the distribution of the number of minimum wages that are specified within each CBA by year. Panel (c) shows the monthly distribution of minimum wage adjustments, pooling all changes observed in our period.

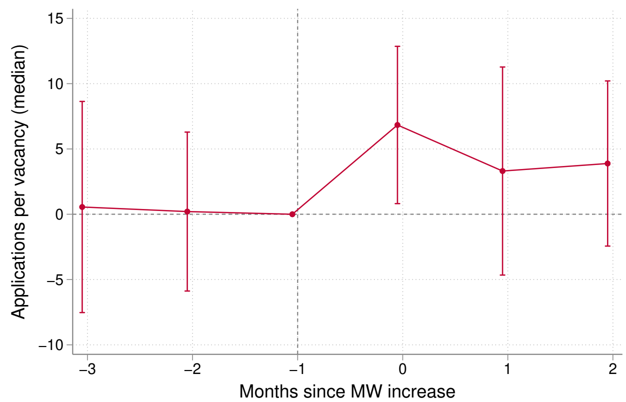
Figure 8: Event Studies: Median Number of Applications per Opening



(a) All vacancies



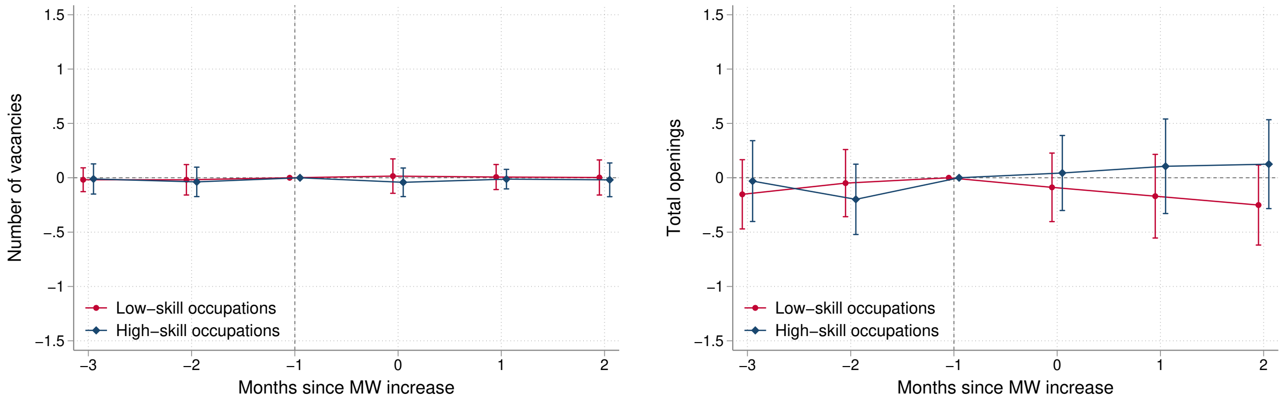
(b) By occupational group



(c) Triple differences

Notes: These figures plot the estimated β_τ coefficients of equation (10) with their corresponding 95% confidence intervals using the median number of applications per vacancy within the sample of vacancies attached to the corresponding industry-by-occupation cell. Panel (a) pools all vacancies. Panel (b) considers interactions with indicators for lower- and higher-skill occupational groups. Panel (c) plots the corresponding triple difference, where the coefficient is interpreted as the difference 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 (see Panel (c) of Figure 7). Standard errors are clustered at the 2-digit industry level.

Figure 9: Event Studies: Total Vacancies and Total Openings



(a) Vacancies (b) Openings

Notes: These figures plot the estimated β_τ coefficients of equation (10) 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 total number of posted vacancies as a dependent variable. Panel (b) uses the total number of openings as the dependent variable. 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 (see Panel (c) of Figure 7). Standard errors are clustered at the 2-digit industry level.

Table 1: Descriptive Statistics for Vacancies, Applicants, and Applications on the BJ platform

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	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. Panel (a) shows statistics for vacancies in our final sample (see Section 2 for details on the sample restrictions). Panel (b) shows statistics for applicants registered in the BJ platform. Panel (c) shows statistics for applicants at the time of application, only considering applications to our final sample of vacancies. In Panel (a), "vocational training" is defined as tertiary-level training, whereas the variable additionally captures lower levels of vocational training in Panel (b).

Table 2: Descriptive Statistics for Amenities

	All vacancies	Posts wage	Does not post wage
At least one amenity	0.45	0.39	0.46
Number of amenities	0.70	0.57	0.73
Individual amenities:			
Bonuses and commissions	0.07	0.07	0.06
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 the amenities advertised in our final sample of vacancies (see Section 2 for details on the sample restrictions). Adverstised amenities were elicited following Adamczyk et al. (Forthcoming). The table details whereas vacancies advertise at least one amenity, the number of amenities advertised per vacancy, and provides information for each of the five individual amenities. Statistics are also shown separately between vacancies that post a wage and vacancies that do not post a wage.

Table 3: Cross-Sectional Patterns of Directed Search

Panel (a): All vacancies

	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\alpha}$	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
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)
$\widehat{\alpha}_{LS}$	0.497	0.464	0.414	0.401	0.531	0.322
	(0.047)	(0.047)	(0.051)	(0.048)	(0.055)	(0.049)
$\widehat{\alpha}_{HS}$	-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
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 of equation (2). Panel (b) presents the estimated $(\alpha_{LS}, \alpha_{HS})$ coefficients of equation (3). The dependent variable is the log number of applications, and the key regressor is the log posted wage, so coefficients are interpreted as cross-sectional elasticities. Column (1) shows results with no controls in Panel (a) and includes a control for the 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 amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). 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 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)
$\widehat{\alpha}_{LS}$	0.142	0.631	0.616	0.281	0.006	0.738
	(0.075)	(0.041)	(0.051)	(0.052)	(0.074)	(0.041)
$\widehat{\alpha}_{HS}$	-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
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)
$\widehat{\alpha}_{LS}$	0.203	0.654	0.833	0.824	0.629	0.664
	(0.057)	(0.044)	(0.050)	(0.053)	(0.051)	(0.042)
$\widehat{\alpha}_{HS}$	-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
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 of equation (3). 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, so coefficients are interpreted as cross-sectional elasticities. 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 amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development), and 1-digit occupation fixed effects. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table 5: Correlation Between Advertised Amenities and Posted Wages

Panel (a): At Least One Amenity

	(1)	(2)	(3)	(4)	(5)	(6)
At least one amenity	-0.034	-0.039	-0.040	-0.037	-0.035	-0.023
	(0.013)	(0.011)	(0.011)	(0.012)	(0.007)	(0.008)
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	0.001	0.037	0.082	0.099	0.064	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 (5). The dependent variable is the log posted wage, and the key regressors are indicators for advertised amenities, so coefficients are interpreted as cross-sectional semi-elasticities. 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 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, year fixed effects, and controls for advertised amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). 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 6: Correlation Between Advertised Amenities and Posted Wages: By Occupation Group

	(1)	(2)	(3)	(4)	(5)	(6)
At least one (lower-skill occ.)	-0.057	-0.058	-0.057	-0.052	-0.045	-0.029
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
At least one (higher-skill occ.)	0.008	-0.003	-0.011	-0.006	-0.014	-0.008
	(0.020)	(0.017)	(0.018)	(0.022)	(0.015)	(0.010)
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	15,835	15,501	15,501	14,626	13,878	10,759
Adj. R^2	0.041	0.066	0.083	0.100	0.064	0.401

Notes: This table presents the estimated $(\alpha^a_{LS}, \alpha^a_{HS})$ coefficients of equation (6). The dependent variable is the log posted wage, and the key regressor is an indicator of advertising at least one amenity, so coefficients are interpreted as cross-sectional semi-elasticities. 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 amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). 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 7: Correlation Between Advertised Amenities and Applications

Panel (a): At Least One Amenity

	(1)	(2)	(3)	(4)	(5)	(6)
At least one	0.043	0.060	0.069	0.078	0.077	0.045
	(0.040)	(0.024)	(0.021)	(0.020)	(0.020)	(0.014)
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	75,928	74,533	74,533	70,592	69,891	58,758
Adj. R^2	0.000	0.067	0.137	0.183	0.183	0.352

Panel (b): By Amenity (Multivariate)

	(1)	(2)	(3)	(4)	(5)	(6)
Bonuses and commissions	0.228	0.117	0.023	-0.038	-0.044	-0.036
	(0.078)	(0.051)	(0.043)	(0.045)	(0.046)	(0.031)
Schedule flexibility	0.043	0.020	0.006	0.026	0.025	-0.010
	(0.026)	(0.023)	(0.027)	(0.026)	(0.026)	(0.028)
Work environment/Impact on society	0.023	0.043	0.033	0.062	0.063	0.050
	(0.054)	(0.039)	(0.035)	(0.029)	(0.027)	(0.013)
Working in teams	0.053	0.054	0.070	0.086	0.085	0.061
	(0.036)	(0.019)	(0.017)	(0.015)	(0.016)	(0.017)
Human capital development	-0.055	-0.014	0.025	0.026	0.027	-0.004
	(0.024)	(0.020)	(0.021)	(0.021)	(0.022)	(0.018)
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	75,928	74,533	74,533	70,592	69,891	58,758
Adj. R^2	0.002	0.068	0.137	0.184	0.184	0.352

Notes: This table presents the estimated α^a coefficients of equation (7). The dependent variable is the log number of applications, and the key regressors are indicators for advertised amenities, so coefficients are interpreted as cross-sectional semi-elasticities. 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 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, year fixed effects, and controls for advertised amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). 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 8: Correlation Between Advertised Amenities and Applications: Heterogeneities

Panel (a): By Occupation Group

	(1)	(2)	(3)	(4)	(5)	(6)
At least one (lower-skill occ.)	0.061	0.042	0.047	0.036	0.035	0.002
	(0.028)	(0.022)	(0.016)	(0.015)	(0.015)	(0.013)
At least one (higher-skill occ.)	0.060	0.091	0.093	0.127	0.128	0.093
	(0.049)	(0.035)	(0.034)	(0.032)	(0.031)	(0.022)
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	0.069	0.112	0.137	0.184	0.184	0.352

Panel (b): By Wage Posting Status

	(1)	(2)	(3)	(4)	(5)	(6)
At least one (post wage)	0.012	0.005	0.007	0.016	0.012	0.073
	(0.033)	(0.027)	(0.024)	(0.024)	(0.024)	(0.023)
At least one (do not post wage)	0.060	0.080	0.087	0.094	0.094	0.040
	(0.041)	(0.024)	(0.022)	(0.021)	(0.020)	(0.015)
Post wage indicator	Yes	Yes	Yes	Yes	Yes	Yes
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	75,928	74,533	74,533	70,592	69,891	58,758
Adj. R^2	0.002	0.069	0.137	0.184	0.184	0.352

Table 8: Correlation Between Advertised Amenities and Applications: Heterogeneities (continued)

Panel (c): By Occupation Group and Wage Posting Status

	(1)	(2)	(3)	(4)	(5)	(6)
At least one (lower-skill occ. + post wage)	-0.069	-0.084	-0.072	-0.067	-0.074	0.005
	(0.037)	(0.031)	(0.027)	(0.027)	(0.028)	(0.019)
At least one (lower-skill occ. + do not post wage)	0.102	0.084	0.085	0.070	0.070	0.002
	(0.030)	(0.023)	(0.019)	(0.018)	(0.018)	(0.017)
At least one (higher-skill occ. + post wage)	0.155	0.150	0.145	0.185	0.208	0.222
	(0.050)	(0.040)	(0.040)	(0.043)	(0.034)	(0.037)
At least one (higher-skill occ. + do not post wage)	0.049	0.087	0.089	0.121	0.120	0.078
	(0.050)	(0.036)	(0.035)	(0.032)	(0.032)	(0.021)
Post wage indicator	Yes	Yes	Yes	Yes	Yes	Yes
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	0.070	0.113	0.137	0.184	0.184	0.352

Notes: Panel (a) presents the estimated $(\alpha^a_{LS}, \alpha^a_{HS})$ coefficients of equation (8). Panel (b) presents the estimated (α^a_W, α^a_N) coefficients of equation (9). Panel (c) presents the analog estimated coefficients for the saturated model with the four interactions. The dependent variable is the log posted wage, and the key regressor is an indicator of advertising at least one amenity, so coefficients are interpreted as cross-sectional semi-elasticities. Column (1) includes a control for the occupational group in Panel (a), a control for wage posting status in Panel (b), and both indicators in Panel (c). Column (2) excludes vacancies receiving more than 1,000 applications and includes 2-digit industry fixed effects, year fixed effects, and controls for advertised amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). 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 9: Applications and At Least One Amenity: 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)
At least one	0.061	0.084	0.076	0.054	0.095	0.018
	(0.032)	(0.021)	(0.020)	(0.020)	(0.022)	(0.019)
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	0.118	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)
At least one	0.046	0.034	0.112	0.116	0.094	0.017
	(0.019)	(0.019)	(0.022)	(0.026)	(0.025)	(0.019)
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	0.198	0.131	0.165	0.157	0.167	0.145

Notes: This table presents the estimated α^a coefficients of equation (7). 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 an indicator of advertising at least one amenity, so coefficients are interpreted as cross-sectional semi-elasticities. 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, and 1-digit occupation fixed effects. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table 10: 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^a coefficients of equation (7). The dependent variable is the log number of applications made by applicants with the characteristic depicted in the column title, and the key regressors are five indicators associated with individual amenities (bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development), so coefficients are interpreted as cross-sectional semi-elasticities. 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, and 1-digit occupation fixed effects. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table 11: 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 of the estimation sample. The unit of observation is a 2-digit industry by 1-digit occupation cell by calendar month. Panel (a) shows summary statistics for all occupations combined. Panel (b) shows summary statistics for the lower-skilled occupational group. Panel (c) shows summary statistics for the higher-skilled occupational group.

Table 12: Difference-in-Differences Results: Applications per Opening, Vacancies, and Openings

Panel (a): All Occupations

	Main Results				Excluding Outliers				Excluding Zeros			
	Med. Apps.	Mean Apps.	Total Vacs.	Total Ops.	Med. Apps.	Mean Apps.	Total Vacs.	Total Ops.	Med. Apps.	Mean Apps.	Total Vacs.	Total Ops.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(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
$\Delta \log \text{MW}$	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.	Mean Apps.	Total Vacs.	Total Ops.	Med. Apps.	Mean Apps.	Total Vacs.	Total Ops.	Med. Apps.	Mean Apps.	Total Vacs.	Total Ops.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(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
$\Delta \log \text{MW}_{LS}$	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
$\Delta \log \text{MW}_{HS}$	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 (11). Panel (b) presents the estimated β coefficients 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 (see Panel (c) of Figure 7). The dependent variables, as depicted in the column titles, include (in levels) the median number of applications, the mean number of applications, the total number of vacancies, and the total number of 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. In each panel, Columns (1)-(4) present the main results, Columns (5)-(8) present results that exclude bin-by-event window observations where the median number of applications exceeded 750, and Columns (9)-(12) exclude bin-by-event window observations for which the outcome is 0 more than 4 months within the event window. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table 13: Differences-in-Difference Results on Applications: Heterogeneity by Applicants Characteristics

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

	Female (1)	Male (2)	Emp. (3)	Unemp. (4)	Age$\leq$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
$\Delta \log \mathrm{MW}_{LS}$	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
$\Delta \log \mathrm{MW}_{HS}$	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
$\Delta \log \mathrm{MW}_{LS}$	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
$\Delta \log \mathrm{MW}_{HS}$	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 (11) in a model that considers interactions with indicators for lower- and higher-skill occupational groups. The dependent variable is the number of applications made by applicants with the characteristic depicted in the column title. 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 (see Panel (c) of Figure 7). 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. 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). Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Directed Search and Non-Wage Amenities: Evidence from an Online Job Board[1]

Online Appendix

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A Methodology for Creating Variables from Free Text Entries

This appendix provides an overview of the methodology used to create variables from free text entries, which is based on Adamczyk et al. (Forthcoming) and Escudero et al. (Forthcoming). We first discuss the creation of skills variables. We then discuss the creation of occupational codes. Finally, we discuss the elicitation of advertised non-wage amenities. Additional details can be found in the aforementioned papers.

A.1 Skills

All skill-related variables are based on the methodology developed in Escudero et al. (Forthcoming). Their approach seeks to provide a comprehensive representation of labor market dynamics across diverse contexts that goes beyond formal qualification measures by covering the skills demanded by employers in job postings 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. In turn, each category is decomposed into sub-categories, giving form to a total of 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 existing literature from labor economics and psychology and has been expanded to adapt it to individual country contexts, with a particular 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 online data within the United States, particularly Deming and Kahn (2018). Other sources used include Heckman and Kautz (2012), Kureková et al. (2016), and Deming and Noray (2020). The first extension is to include manual skills, which are often omitted in U.S.-centered analyses. Then, the second extension expands the conceptual foundations relating to cognitive and socio-emotional skills to facilitate a more comprehensive analysis of online data beyond individuals with high formal qualifications. To achieve these expansions, the taxonomy included additional keywords and expressions drawn from various studies (see Autor et al., 2003; Spitz-Oener, 2006; Almlund et al., 2011; Heckman and Kautz, 2012; Kureková et al., 2016; Hershbein and Kahn, 2018; Atalay et al., 2020; Deming and Noray, 2020), as well as the pilot exercise 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. While some skills subcategories are closely linked, the keywords and expressions used to characterize them are distinct, allowing for the unique identification of skills in the data. 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 the applicability of the retrieved synonyms.

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; S-O
General computer skills	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
Software skills and technical support		
Machine Learning and Artificial Intelligence		
Financial skills		
Writing skills		
Project management		

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; KBHT; 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; KBHT; HK; S-O; 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; S-O

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; S-O; 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; S-O; 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. (Forthcoming), 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), HK for Heckman and Kautz (2012), KBHT for Kureková et al. (2016), and S-O for Spitz-Oener (2006).

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 data present in both the vacancies posted by firms and the job spells of applicants available in their BJ profiles. From vacancy data, the authors elicit the skills that are demanded by the vacancy. From employment history data, the authors elicit the skills applicants report having. The open-text descriptions offer the most viable approach for creating skills variables, as they contain detailed 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. These processes are employed to reformat the text data into a structured format that facilitates the mapping with the skills dictionary.

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. Additionally, we calculated the frequency of keyword occurrences for each skill and use this as an indicator of the degree of intensity with which a particular skill used. See Escudero et al. (Forthcoming) for additional details.

A.2 Occupations

The raw data provided by BJ only classifies vacancies and applicants' job spells into ISCO-08 occupation codes for a limited subset of the data. This missing data problem prevents comprehensive analyses at the occupation level. To solve this problem, Escudero et al. (Forthcoming) employed a similar methodology as the one described aboved to elicit 1- and 2-digit occupational codes for the full sample of vacancies and applicants' job spells. To elicit the occupations posted vacancies seek to fill, the authors leveraged textual information from four open-text fields associated with each vacancy: job title, job description, required level of 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 both vacancies and applicants' job spells already classified by BJ into ISCO-08 occupational codes. The dictionary used originates from the official ISCO-08 international classification. This exercise provided the set of rules used 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 level 1 of the ISCO classification.

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. This process occurs in two steps. 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, 100% of vacancies have an assigned 1-digit occupation code, and 94.8% of them also have a 2-digit occupation code. 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. See Escudero et al. (Forthcoming) for additional details.

A.3 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. (Forthcoming).

To begin, we developed a taxonomy of amenities using the related empirical literature as a starting point and then extending 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 nine job attributes based on the 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.

Given these categories, 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.

We grouped these additional keywords into five broad categories, resulting 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

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.	SS; 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

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. More details are available in Adamczyk et al. (Forthcoming).

To apply this dictionary to the BJ vacancy data, both the terms in the dictionary and the free text

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. (Forthcoming) for additional details. S stands for Sockin (2024), SS for Sockin and Sockin (2019), 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).

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 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.

Out of the 86,062 unique vacancies in the BJ data (total database before applying the filters described in Section 2 to create our final sample of vacancies), 50.6% were assigned at least one amenity. 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), possibly because these

Table A.3: Descriptive statistics of word matches and share of vacancies with amenities

Amenity subgroup	Number of words in the dictionary	Number of words matched	Number of amenities matched	Share of amenities matched (%)
A01–Bonuses and commissions	48	5,988	5,644	6.56
A02–Hourly work or overtime	17	807	787	0.91
A03–Paid time off	42	186	183	0.21
A04–Health insurance	39	39	38	0.04
A05–Retirement contributions	17	33	33	0.04
A06–Food, subsidies and discounts	76	1,513	1,348	1.57
A07–Office space and amenities	39	750	454	0.53
A08–Location and commuting	28	1,516	1,477	1.72
A09–Work equipment and allowances	40	442	439	0.51
A10–Work schedule flexibility	39	5,234	4,835	5.62
A11–Workplace safety	17	925	914	1.06
A12–Job security	21	4,507	4,437	5.16
A13–Work environment and impact on society	83	16,578	15,367	17.86
A14–Physical effort and pace of work	63	2,876	2,804	3.26
A15–Working in teams	16	17,418	16,080	18.68
A16–Human capital development	44	24,896	19,454	22.60
Totals number of words and amenities matched		83,708	74,294	

Notes: Analysis done on the base of 86,062 unique job adverts. See Adamczyk et al. (Forthcoming) for more details.

are legally mandated benefits that may not warrant explicit mention in the Uruguayan context. A comprehensive list of the share of vacancies with the assigned amenity can be found in Table A.3.

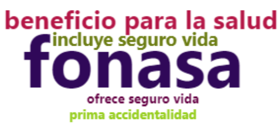
Regarding individual keywords, “trabajar en equipo (teamwork)”, which belongs to the working in teams category, is the most frequently matched (with a total of 12,579 matches). Typically, in each subcategory, a few keywords dominate the majority of matches, with other terms making smaller contributions. 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. It is important to note that the use of keywords and expressions to create amenity variables 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, as well as for a selection of other words deemed necessary by the authors of this study and Adamczyk et al. (Forthcoming). 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.

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

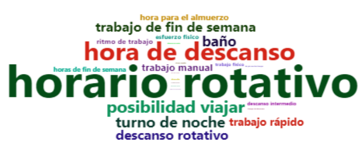
(i) A09–Work equipment

(j) A10–Work schedule flexibility

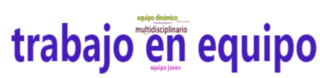
(k) A11–Workplace safety

(l) A12–Job security

(m) A13–Work environment



(n) A14–Physical effort, pace of work



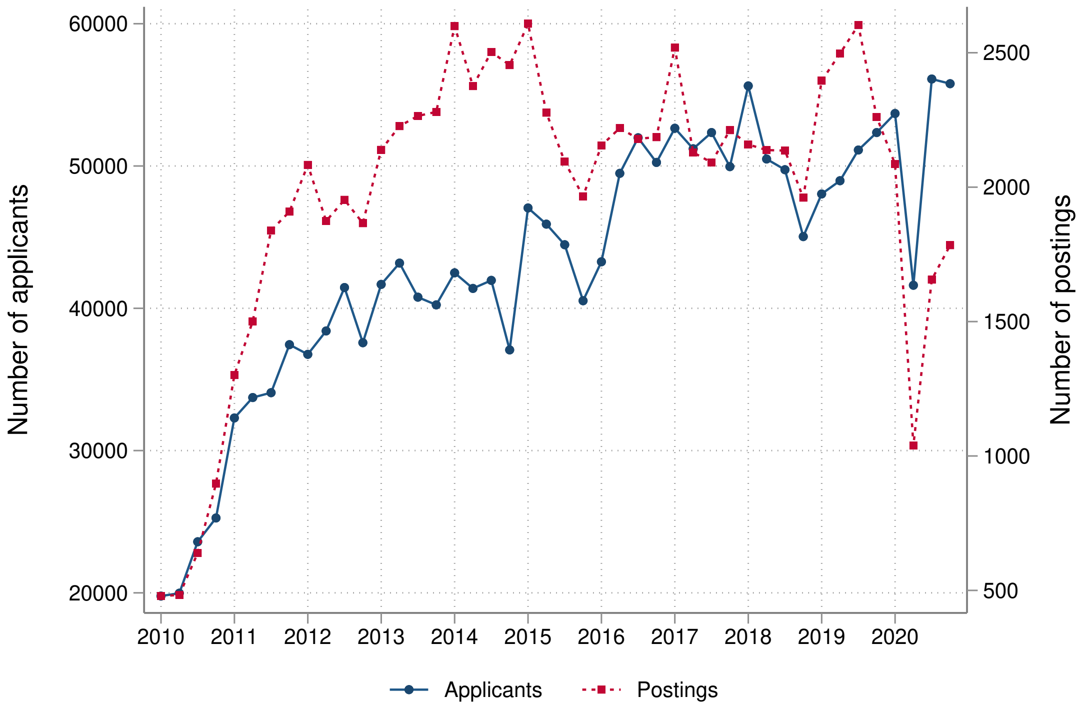
(o) A15–Working in teams

(p) A16–Human capital development

Notes: Authors' elaboration based on Adamczyk et al. (Forthcoming). The analysis is based on the full sample of 86,062 unique job adverts. 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.

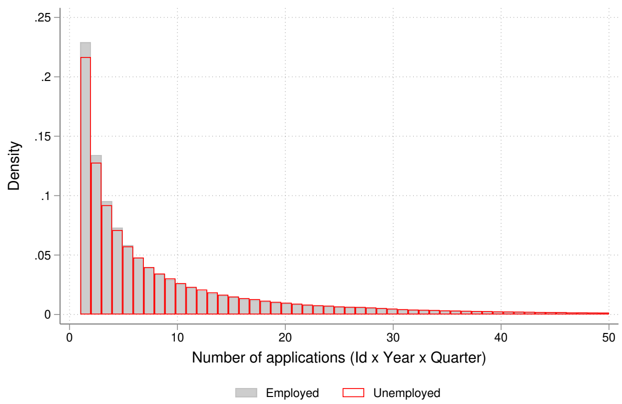
B Additional Figures and Tables

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

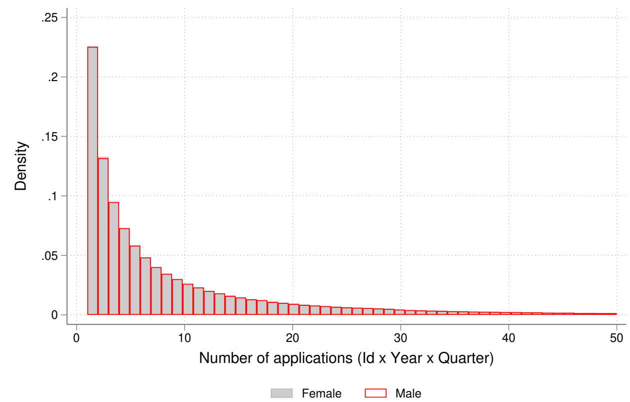


Notes: This figure shows, for each quarter between 2010 and 2020, the number of active applicants (i.e., IDs that made at least one application) and the number of posted vacancies in the BJ platform.

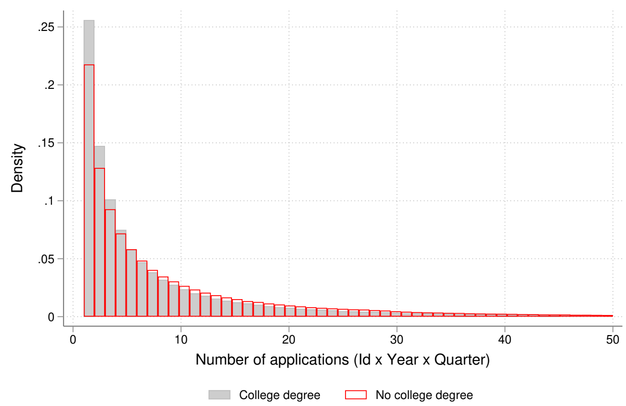
Figure B.2: Distribution of Number of Applications at the Applicant-by-Spell Level Excluding IDs Observed Only One Quarter



(a) By employment status



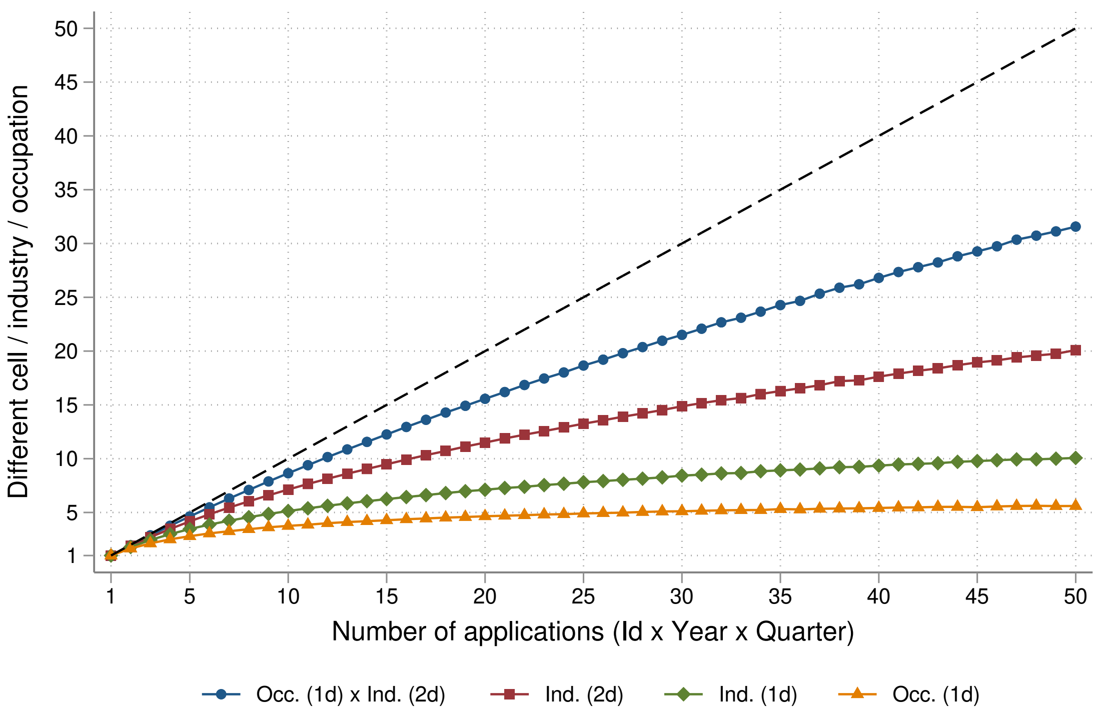
(b) By gender



(c) By education

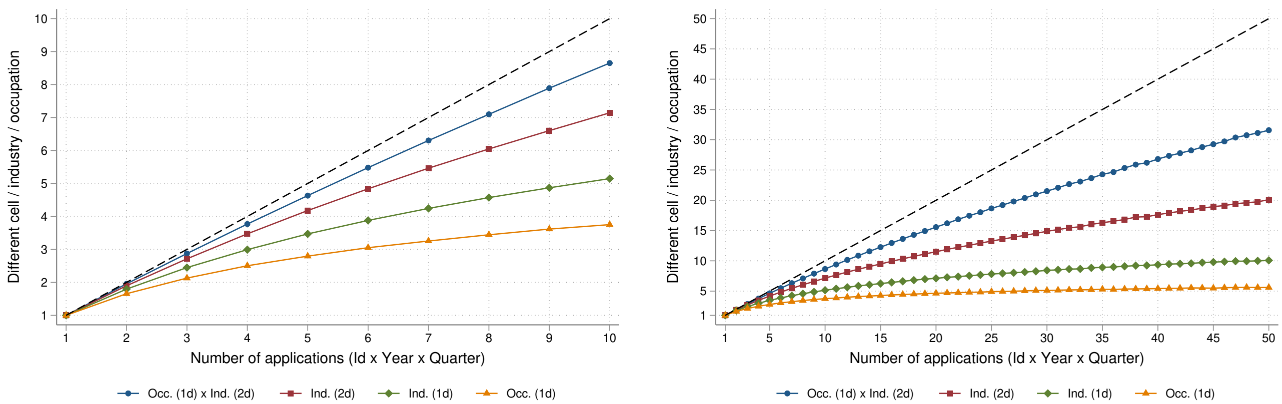
Notes: This figure shows histograms for the number of applications made by applicants in a quarter-by-year to our final sample of posted vacancies (see Section 2 for details on the sample restrictions). This figure is restricted to applicant IDs that are observed in at least two different calendar quarters. Panel (a) distinguishes applicants by employment status. Panel (b) distinguishes applicants by gender. Panel (c) 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.

Figure B.3: Portfolio Diversification: Different Groups, Considering up to 50 Applications



Notes: This figure plots the statistic described in equation (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 50 applications.

Figure B.4: Portfolio Diversification: Excluding IDs Observed Only One Quarter

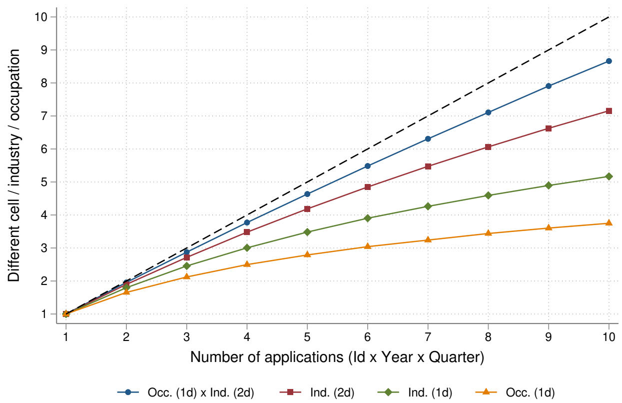


(a) Up to 10 applications

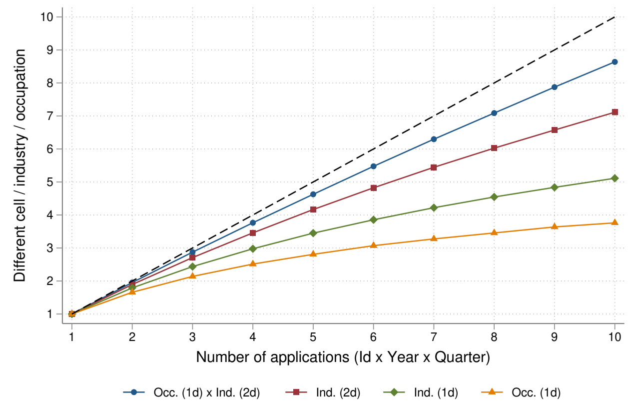
(b) Up to 50 applications

Notes: This figure plots the statistic described in equation (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). This figure is restricted to applicant IDs that are observed in at least two different calendar quarters. "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). The figure in Panel (a) is censored at 10 applications. The figure in Panel (b) is censored at 50 applications.

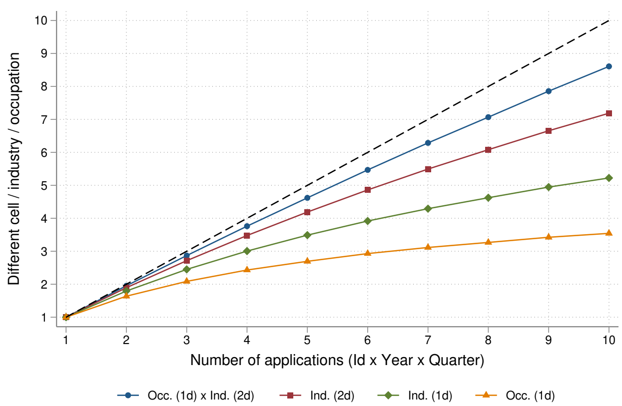
Figure B.5: Portfolio Diversification: Heterogeneity



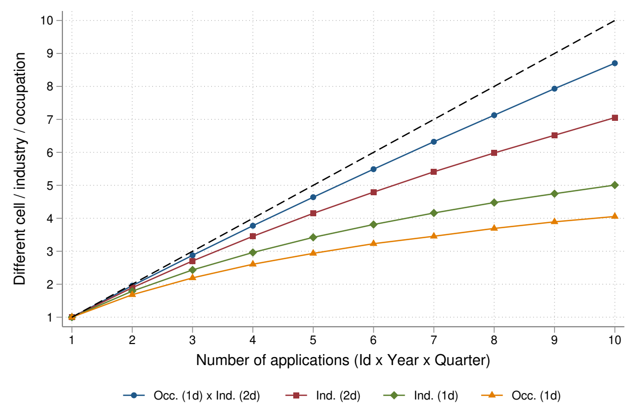
(a) Employed



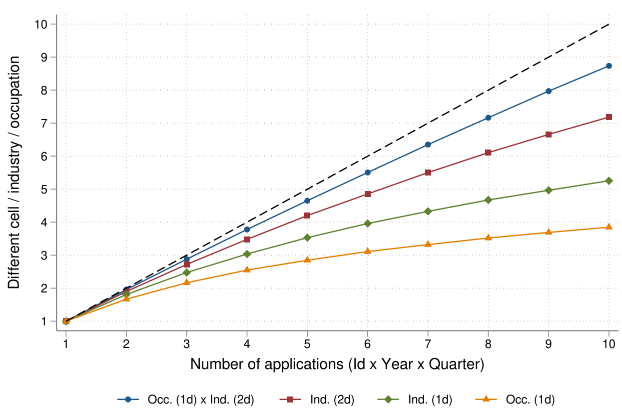
(b) Unemployed



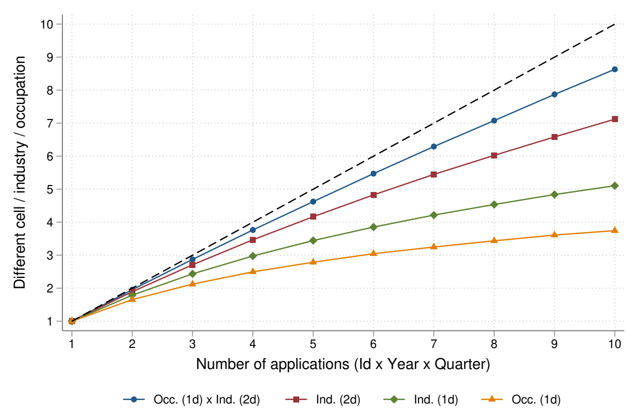
(c) Female



(d) Male



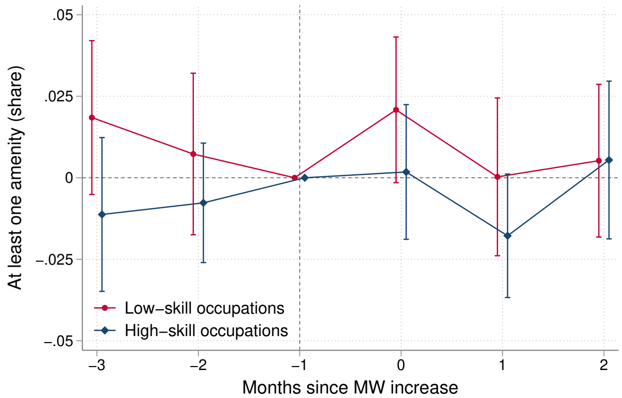
(e) College degree



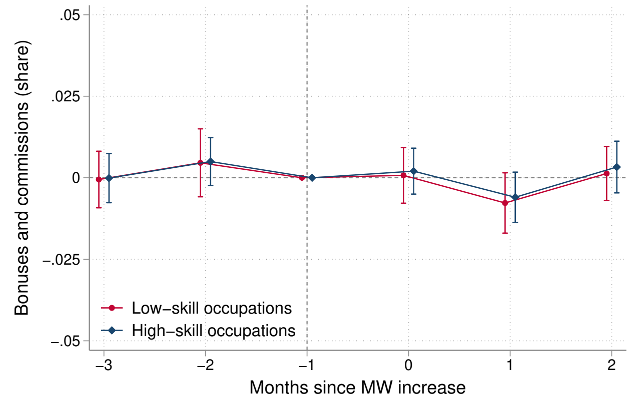
(f) No college degree

Notes: This figure plots the statistic described in equation (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.

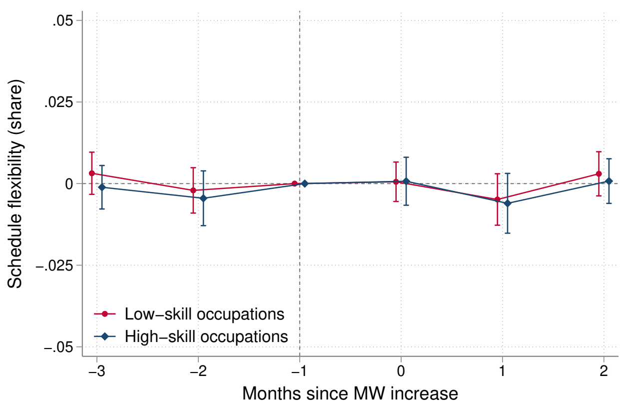
Figure B.6: Event Studies: Advertised Non-Wage Amenities



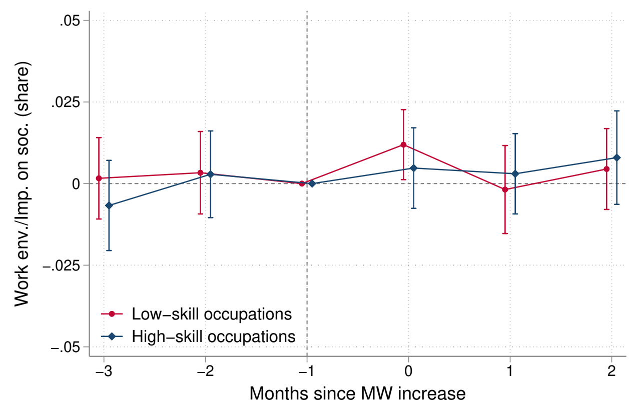
(a) At least one amenity



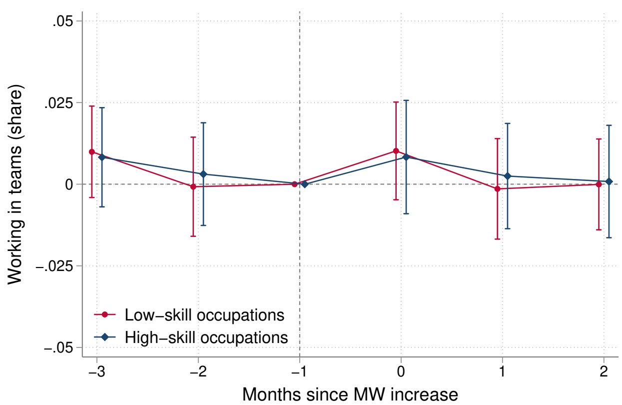
(b) Bonuses and commissions



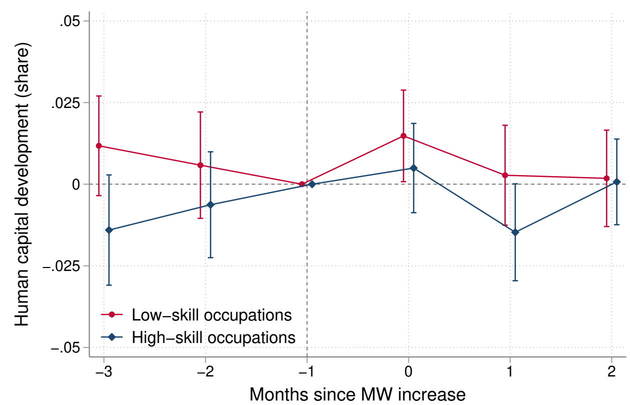
(c) Schedule flexibility



(d) Work environment/Impact on society



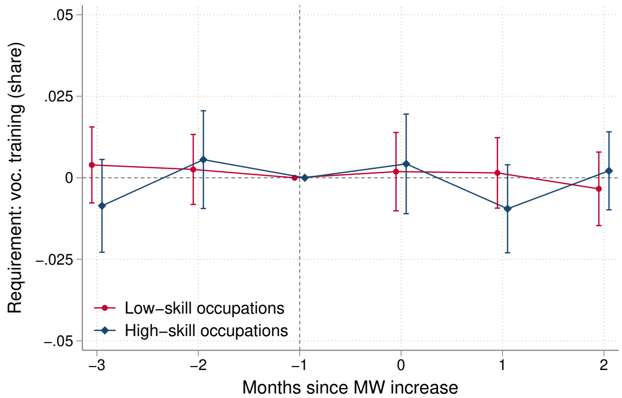
(e) Working in teams



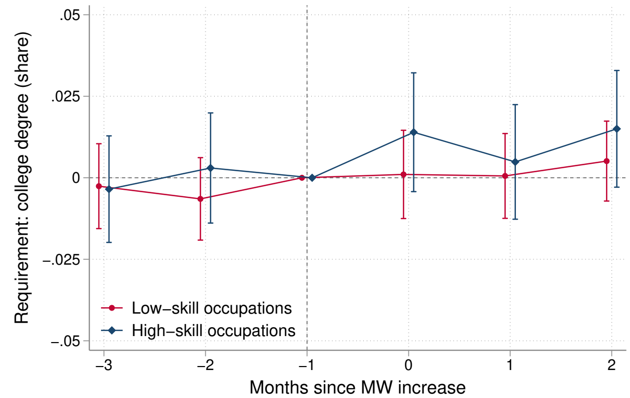
(f) Human capital development

Notes: These figures plot the estimated β_τ coefficients of equation (10) 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 at least one amenity as a dependent variable. Panel (b) uses the share of vacancies that advertise bonuses and commissions as a dependent variable. Panel (c) uses the share of vacancies that advertise schedule flexibility as a dependent variable. Panel (d) uses the share of vacancies that advertise work environment/impact on society as a dependent variable. Panel (e) uses the share of vacancies that advertise working in teams as a dependent variable. Panel (f) uses the share of vacancies that advertise human capital development as a dependent variable. 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 (see Panel (c) of Figure 7). Standard errors are clustered at the 2-digit industry level.

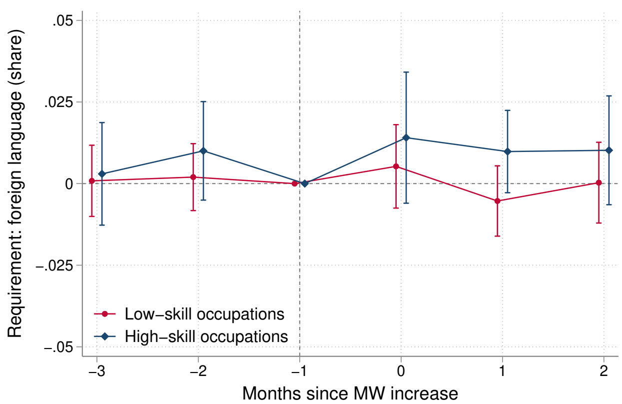
Figure B.7: Event Studies: Education and Skill Requirements



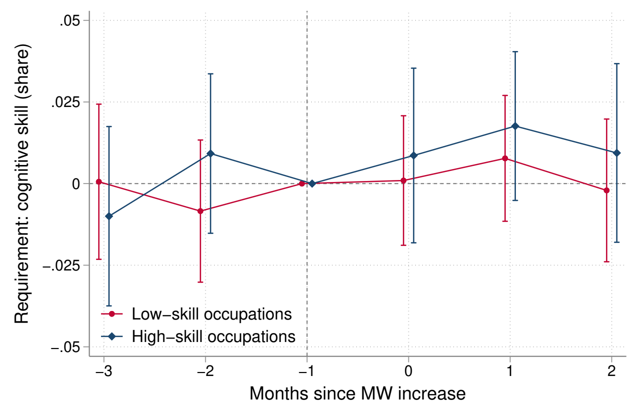
(a) Vocational training



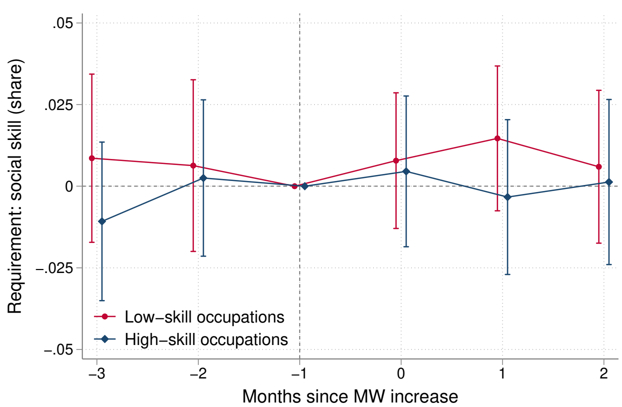
(b) College degree



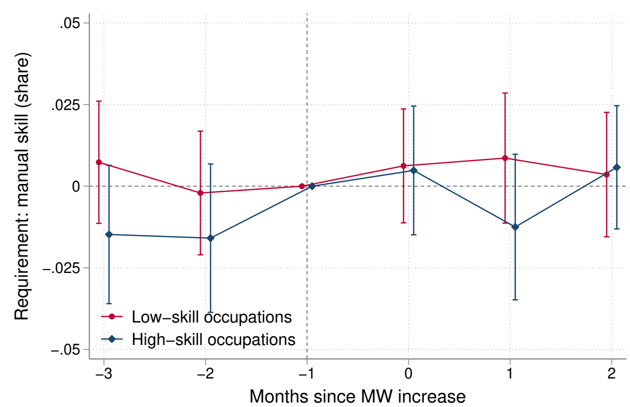
(c) Foreign language



(d) Cognitive skills



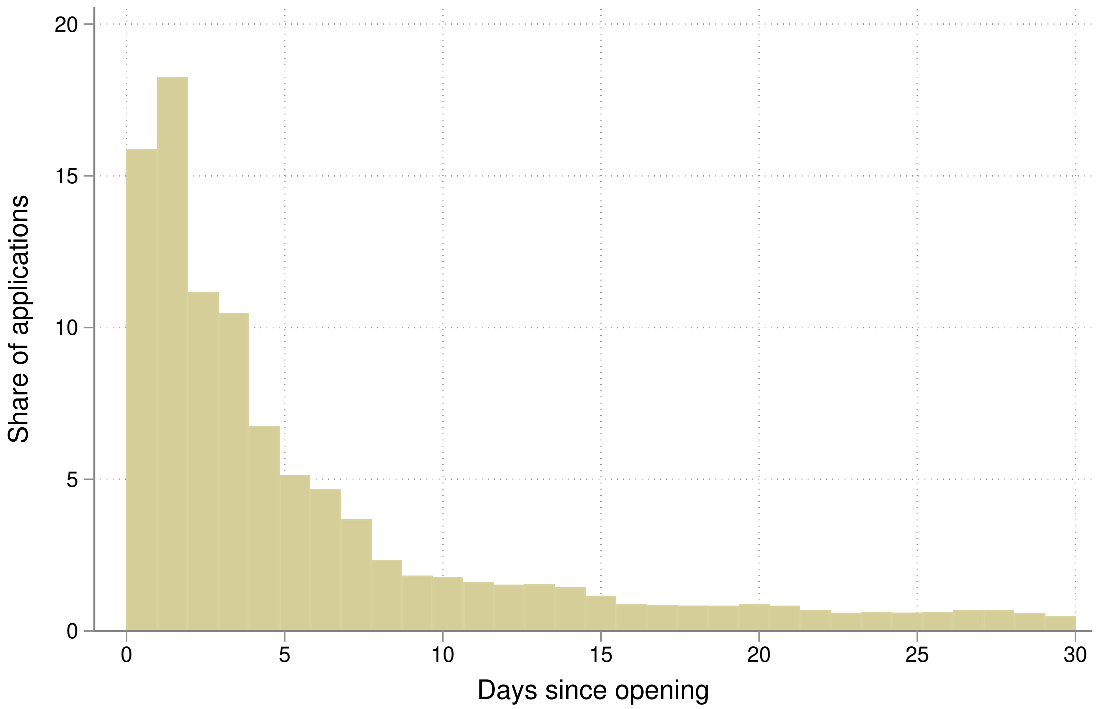
(e) Socio-emotional skills



(f) Manual skills

Notes: These figures plot the estimated β_τ coefficients of equation (10) 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 as a dependent variable. Panel (b) uses the share of vacancies that require a college degree as a dependent variable. Panel (c) uses the share of vacancies that require knowing a foreign language as a dependent variable. Panel (d) uses the share of vacancies that require cognitive skills as a dependent variable. Panel (e) uses the share of vacancies that require socio-emotional skills as a dependent variable. Panel (f) uses the share of vacancies that require manual skills as a dependent variable. 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 (see Panel (c) of Figure 7). Standard errors are clustered at the 2-digit industry level.

Figure B.8: 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.

Table B.1: Descriptive Statistics for Amenities: All Amenities

	All vacancies	Post wage	Does not post wage
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 (see Section 2 for details on the sample restrictions). Adverstised amenities were elicited following Adamczyk et al. (Forthcoming). 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: Different Posted Wage Definition

Panel (a): Midpoint of Salary Range

	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\alpha}$	-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
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)
$\widehat{\alpha}$	-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
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)
$\widehat{\alpha}$	-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
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

This table presents the estimated α coefficient of equation (2) using different definitions of posted wage. The dependent variable is the log number of applications, and the key regressor is the log posted wage, so coefficients are interpreted as cross-sectional elasticities. 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 amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). 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: 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)
$\widehat{\alpha}$	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
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)
$\widehat{\alpha}$	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
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

Panel (a) presents the estimated α coefficient of equation (2) for lower-skill occupations. Panel (b) presents the estimated α coefficient of equation (2) for higher-skill occupations. The dependent variable is the log number of applications, and the key regressor is the log posted wage, so coefficients are interpreted as cross-sectional elasticities. 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 amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). 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.4: Requirements by Occupational Group

Panel (a): All Vacancies

	All	Lower-skill occupations	Higher-skill occupations
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

Panel (b): Vacancies that Post a Wage

	All	Lower-skill occupations	Higher-skill occupations
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

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 (see Section 2 for details on the sample restrictions). 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.5: Cross-Sectional Patterns of Directed Search: Heterogeneity by Requirements

Panel (a): Formal Requirements

	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\alpha}_{LS}$	0.216	0.225	0.246	0.236	0.462	0.255
	(0.055)	(0.061)	(0.055)	(0.055)	(0.071)	(0.075)
$\widehat{\alpha}_{HS}$	-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
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)
$\widehat{\alpha}_{LS}$	0.494	0.464	0.418	0.406	0.546	0.328
	(0.049)	(0.050)	(0.055)	(0.051)	(0.058)	(0.048)
$\widehat{\alpha}_{HS}$	-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
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

Notes: This table presents the estimated $(\alpha_{LS}, \alpha_{HS})$ coefficients of equation (3). The dependent variable is the log number of applications, and the key regressor is the log posted wage, so coefficients are interpreted as cross-sectional elasticities. 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). 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 amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). 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.6: Applicant-Level Predictors of Posted Wage

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.047	-0.049	-0.057	-0.058	-0.046	-0.024
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Employed	0.058	0.057	0.052	0.050	0.041	0.025
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.007	0.006	0.006	0.006	0.005	0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Vocational training	0.045	0.045	0.039	0.036	0.033	0.022
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
College	0.120	0.125	0.108	0.100	0.069	0.047
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Cognitive skill	0.066	0.062	0.053	0.050	0.041	0.027
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Socio-emocional skill	0.008	0.007	0.007	0.008	0.008	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Manual skill	0.014	0.014	0.015	0.015	0.010	0.007
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
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
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	3,589,781	2,917,345	2,917,345	2,790,285	2,709,349	2,080,132
Adj. R^2	0.051	0.119	0.137	0.151	0.140	0.453

Notes: This table presents the estimated $(\alpha_F, \alpha_E, \alpha_A, \alpha_V, \alpha_C, \alpha_{CS}, \alpha_{SK}, \alpha_{MS})$ coefficients of equation (4). The dependent variable is the log posted wage of the application, and the key regressors are individual characteristics of the applicant. 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 amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). 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: Correlation Between Advertised Amenities and Posted Wages: By Occupation Group

	(1)	(2)	(3)	(4)	(5)	(6)
Bonuses and commissions (lower-skill occ.)	-0.083	-0.082	-0.082	-0.072	-0.054	-0.025
	(0.025)	(0.024)	(0.027)	(0.025)	(0.025)	(0.021)
Bonuses and commissions (higher-skill occ.)	-0.152	-0.132	-0.125	-0.077	-0.071	-0.067
	(0.040)	(0.042)	(0.040)	(0.046)	(0.047)	(0.040)
Schedule flexibility (lower-skill occ.)	-0.276	-0.285	-0.292	-0.288	-0.268	-0.238
	(0.024)	(0.027)	(0.028)	(0.030)	(0.031)	(0.040)
Schedule flexibility (higher-skill occ.)	-0.294	-0.305	-0.319	-0.361	-0.262	-0.208
	(0.029)	(0.031)	(0.030)	(0.033)	(0.032)	(0.035)
Work environment/Impact on society (lower-skill occ.)	-0.054	-0.052	-0.050	-0.042	-0.026	-0.009
	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)
Work environment/Impact on society (higher-skill occ.)	-0.089	-0.096	-0.095	-0.073	-0.035	-0.001
	(0.028)	(0.024)	(0.023)	(0.026)	(0.019)	(0.021)
Working in teams (lower-skill occ.)	0.040	0.035	0.035	0.031	0.027	0.018
	(0.013)	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)
Working in teams (higher-skill occ.)	0.104	0.095	0.085	0.081	0.062	0.049
	(0.025)	(0.025)	(0.026)	(0.032)	(0.035)	(0.011)
Human capital development (lower-skill occ.)	-0.002	-0.002	-0.004	-0.003	-0.011	0.008
	(0.014)	(0.014)	(0.014)	(0.013)	(0.012)	(0.014)
Human capital development (higher-skill occ.)	0.091	0.080	0.074	0.076	0.030	0.023
	(0.015)	(0.012)	(0.014)	(0.016)	(0.013)	(0.018)
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	15,835	15,501	15,501	14,626	13,878	10,759
Adj. R^2	0.063	0.088	0.105	0.121	0.084	0.411

Notes: This table presents the estimated $(\alpha^a_{LS}, \alpha^a_{HS})$ coefficients of equation (6). The dependent variable is the log posted wage, and the key regressors are indicators for advertised amenities, so coefficients are interpreted as cross-sectional semi-elasticities. 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 amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). 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.8: Correlation Between Advertised Amenities and Applications: By Occupation Group

	(1)	(2)	(3)	(4)	(5)	(6)
Bonuses and commissions (lower-skill occ.)	-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 (higher-skill occ.)	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 (lower-skill occ.)	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 (higher-skill occ.)	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 (lower-skill occ.)	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 (higher-skill occ.)	-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 (lower-skill occ.)	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 (higher-skill occ.)	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 (lower-skill occ.)	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 (higher-skill occ.)	-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 (8). The dependent variable is the log number of applications, and the key regressors are indicators for advertised amenities, so coefficients are interpreted as cross-sectional semi-elasticities. 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 amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). 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.9: Correlation Between Advertised Amenities and Applications: By Wage Posting Status

	(1)	(2)	(3)	(4)	(5)	(6)
Bonuses and commissions (post wage)	-0.072	-0.142	-0.180	-0.213	-0.247	-0.115
	(0.090)	(0.076)	(0.079)	(0.072)	(0.080)	(0.065)
Bonuses and commissions (do not post wage)	0.307	0.187	0.081	0.009	0.010	-0.014
	(0.087)	(0.060)	(0.052)	(0.055)	(0.055)	(0.041)
Schedule flexibility (post wage)	-0.079	-0.100	-0.127	-0.106	-0.109	-0.062
	(0.080)	(0.074)	(0.079)	(0.070)	(0.071)	(0.053)
Schedule flexibility (do not post wage)	0.067	0.044	0.029	0.049	0.048	-0.000
	(0.029)	(0.025)	(0.027)	(0.029)	(0.029)	(0.035)
Work environment/Impact on society (post wage)	-0.031	0.023	-0.011	-0.008	-0.007	0.019
	(0.062)	(0.058)	(0.050)	(0.050)	(0.049)	(0.035)
Work environment/Impact on society (do not post wage)	0.032	0.045	0.041	0.076	0.076	0.055
	(0.058)	(0.040)	(0.038)	(0.032)	(0.032)	(0.015)
Working in teams (post wage)	0.103	0.062	0.083	0.116	0.123	0.130
	(0.033)	(0.027)	(0.027)	(0.027)	(0.027)	(0.037)
Working in teams (do not post wage)	0.053	0.059	0.069	0.081	0.080	0.051
	(0.037)	(0.021)	(0.020)	(0.020)	(0.020)	(0.018)
Human capital development (post wage)	0.000	0.000	0.031	0.020	0.025	0.046
	(0.041)	(0.027)	(0.027)	(0.031)	(0.029)	(0.034)
Human capital development (do not post wage)	-0.061	-0.011	0.024	0.027	0.026	-0.012
	(0.024)	(0.023)	(0.023)	(0.024)	(0.024)	(0.019)
Post wage indicator	Yes	Yes	Yes	Yes	Yes	Yes
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	75,928	74,533	74,533	70,592	69,891	58,758
Adj. R^2	0.005	0.070	0.138	0.185	0.185	0.352

Notes: This table presents the estimated (α_W^a, α_N^a) coefficients of equation (9). The dependent variable is the log number of applications, and the key regressors are indicators for advertised amenities, so coefficients are interpreted as cross-sectional semi-elasticities. Column (1) includes a control for whether the vacancy posts a wage. Column (2) excludes vacancies receiving more than 1,000 applications and includes 2-digit industry fixed effects, year fixed effects, and controls for advertised amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). 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.10: Correlation Between Advertised Amenities and Applications: By Occupation Group and Wage Posting Status

	(1)	(2)	(3)	(4)	(5)	(6)
Bonuses and commissions (lower-skill occ. + post wage)	-0.305	-0.337	-0.256	-0.284	-0.295	-0.148
	(0.080)	(0.077)	(0.084)	(0.081)	(0.081)	(0.064)
Bonuses and commissions (lower-skill occ. + do not post wage)	-0.065	-0.092	0.004	-0.042	-0.042	-0.048
	(0.060)	(0.059)	(0.058)	(0.059)	(0.059)	(0.035)
Bonuses and commissions (higher-skill occ. + post wage)	0.306	0.221	0.187	0.186	0.077	0.074
	(0.152)	(0.144)	(0.145)	(0.108)	(0.124)	(0.117)
Bonuses and commissions (higher-skill occ. + do not post wage)	0.439	0.292	0.257	0.147	0.148	0.086
	(0.100)	(0.079)	(0.079)	(0.081)	(0.081)	(0.085)
Schedule flexibility (lower-skill occ. + post wage)	-0.186	-0.243	-0.264	-0.262	-0.267	-0.190
	(0.103)	(0.097)	(0.102)	(0.099)	(0.099)	(0.072)
Schedule flexibility (lower-skill occ. + do not post wage)	0.112	0.068	0.026	0.032	0.031	-0.028
	(0.047)	(0.046)	(0.048)	(0.047)	(0.047)	(0.044)
Schedule flexibility (higher-skill occ. + post wage)	0.071	0.134	0.148	0.249	0.253	0.219
	(0.062)	(0.058)	(0.060)	(0.058)	(0.054)	(0.067)
Schedule flexibility (higher-skill occ. + do not post wage)	0.030	0.024	0.035	0.069	0.069	0.025
	(0.043)	(0.032)	(0.033)	(0.032)	(0.032)	(0.047)
Work environment/Impact on society (lower-skill occ. + post wage)	-0.059	0.004	-0.016	-0.010	-0.014	0.005
	(0.067)	(0.061)	(0.056)	(0.055)	(0.055)	(0.040)
Work environment/Impact on society (lower-skill occ. + do not post wage)	0.164	0.145	0.140	0.137	0.137	0.083
	(0.038)	(0.039)	(0.041)	(0.042)	(0.042)	(0.025)
Work environment/Impact on society (higher-skill occ. + post wage)	-0.040	-0.001	0.007	0.011	0.026	0.067
	(0.072)	(0.068)	(0.067)	(0.067)	(0.079)	(0.061)
Work environment/Impact on society (higher-skill occ. + do not post wage)	-0.078	-0.049	-0.049	0.014	0.014	0.025
	(0.060)	(0.043)	(0.041)	(0.036)	(0.036)	(0.019)
Working in teams (lower-skill occ. + post wage)	0.150	0.074	0.054	0.073	0.081	0.062
	(0.051)	(0.040)	(0.036)	(0.033)	(0.033)	(0.037)
Working in teams (lower-skill occ. + do not post wage)	0.137	0.108	0.076	0.072	0.071	0.037
	(0.036)	(0.030)	(0.029)	(0.027)	(0.027)	(0.022)
Working in teams (higher-skill occ. + post wage)	0.141	0.117	0.117	0.177	0.191	0.242
	(0.041)	(0.043)	(0.042)	(0.056)	(0.057)	(0.052)
Working in teams (higher-skill occ. + do not post wage)	0.062	0.064	0.068	0.092	0.091	0.063
	(0.037)	(0.025)	(0.025)	(0.023)	(0.023)	(0.019)
Human capital development (lower-skill occ. + post wage)	0.016	0.006	0.008	0.002	-0.009	0.037
	(0.044)	(0.038)	(0.039)	(0.042)	(0.041)	(0.034)
Human capital development (lower-skill occ. + do not post wage)	-0.011	0.008	0.009	0.009	0.009	-0.051
	(0.039)	(0.036)	(0.036)	(0.034)	(0.034)	(0.025)
Human capital development (higher-skill occ. + post wage)	0.074	0.055	0.043	0.033	0.073	0.050
	(0.059)	(0.057)	(0.059)	(0.070)	(0.064)	(0.061)
Human capital development (higher-skill occ. + do not post wage)	-0.010	0.034	0.042	0.046	0.046	0.024
	(0.019)	(0.021)	(0.021)	(0.025)	(0.025)	(0.024)
Post wage indicator	Yes	Yes	Yes	Yes	Yes	Yes
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	0.073	0.116	0.139	0.186	0.186	0.353

Notes: This table presents the estimated coefficients of the saturated version of equations (8) and (9) that includes cross-interactions between occupational group and wage-posting status. The dependent variable is the log number of applications, and the key regressors are indicators for advertised amenities, so coefficients are interpreted as cross-sectional semi-elasticities. Column (1) includes a control for whether the vacancy posts a wage and 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 amenities (indicators for bonuses and commissions, schedule flexibility, work environment/impact on society, working in teams, and human capital development). 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.11: Applicant-Level Predictors of Advertised Amenities

	At least one (1)	Bonuses and commissions (2)	Schedule flexibility (3)	Work env./ Imp. on soc. (4)	Working in teams (5)	Human K develop. (6)
Female	-0.006	0.013	0.015	0.008	-0.009	-0.013
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Employed	0.001	-0.007	-0.008	-0.004	0.004	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.002	-0.000	-0.002	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Vocational training	-0.001	-0.010	-0.006	-0.006	0.005	0.002
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
College	0.017	-0.016	-0.007	-0.009	0.021	0.019
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Cognitive skill	-0.000	-0.014	-0.007	-0.006	0.008	0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Socio-emocional skill	0.008	0.007	-0.004	0.003	0.001	0.005
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Manual skill	-0.009	-0.003	-0.007	-0.007	-0.003	-0.007
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
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	12,523,693	12,463,489	12,463,489	12,463,489	12,463,489	12,463,489
Adj. R^2	0.029	0.106	0.030	0.029	0.020	0.031

Notes: This table presents the estimated $(\alpha_F, \alpha_E, \alpha_A, \alpha_V, \alpha_C, \alpha_{CS}, \alpha_{SK}, \alpha_{MS})$ coefficients of version of equation (4) that use amenity indicators as dependent variables. Each column considers a different dependent variable, and the key regressors are individual characteristics of the applicant. Regressions exclude vacancies receiving more than 1,000 applications and include 2-digit industry fixed effects, year fixed effects, and 1-digit occupation fixed effects. Standard errors (reported in parentheses) are clustered at the 2-digit industry level.

Table B.12: Average Hourly Wages and Minimum Wages, by Occupation in 2011 and 2020

	Year	Hourly mean minimum wage (1)	Median hourly wage (2)	Ratio (1)/(2) (3)	Mean hourly wage (4)	St. dev. hourly wage (5)
Lower-skill occupations						
Clerical support workers	2011	42.47	378.89	0.11	448.14	256.93
Clerical support workers	2020	81.90	750.00	0.11	836.60	412.78
Service & sales workers	2011	39.13	221.02	0.18	270.54	166.84
Service & sales workers	2020	69.80	500.00	0.14	570.85	273.63
Plant & machine operators, & assemblers	2011	40.40	301.39	0.13	334.80	169.97
Plant & machine operators, & assemblers	2020	80.49	625.00	0.13	679.00	294.70
Elementary occupations	2011	33.99	226.04	0.15	258.25	141.27
Elementary occupations	2020	66.75	500.00	0.13	542.32	243.66
Higher-skill occupations						
Managers	2011	52.59	861.12	0.06	908.68	342.84
Managers	2020	149.71	1500.00	0.10	1577.74	638.62
Professionals	2011	48.87	663.06	0.07	697.53	295.05
Professionals	2020	125.01	1285.71	0.10	1352.27	530.47
Technicians & assoc. professionals	2011	47.15	442.04	0.11	499.48	276.21
Technicians & assoc. professionals	2020	104.51	909.09	0.11	1017.46	480.12
Craft & related trades workers	2011	51.91	312.55	0.17	348.02	183.80
Craft & related trades workers	2020	86.98	681.82	0.13	730.03	328.81

Notes: This table shows average hourly wages and minimum wages by 1-digit occupation built from survey data for years 2011 and 2020. The aggregated minimum wage numbers in Column (1) are based on mean minimum wages within 2-digit industries, which were weighted depending on their share within the 1-digit occupations. Numbers in Column (1) were also converted from full-time equivalents to the hourly level by dividing monthly minimum wage levels by 200 monthly hours. Hourly wage data in Columns (2), (4), and (5) are computed using Uruguay's nationally representative household survey, the Encuesta Continua Hogares restricted to employees and excluding the top 1 percent of wages. To compare the economic significance of the minimum wages across broad occupations, in Column (3), hourly mean minimum wages are expressed as a share of median hourly wages. The wage and minimum wage data are shown in 2020 Uruguayan pesos.

Table B.13: 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 (12)). 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-skilled occupational group. Panel (c) shows summary statistics for the higher-skilled 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.14: 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 (12). 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.15: Difference-in-Differences Results: Non-Wage Amenities

	At least one (1)	Bon. and Comm. (2)	Sch. Flex (3)	Work. Env. (4)	Work. Teams (5)	HK Dev. (6)
$\hat{\beta}_{LS}$	0.000	-0.003	-0.001	0.003	-0.000	0.001
	(0.006)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
$\hat{\beta}_{HS}$	0.003	-0.002	0.000	0.007	0.000	0.004
	(0.006)	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)
Observations	54,648	54,648	54,648	54,648	54,648	54,648
$\Delta \log \mathrm{MW}_{LS}$	0.059	0.059	0.059	0.059	0.059	0.059
Pre-event outcome (LS)	0.346	0.073	0.042	0.122	0.132	0.160
Elasticity (LS)	0.010	-0.751	-0.319	0.440	-0.019	0.064
$\Delta \log \mathrm{MW}_{HS}$	0.057	0.057	0.057	0.057	0.057	0.057
Pre-event outcome (HS)	0.349	0.027	0.038	0.111	0.152	0.186
Elasticity (HS)	0.142	-1.228	0.171	1.032	0.013	0.358

Notes: This table presents the estimated β coefficient of equation (11) 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 (see Panel (c) of Figure 7). The dependent variables, as depicted in the column titles, include (in levels) the share of vacancies advertising at least one amenity, the share of vacancies advertising bonuses and commissions, 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.16: 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 (11) 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 (see Panel (c) of Figure 7). 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.

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