The Role of Wages and Job Benefits in Job Search Evidence from a Large-Scale Online Field Experiment*

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Abstract

This paper studies the role of wages and job benefits in job search behavior using a large-scale randomized control trial on 112 online job boards. We quantify the elasticity of job seekers' applications to posted wages and their willingness to pay for twelve different job benefits by randomly providing the users of the job boards with supplementary information regarding wages and benefits associated with the positions explored—information sourced from a market-leading employer review platform. The revealed-preference estimates suggest a quantitatively small wage elasticity of applications: A 10% higher wage increases job seekers' likelihood of viewing and applying to an ad by 3-5%. Job seekers in lower-paid occupations exhibit a higher sensitivity to wages. Certain job benefits are highly valued by job seekers: Home office is valued at about 17 percent of wages, company car at 14 percent, and company-provided child care and parking spots at around 9 percent of wages. The average position offers job benefits worth 23 percent of wages. We also document that higher-paying companies tend to offer more benefits. Taking the distribution and valuation of job benefits into

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account, we show that inequality in job value is significantly higher than inequality in wages.

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1 Introduction

Most jobs do not only offer a wage but come with a range of pecuniary and non-pecuniary benefits. Recent experimental evidence shows that workers have high valuation for non-wage job benefits such as the flexibility to set their own schedules (Mas and Pallais, 2017; Adams-Prassl et al., 2023), the opportunity to telecommute (Nagler et al., 2022; Aksoy et al., 2022), job stability (Wiswall and Zafar, 2018), or paid time off (Maestas et al., 2023). Together, this evidence suggests that job benefits may be almost as important as wages in terms of workers' job choice and total compensation (Maestas et al., 2023; Colonnelli et al., 2023; Taber and Vejlin, 2020). Despite this, most of the literature on job search behavior and inequality in the labor market still focuses on wages. What role do benefits play in the job search process? How much do job seekers value certain benefits relative to wages? And if we consider the incidence and valuation of job benefits, does that exacerbate or reduce inequality between firms and groups of workers?

To shed light on these questions we use data from the market-leading employer review platform in German-speaking countries to document the extent and distribution of job benefits and design a large-scale online field experiment on 112 job platforms to study the role of benefits in the job search process. The employer rating company collects user ratings of firms along multiple dimensions. Among other things, they collect wages and information on the availability of job benefits. A comparison with official statistics shows that the user-provided wage estimates almost perfectly reproduce average wages across occupations at the 2-digit level. In a first step, we draw upon 74 thousand user ratings in Switzerland to document how 12 job amenities are distributed across firms. A large literature has documented that wage policies differ widely across firms (Abowd et al., 1999). This naturally leads to the question of whether firms offer high wages to compensate for fewer or worse amenities (Rosen, 1986; Sorkin, 2018). Alternatively, consistent with rent sharing, high-wage firms may be better all around and offer also more and better job amenities (Card et al., 2018). We provide evidence for the latter view: there is a positive relationship between job amenities and firm wages. Vacancies in the highest wage decile offer about two job benefits more compared to those in the lowest decile, a 50 percent increase relative to the 4 benefits offered on average by low-paying vacancies. The share of firms offering home office, for example, increases from less than 40 percent in the lowest-paying decile to around 80 percent in high-paying vacancies. Thus, high-wage vacancies are also better in terms of offered job benefits.

But how do these offered job benefits affect the search behavior of job seekers, and how much do job seekers value these? To shed light on these questions, we use data from the market-leading employer rating platform and design a large-scale field experiment on one of the largest collections of job board websites in Switzerland.

During three months in 2023, we provided job seekers on 112 job ad platforms in Switzerland belonging to a market leader in online job search platforms, randomly with additional information about wages and job benefits. Depending on the treatment arm, visitors were shown a firm's average or median wage in an occupation and firm-level information on the availability of certain job benefits from the employer rating platform. This information was shown both (i) in the summary search list tabulating all available job ads satisfying the user's search criteria, and also (ii) on the page detailing the full vacancy ad. Job seekers in the control group were shown the usual search list without the additional information. This list only contained information on the occupation, location, and company name belonging to the vacancy. We track job seekers' click behavior and observe ads displayed on the screen of job seekers, whether they click on certain job ads, and other actions such as applications to vacancies, printing, saving, or sharing of vacancies. We then estimate the effect of higher wages and the availability of certain job benefits on the click behavior of job seekers. The control group identifies the general attractiveness of the job vacancy, whereas the variation of wages and job benefits across vacancies in the treatment group identifies a click elasticity to wages and job benefits, holding the general attractiveness constant.

Our results based on 184 thousand vacancies and 245 thousand users viewing over 8.6 million vacancy impressions show that job benefits play an important role in the search process of job seekers. Out of the job benefits considered, home office plays the largest role. All else equal, a job vacancy indicating the possibility to work from home receives a 0.3 percentage point higher click rate, a 7 percent increase relative to the average probability. Company car, company-provided childcare, and the provision of a parking slot also increase the probability of job seekers clicking on the vacancy by between three and five percent. The presence of a company doctor or a canteen, the ability to work flexible hours, employee events, food allowance, coaching, health measures, and good public transportation connections do not influence jobseekers' views of and applications to vacant jobs. In comparison, we find that a 10 percent higher wage increases the probability of clicking on the job ad by three to five percent. Using these estimates, we can back out a willingness-to-pay estimate for job benefits by taking the ratio of the click elasticity with respect to benefits and with respect to wages. This willingness-to-pay estimate measures by how much a firm could reduce its posted wage by additionally offering a job benefit, while holding the general interest for the job vacancy constant. The highest valued job benefit is home office, which we estimate a willingness to pay of 19 percent of wages. The job benefit with the second highest valuation is company car, with a willingness to pay of about 14 percent of wages. Child care is also highly valued with 9 percent of wages. This on average amount to a valuation of around 670 Swiss franc (CHF) for employer-provided child care, suggesting a high convenience factor to workers. Interestingly, we find that child-care in female dominated occupation is not valued at all, while we find a significantly higher valuation in occupations with more than 70 percent male employment. Given that mothers typically work part-time in Switzerland, this suggests that child-care facilities are more useful at the location of the full-time job. Having a parking lot is also priced highly by job seekers, we estimate a willingness-to pay of around 10 percent of wages. Most job benefits are valued higher in high wage vacancies, suggesting that job benefits are complements to salaries.

The high willingness-to-pay estimates of many job benefits show that job seekers value more aspects of jobs than purely wages. But how much do these benefits quantitatively matter in practice? To answer this question we compute the value of the jobs advertised during our experiment period taking the offered benefits and their valuations into account. For each vacancy where we have wage information from the employer rating platform, we compute the job value, which is the sum of wages and the CHF value of the benefits for which we find a statistically significant willingness-to-pay. On average, a vacancy offers 1660 CHF worth of job benefits, which constitute a 23 percent increase over pure wages. How much do these willingness-to-pay estimates affect our understanding of inequality? We find that job value inequality is significantly higher compared to wage inequality. The Gini coefficient for job value inequality is 0.194 compared to 0.173 for wages, and the P90/P10 ratio of job values is 2.4 compared to 2.15 for wages. The reason behind this is, as we discussed earlier, high wage vacancies typically also offer more benefits. Summarizing, our paper provides experimental evidence that job benefits not only affect the search behavior of job seekers, but also affect our understanding of inequality across workers.

Our paper relates to several strands of literature. First, our paper contributes to the literature studying the role of job benefits in the labor market. A growing number of studies infer job seekers' valuation of certain benefits such as the opportunity to work from home using hypothetical (Eriksson and Kristensen, 2014; Wiswall and Zafar, 2018; Aksoy et al., 2022; Maestas et al., 2023; Nagler et al., 2023) and incentivized (Colonnelli et al., 2023) choice experiments. We, in contrast, estimate job seekers' willingness-to-pay from actual choices during their real-world online search process. Our revealed-preference approach is related to the experimental designs of Mas and Pallais (2017) and He et al. (2021), who estimate job seekers' willingness-to-pay for certain job aspects by experimentally varying the job package offered to workers recruited for particular firms. While these studies focus specific entry-level jobs (Mas and Pallais, 2017) or jobs in an IT firm (He et al., 2021), our experimental data covers almost all major industries and occupations of the Swiss labor market. Our experiment thus combines the benefits of an incentive-compatible intervention with the job-seeker coverage of some of the largest hypothetical choice experiments. In addition, we estimate the workers' WTP for benefits such as employers' provision of childcare or a company car that have so far escaped scientific scrutiny.

Our paper also relates to papers that estimate the value of job amenities indirectly from worker movements (Sorkin, 2018; Taber and Vejlin, 2020; Bonhomme and Jolivet, 2009; Lamadon et al., 2022). Several of these papers interpret worker moves to lower-paying jobs as being compensated by the amenity value. The advantage of our experimental approach is that we do not rely on the assumption that every transition to a lower paying job must be driven by compensating increase in the amenity value. Using data from a large employer review platform in the US, Sockin (2022), like us, provides evidence for higher paying firms offering more job benefits. While Sockin (2022) estimates job seekers' valuations from observational data, we estimate the valuations using experimental variation where we can control unobservable characteristics that affect the attractiveness of the vacancy.

Third, our paper relates to the small literature on the sensitivity of job seekers' clicks and applications to posted wages. Our estimate of the wage elasticity of applications in the range of 0.3–0.5 is towards the lower end of previous experimental (Dal Bó et al., 2013; Dube et al., 2020; Abebe et al., 2021; Belot et al., 2022; He et al., 2023; Cullen et al., 2024) and non-experimental (Banfi and Villena-Roldan, 2019; Marinescu and Wolthoff, 2020) estimates from regular labor markets, which range from 0.22 to 1.1.[1] One explanation is that many previous estimates concern low-skilled job seekers and were often estimated in relatively poor countries. Our estimates of the wage elasticity, which cover a wider range of occupations than any of the previous estimates, suggest that the wage elasticity of applications is substantially higher in lower-paid occupations, while job seekers in the top tercile of the occupational wage distribution are almost insensitive to posted wages.

Finally, we combine our willingness-to-pay estimates with novel employer review data on the presence of job benefits in firms to contribute to the literature on the implications of non-wage job characteristics for compensation inequality. In line with most previous

[1] Dube et al. (2020) and Cullen et al. (2024) estimate the wage elasticity in spot markets for unskilled labor. While the former find a very low elasticity (0.1), the latter find a comparatively large one (>3).

papers, we find that non-wage characteristics are worse in low-wage jobs (Pierce, 2001; Marinescu et al., 2021; Sockin, 2022; Dube et al., 2022; Maestas et al., 2023) and that non-wage characteristics exacerbate labor market inequality. These results are also line with a growing number of papers that use theoretical models to back out the implications of all non-wage characteristics on inequality in workers' job values (e.g., Taber and Vejlin, 2020; Lamadon et al., 2022; Berger et al., 2023; Lehmann, 2023)

2 Data Description

Our data is derived from two main sources. The first is a leading employer review platform in the German-speaking region in Switzerland, providing comprehensive information on wages and benefits. Our second data partner, jobchannel, stands as one of the top job platform providers in Switzerland.[2] The wage and benefit data is then linked to the job vacancies posted across all of jobchannel's online platforms for our experiment. Additionally, jobchannel provided us with detailed user activity data, collected via Google Analytics (GA), for all their platforms during the period of our experiment.

2.1 Employer review data

The review platform we partnered with collects online employer reviews, focusing separately on fringe benefits and wages. Figure B1 and B2 show snapshots of benefit and wage review forms on the platform, respectively. As shown in figure B1, the reviewers are presented a list of fringe benefits,[3] and are asked if the benefits are available at their firm. Our study focuses on 12 specific fringe benefits, including flexible working hours, home office, childcare facilities, convenient transportation connections, company car, parking pot, employee events, coaching, health measures (such as fitness centers), company doctor, canteens, and food allowance. The wage review form asks for the workers' pay including any additional bonus pays and monetary remunerations. We computed average monthly pay for all reviews, whether the pay was initially reported on an annual or monthly basis, to get a consistent monthly measure of wages.[4]

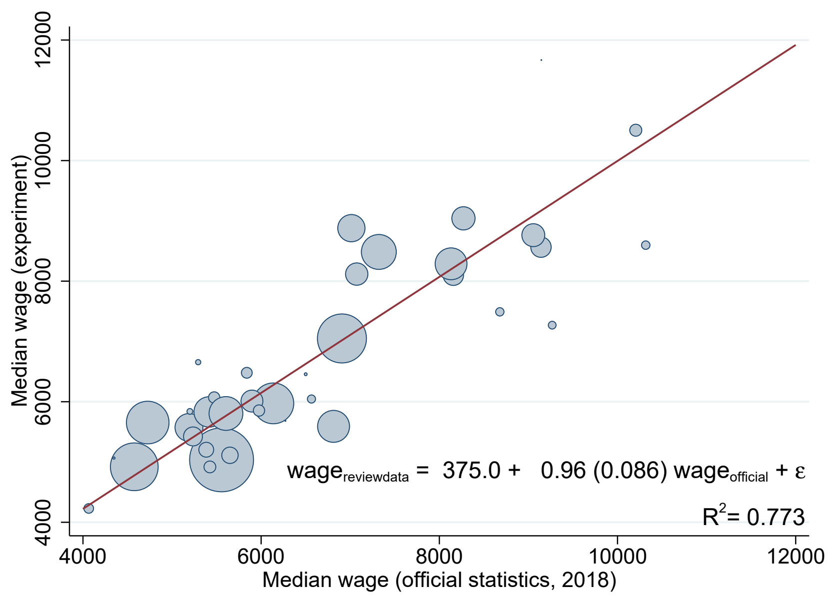
[2]jobchannel holds a market share of approximately 15 to 20% among Swiss job platforms.

[3]The order of presentation is random and changes respectively for different reviewers.

[4]Workers can choose either monthly or annual pay frequency. Since one or two additional monthly payments are common in Switzerland, reviewers who select the monthly payment are asked about the number of monthly payments in a year. We calculate the annual payment for all wage reviews and divide it by 12 to get a consistent monthly measure of wages.

Note that while the wage review form asks for the employee's occupation (job title), the benefit reviews do not ask for such information. As a result, we aggregate benefit review data at the firm level and wage review data at the occupation-by-firm level in order to match these data to posted vacancies. We do so by computing the share of reviews indicating the availability of a specific benefit at each firm and calculating either mean or median wages at the occupation-by-firm level.[5] Figure 1 illustrates our measure of median wages at the occupation level (2-digit ISCO) across all the matched posted vacancies in the experiment period, against the median wage at the occupation from the official statistical records. Additionally, figure 1 presents the results of a regression analysis comparing our median wage measure to the official median wage statistics, and as we can see the coefficient is not significantly different from 1.[6] Figure B4 presents a similar comparison of our mean wage measure with the official statistics for mean wages across different occupation.

Figure 1: Median wage among job ads viewed in the experiment vs official median wages (Federal Statistics, 2018), by ISCO 2-digit occupation code



[5]We drop benefit information from firms that have less than 3 benefit reviews. Respectively, we only keep wage reviews in which there are at least 3 reviews at the occupation X firm level, to minimize any potential measurement errors.

[6]Note that however, according to the regression results, our measure of median wages is on average 375 CHF higher than the official statistics on median wages. As shown later in table 2, due to the selection on the number of reviews, the firms in the vacancy data that could be matched to the wage data, are significantly larger compared to the full population of Swiss firms. To the extent that larger firms pay higher wages, this difference is due to the sample selection.

2.2 Vacancies and experimental data

Our experiment was conducted across all 112 job platforms of jobchannel. The benefit and wage data are matched to the job vacancies on these platforms and are shown for the matched vacancies according to the experimental design. jobchannel provided us with a database containing detailed information on the job ads and employers. Additionally, we tracked and stored the activities of users who accepted the statistics cookies on the job platform using Google Analytics.[7]

Google Analytics identifies each user using a unique combination of parameters, including the user's IP address.[8] This identification allows for consistent tracking of a user's activities across different job search sessions on the platforms. In each session, we record several activities, including users' filtered job searches where they can filter job ads by job title keywords, region, occupation, full-/part-time arrangement, and firm size. Furthermore, when users scroll through the search list, an event called 'impression' is logged for each ad that appears and is scrolled past on the device's screen. Users' interactions with the job ads, like clicking on the job ads and subsequently viewing more details in a separate tab or window, are also recorded. Finally, actions indicating further interest in an ad, such as adding it to their watchlist, clicking on the 'apply now' button, or sharing the job ad, are tracked.

We identified and excluded heavy users and potential bots from our data using specific user activity criteria.[9] Additionally, we excluded data from March 5th and 6th due to technical issues that prevented the experimental treatment from being shown in some sessions. Sessions where users were exposed to two or more distinct treatments, a scenario occurring in less than 0.05% of the cases, were also omitted. Our final analysis sample includes only activities stemming from users scrolling through the job ad list displayed automatically upon opening a job platform's main page or from specific job ad searches followed by scrolling through the results.[10] Ultimately, our analysis relies on job ads that could be matched with

[7]Note that since we can only get the activity data for users who accept the statistics cookies, our sample is merely consisted of job seekers who accept the statistics cookies at the beginning of their sessions. According to jobchannel's internal statistics, around 50% of their job platform users accept the statistics cookies.

[8]Google Analytics "fingerprints" devices by collecting a variety of information about a user's device, such as the browser type, operating system, screen resolution, and installed fonts. This information can be used to create a unique fingerprint for the device. Google Analytics can also collect the user's IP address. This information can be used to approximate the user's location and track their activity across different devices.

[9]We discuss the data-cleaning details, including the criteria for choosing heavy sessions and potential bots, in appendix A.

[10]In few cases, users might view details of an ad without having seen that in a list and actively choosing it among the job ads in the list, i.e. an "ad view" activity is recorded without having an "impression" event for that ad. This could happen for example because the ad was emailed to the user in a suggestion email from jobchannel or because they have seen an advertisement of the job ad on an external website and were

the review information, thus qualifying for inclusion in the information experiment. Consequently, the effective analysis sample is confined to user activities associated with these matched job ads.[11]

Following the cleaning procedure and exclusion of unmatched job ads, our final sample consisted of 245,618 users, which correspond to approximately 145k job seekers,[12] with a total of 345,819 search sessions covering 184,015 matched job ads. Descriptive statistics for job search sessions and users are presented in table 1.

On average, each session lasted about 8 minutes, with job seekers conducting 1.7 filtered searches per session. They see (scroll through) around 50 ads on average in each job search session, of which 25 are among the job ads matched with review information. Approximately 30% of the sessions were conducted by job seekers in Zurich, while 75% were from those in Switzerland. We lack specific information on job seekers' occupations, as we can only identify them as GA users, we are limited to the user characteristics extracted by GA. However, we assign an occupation to a job search session if over 50% of the seen job ads (impressions) are associated with a particular occupation. Occupations were assigned at the ISCO 1-digit level to approximately 70% of the sessions. In 24% of the sessions, job seekers predominantly searched for professional occupations, followed by technicians and associate professionals, clerical support, and service and sales occupations, each constituting approximately 17% of the job search sessions. On average, each GA user had 1.75 job search sessions during the experiment period.

The characteristics of job ads are summarized in Table 2. Among them, 58% could be matched to the review data. Almost all of these matched job ads had benefit review data available, while around 18% included wage review data, with the average reviewed wage being approximately 6,700 CHF. Compared to the overall sample, the matched job ads have a higher representation in manufacturing and trade industries and a lower representation in administrative, support services, and hospitality. 40% of the matched job ads are linked to

redirected to the ad details page after clicking on that.

[11] In around 4% of the impressions in the analysis sample, the treatment information were not shown due to technical problems, even though the user was in one of the information treatment arms and the job ad had available benefit or wage information. We also exclude such cases from our sample.

[12] In most cases, Google Analytics is able to detect a user even when they start a session from multiple devices, but in some cases, there are not enough characteristics to identify the same user on a different device or in a different location. Therefore, one job seeker might appear in the data with multiple GA user IDs. To get the statistics on how many user IDs a job seeker has on average in the data, we use the sample of job seekers who have registered on any of the platforms and can therefore be identified from their login user ID. More than 75% of the job seekers with a login ID, are only associated one GA user ID in the data and on average a job seeker has 1.66 GA user IDs in our sample. Therefore, 245k GA user IDs is equivalent to approximately 145k job seekers.

Table 1: Summary of Session and User Characteristics

	Full Sample	Analysis Sample (Matched Sample)
A. Session Statistics		
Avg session length (min) (SD)	7.99	8.19
	(13.42)	(13.58)
Avg filtered searches per session (SD)	1.72	1.75
	(1.31)	(1.33)
Avg total impressions per session (SD)	48.34	50.49
	(74.23)	(75.47)
Avg in-sample impressions per session (SD)	40.75	24.91
	(64.44)	(41.83)
Avg total views per session (SD)	2.59	2.67
	(4.24)	(4.31)
Avg in-sample views per session (SD)	2.18	1.31
	(3.71)	(2.42)
Avg total actions per session (SD)	0.32	0.33
	(1.52)	(1.46)
Avg in-sample actions per session (SD)	0.21	0.12
	(0.91)	(0.60)
Region (%)		
Zurich	30.68	30.83
Switzerland	74.76	75.12
Germany/France/Italy/Austria	7.53	7.48
Device properties (%)		
Mobile	56.88	56.85
Desktop	41.45	41.45
Language: DE	83.26	83.67
Language: EN	6.8	6.76
Has assigned occupation (%)	69.73	69.23
Assigned occupation (%):		
Professionals	24.02	24.23
Technicians and associate professionals	15.96	16.15
Clerical support workers	17.14	17.25
Service and sales workers	17.33	17.75
Craft and related trades workers	6.18	5.72
Plant and machine operators, and assemblers	6.72	6.72
Elementary occupations	7.35	6.8
Number of sessions	364,862	345,819
B. User Statistics		
Avg sessions per user	1.43	1.41
Median of sessions per user	1	1
Has a platform login ID (%)	3.83	3.94
Number of users	255,597	245,618

professional occupations. This is followed by technical and associate professionals, clerical support, and service and sales industries, comprising 21%, 16.3%, and 13.3% of the matched job ads, respectively. The distribution of job ads across different occupations in the full sample is similar to that in the matched sample. The firms in the matched sample are generally larger than those in the full sample, mainly due to the selection criterion of having at least three reviews per firm in the review data. The average vacancy duration for a job ad in the matched sample is 80 days, slightly lower than the 84 days observed in the full sample. On average, each job ad receives approximately 47 impressions, 2.5 views, and 0.25 actions from in-sample users, consistent across both the full and matched samples.

2.3 Data coverage

To assess the representativeness of the job ads in our sample relative to the entire universe of job postings in Switzerland, we created a scatterplot (Figure 2) comparing the number of job ads in our matched sample, active as of March 31st, against the job openings reported by the Federal Statistical Office on the same date. This scatterplot, plotted at the NACE 2-digit level for each industry, includes a 45-degree line for reference. Similarly, Figure B5 provides the same comparison for our full sample, which includes both matched and non-matched job ads active on March 31st. While some industries, such as administrative and support services, education, and the public sector, show a higher number of job ads in our full sample compared to the official job opening statistics,[13] overall, our job ads, especially those in the matched sample, represent a consistent proportion of the total job openings across all industries. This consistency suggests that the job ads in the sample have a distribution across industries that closely mirrors the distribution in the overall job market.

Next, we compare the occupations of users in our analysis sample with the official employment statistics in Switzerland. For this comparison, we assigned an occupation to each user in the same way as we did for sessions. Specifically, a user is assigned to an occupation at the ISCO 2-digit level if more than 50% of the job ads they viewed (impressions) across all their sessions are associated with that occupation. Figure 3 displays this comparison, showing the number of users in our sample against the employment levels in Switzerland by ISCO 2-digit occupation codes, as obtained from the Federal Statistical Office.

[13] This discrepancy could stem from measurement errors in industry codes in our data.

Table 2: Summary of Job Ad Characteristics

	Full Sample	Without Review Information	Analysis Sample (Matched Sample)	With Wage Information
Has posted wage (%)	0.62	0.04	1.04	1.54
Has review wage (%)	10.33	0	17.65	100
Avg review wage (mean) (SD)	6,690		6,690	6,690
	(2,128)		(2,128)	(2,128)
Has benefit information (%)	58.54	0	100	99.98
Ad in English (%)	7.55	5.81	8.78	6.78
Ad in German (%)	83.05	82.61	83.37	86.22
Avg minimum FTE	83.99	84.7	83.49	81.95
Avg maximum FTE	93.7	93.47	93.85	93.03
Temporary position (%)	6.86	7.53	6.39	4.56
Industry (%):				
Admin. and support services	8.32	16.4	2.6	5.05
Manufacturing	14.82	9.81	18.37	15.84
Construction	4.74	6.64	3.39	2.75
Trade	10.98	7.73	13.27	21.32
Hospitality	7.45	9.64	5.9	6.67
Public sector	26.38	25.17	27.24	17.32
Occupation (%):				
Professionals	29.14	27.89	30.05	20.66
Techn./Assoc. prof.	19.74	17.96	21.04	21.49
Clerical support	14.24	11.48	16.26	29.73
Services and sales	14.35	15.74	13.33	15.64
Craft and related trades	10.91	14.14	8.55	8.03
Plant, machine oper., assemb.	2.66	2.84	2.53	2.11
Elementary	4.24	5.2	3.53	0.98
Firm Size (%):				
1-10	17.7	36.69	4.37	1.14
11-100	36.21	49.09	27.18	13.76
101-1000	27.61	9.96	40.00	40.4
$\geq$ 1001	18.48	4.26	28.45	44.7
Avg vacancy duration (SD)	84.35	92.65	78.73	74.39
	(172.72)	(172.72)	(122.33)	(115.96)
Avg (in-sample) impressions (SD)	47.29	47.98	46.8	50.78
	(133.05)	(133.05)	(113.21)	(118.02)
Avg (in-sample) views (SD)	2.53	2.61	2.47	2.89
	(10.97)	(10.97)	(8.40)	(9.42)
Avg (in-sample) actions (SD)	0.24	0.25	0.23	0.29
	(1.18)	(1.18)	(0.99)	(1.23)
Number of job ads	314,341	130,326	184,015	32,479

Table 3: Summary of Firm Characteristics

	Full Sample	Without Review Information	Analysis Sample (Matched Sample)	With Wage Information	Official Statistics (2021)
Average number of job ads	7.63	4.03	20.70	17.95	
Recruiting agency (%)	0.38	0.49	0.01	0	
Has benefit information (%)	21.57	0	99.97	99.83	
Avg share of ads with review wage (%)	1.24	0	5.77	100	
Avg share of ads with posted wage (%)	0.03	0.01	0.11	0.36	
Firm Size (%):					
1-10	49.12	57.28	19.44	7.68	$\sim 89.76^*$
11-100	42.60	39.27	54.70	42.74	~ 9.41
101-1000	6.51	2.86	19.75	35.28	~ 0.79
≥ 1001	1.78	0.59	6.11	14.30	~ 0.05
Industry (%):					
Admin. and support service	3.03	3.19	2.43	2.65	
Manufacturing	13.73	11.02	23.57	22.81	
Construction	10.37	11.18	7.43	7.62	
Trade	12.24	12.04	12.97	13.09	
Hospitality	10.77	12.54	4.31	2.82	
Public sector	17.68	18.81	13.54	15.74	
Number of firms	41,204	32,315	8,892	1,811	609,518

* The firm size categories from official statistics are slightly different from the categories in our job ad database. The categories are: 1-9, 10-99, 100-250, and larger than 250, and the statistics are shown in the table for these categories, respectively.

Figure 2: Matched Job ads viewed during experiment vs. job openings in Switzerland on March 31, by industry

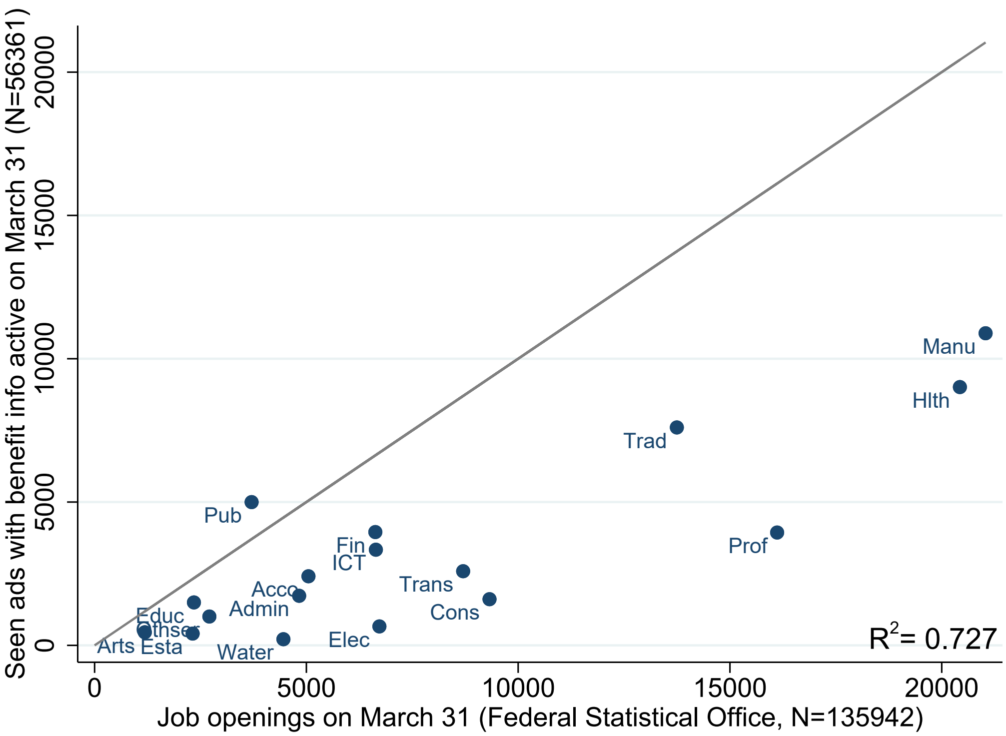
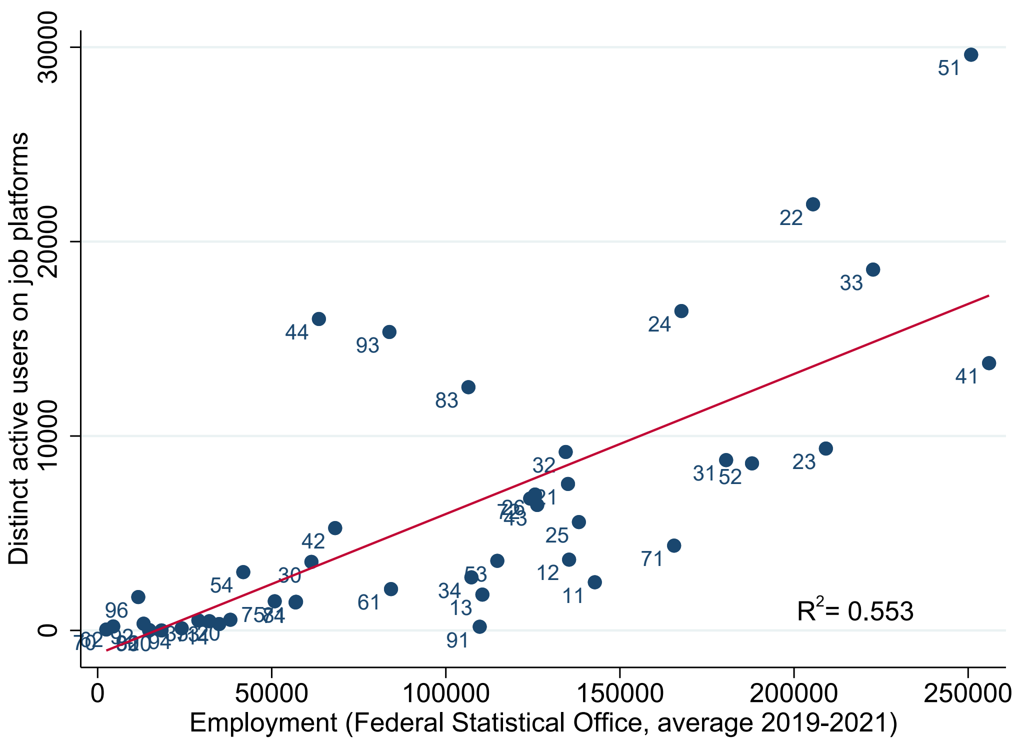


Figure 3: Users in experiment vs. employment in Switzerland by ISCO 2-digit occupations



3 Experimental Setup

We collaborate with two implementing partners – one of the market leaders of job vacancy websites in Switzerland (jobchannel) and the market-leading employer review platform for German-speaking countries – to conduct a large-scale online field experiment in which we randomize job seekers' access to simple information about wages and job benefits (retrieved from the review platform) that are associated with the companies posting job ads on jobchannel.

Our experimental sample consists of job seekers who visited any of the websites managed by jobchannel between March and May 2023, and who accepted the statistic cookies. In their daily operations, jobchannel runs A/B tests on their websites and collects information on users' behavior on a regular basis: as such, participants did not have to be informed about our specific experiment, nor about the fact that jobchannel was collecting information about their behavior for this specific experiment. Moreover, even outside of the experimental period, users are asked whether they want to accept the cookies used on the website. As such, we are able to observe the effect of providing information to job seekers as they naturally interact on job vacancy websites.

In each of the three months, some of the jobseekers were randomized into a control group and were not shown any extra information other than the one typically displayed on jobchannel's websites. Figure 4 displays an example of the search results that a user would see when looking for vacancies on one of the websites: this is a list of available vacancies with simple information available about each of them, such as the title of the vacancy chosen by the firm posting it (which typically includes the indication of the position and other details such as whether the job is full- or part-time), the name and location of the firm, as well as a 5-star rating from users of the review platform (when available). Jobseekers can click on each of these ads to read more details about them, scroll through the page to see other vacancies, and click on other pages to see even more vacancies.

Jobseekers randomized in one of the treatment groups were instead shown extra information about the vacancies, such as the wage that the firm posted the ads typically pay for that type of position, or the benefits available to employees at that firm. This information is recovered from the reviews of employees at that firm, which we access from our partner operating the review platform, and we aggregate for and display to the users of jobchannel whenever the information is available. As an example, Figure 5 shows that the same search results described above would have looked like for a user randomized into the treatment group in which we display information about average wages, and the availability of three different benefits: flexible working hours, home office, and childcare. The search results contain all the same information as in the control group. Moreover, for each vacancy, jobchannel displays also an additional box with information on benefits and wages. The first two vacancies, for example, show that none of the three benefits is (reported to be) available at this firm as all three are greyed out. Moreover, we do not report any information on wages as this information was not available on the review platform for this specific firm and position. Note that the key difference with respect to the control group for these vacancies is that users receive information about the unavailability of these benefits. Contrast this with the third vacancy, in which the availability of flexible working hours is indicated by the tick and the fact that this text appears in black. Moreover, since the information was available, we also reported the average monthly wage at this firm for this position. The same information available on the listing of search results was also made available on the page of each specific ad.

In each of the three months of our intervention, users were randomized to eight different treatment groups the composition of which varied by month, as summarized in Figures 6, 7, and 8. In each month, there was always a control group of users not being shown any extra information with respect to the status quo.

In both March and April, we also had two treatments groups, average wage and median wage, in which jobseekers were shown respectively the average and median wages reported by users of the review platform for similar positions at the firm posting the ad (whenever this information was available): we randomized whether we displayed the median or the average wage in order to generate within job posting random variation in the wages shown across treatment groups. Note that to describe the statistic being displayed, we used a generic German word that can mean either average or median: as such, from the point of view of the user, the only difference between the two treatment groups was the actual number displayed as a wage.

In March, users in all the remaining treatment groups were also shown the average wage. On top of that, however, they were also shown information about the availability of certain benefits. We grouped a total of twelve benefits in groups of three, and users were randomized into one of these groups: i) flexible working hours, home office, and childcare; ii) parking spot, good transportation, and company car; iii) canteen, food allowance, and coaching; iv) childcare, health services, and company doctor; v) flexible working hours, coaching, and employee events. For all vacancies for which this information was available, job seekers were shown an icon indicating the presence of a given job benefit in the firm. The benefit was marked as present as long as a given percentage of the reviewers on the review board indicated the presence of that benefit. For March, this percentage was set at 20%.

In April, beyond the three groups (control, average waves, and median wages) described below, all the other treatments displayed information about wages and the availability of a single group of three benefits: flexible working hours, home office, and childcare. Just as in March, one group was shown average wages and the availability of these three benefits using a threshold of 20% of users on the review board reporting the benefit. However, in order to generate within job posting random variation in the availability of benefits being displayed across treatment groups, we also introduced a treatment group in which we used instead a threshold of 50%. As a result, if for example 30% of users reported a given benefit, the same vacancy would appear as having the benefit in the first treatment group but not in the second one. Two other treatment groups replicated the ones just described but had the median wage displayed instead of the average. Finally, in order to test the importance of order effect, in the eighth treatment group of April, we changed the order in which benefits were displayed, having childcare listed first and flexible working hours shown last.

In May, beyond the control group, we had seven treatment groups in which users were shown average wages as well as the availability of groups of three benefits, with the availability always based on the 20% threshold. However, how benefits were grouped in triples was changed with respect to March. We made sure to generate the groups in such a way that each benefit would appear exactly in three treatment groups (in either March or May) and never with the same two benefits more than once. Doing so allows us to have independent variation in the displaying of the different benefits and so to estimate the separate effect of displaying each of them.

As displayed in Figures 9, 10, and 11 the randomization was effective, with observable characteristics being well-balanced across the treatment groups in each of the three months.

Figure 4: Screenshot Control Group

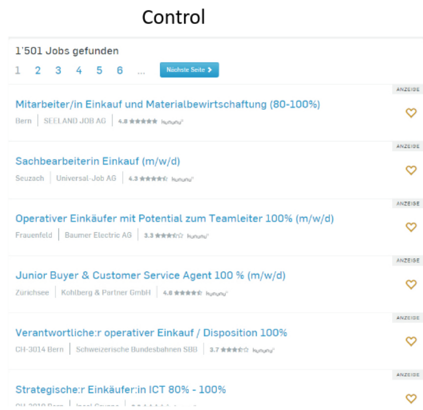


Figure 5: Screenshot Treatment Group

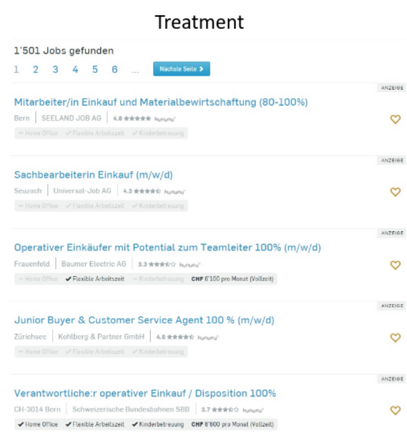


Figure 6: Treatments March

Condition	*Wage*	*Fringe Benefit 1*	*Fringe Benefit 2*	*Fringe Benefit 3*	*%*	*Users*
Control Group	no additional information (business-as-usual)					19,059
Average wage	Average					19,446
Median wage	Median					19,728
Family	Average	Flexible working hours	Home office	Childcare	20%	19,280
Commute	Average	Parking spot	Good transportation	Company car	20%	19,233
Nutrition	Average	Canteen	Food allowance	Coaching	20%	19,226
Health	Average	Childcare	Health services	Company doctor	20%	19,421
Work environment	Average	Flexible working hours	Coaching	Employee events	20%	19,191

Figure 7: Treatments April

Condition	Wage	Fringe Benefit 1	Fringe Benefit 2	Fringe Benefit 3	%	Users
Control Group	no additional information (business-as-usual)					15,502
Average wage	Average					15,553
Median wage	Median					15,625
Family	Average	Flexible working hours	Home office	Childcare	20%	15,659
Family 50	Average	Flexible working hours	Home office	Childcare	50%	15,461
Family Median	Median	Flexible working hours	Home office	Childcare	20%	15,624
Family Median 50	Median	Flexible working hours	Home office	Childcare	50%	15,693
Family Reordered	Average	Childcare	Home office	Flexible working hours	20%	15,654

Figure 8: Treatments May

Condition	Wage	Fringe Benefit 1	Fringe Benefit 2	Fringe Benefit 3	%	Users
Control Group	no additional information (business-as-usual)					16,882
May 1	Average	Good transportation	Canteen	Health services	20%	16,626
May 2	Average	Company car	Company doctor	Employee events	20%	17,100
May 3	Average	Childcare	Food allowance	Employee events	20%	17,082
May 4	Average	Flexible working hours	Home office	Parking spot	20%	17,072
May 5	Average	Home office	Parking spot	Company car	20%	17,095
May 6	Average	Good transportation	Food allowance	Health services	20%	16,995
May 7	Average	Company doctor	Canteen	Coaching	20%	16,877

Figure 9: Balance March

	0	1	2	3	4	5	6	7	p-value
Share in Zurich	0.222	0.220	0.220	0.215	0.217	0.220	0.213	0.213	0.535
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	
Share in Switzerland	0.529	0.524	0.520	0.518	0.514	0.522	0.514	0.515	0.203
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	
Share in Germany/France/Italy/Austria	0.055	0.057	0.056	0.053	0.055	0.054	0.054	0.054	0.897
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
mobile	0.584	0.585	0.593	0.586	0.584	0.583	0.586	0.583	0.795
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	
desktop	0.396	0.395	0.389	0.396	0.398	0.400	0.398	0.398	0.776
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	
Language: DE	0.837	0.836	0.840	0.837	0.839	0.841	0.844	0.840	0.792
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	
Hour of the first session: 8-14	0.369	0.363	0.372	0.375	0.377	0.370	0.366	0.369	0.339
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	
Hour of the first session: 14-20	0.346	0.348	0.349	0.340	0.338	0.338	0.343	0.344	0.431
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	
Probability of opening an ad cond. on impression	0.055	0.053	0.060	0.059	0.056	0.056	0.060	0.059	0.614
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	
Probability of applying for an ad cond. on view	0.118	0.122	0.119	0.124	0.129	0.119	0.100	0.113	0.343
	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.006)	(0.007)	
Number of Users	11,879	12,304	12,471	12,266	12,311	12,219	12,341	12,212	
Number of users active in Feb	1,016	1,089	1,033	1,012	1,059	1,056	1,050	1,068	

Figure 10: Balance April

	0	1	2	3	4	5	6	7	p-value
Share in Zurich	0.216	0.206	0.208	0.205	0.208	0.213	0.201	0.207	0.268
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	
Share in Switzerland	0.521	0.519	0.517	0.504	0.513	0.514	0.505	0.509	0.119
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	
Share in Germany/France/Italy/Austria	0.060	0.062	0.055	0.059	0.063	0.060	0.062	0.059	0.428
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
mobile	0.570	0.573	0.575	0.573	0.570	0.569	0.576	0.566	0.859
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	
desktop	0.410	0.408	0.408	0.409	0.412	0.411	0.406	0.415	0.930
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	
Language: DE	0.838	0.839	0.841	0.847	0.847	0.845	0.837	0.838	0.219
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	
Hour of the first session: 8-14	0.368	0.375	0.369	0.369	0.378	0.378	0.377	0.369	0.498
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	
Hour of the first session: 14-20	0.345	0.346	0.344	0.344	0.342	0.340	0.335	0.345	0.776
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	
Probability of opening an ad cond. on impression	0.063	0.048	0.066	0.061	0.067	0.054	0.057	0.062	0.043
	(0.005)	(0.003)	(0.005)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)	
Probability of applying for an ad cond. on view	0.116	0.114	0.135	0.124	0.121	0.124	0.116	0.115	0.896
	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	
Number of Users	10,166	10,070	10,105	10,308	10,206	10,311	10,207	10,187	
Number of users active in Feb	508	448	512	505	473	525	494	487	

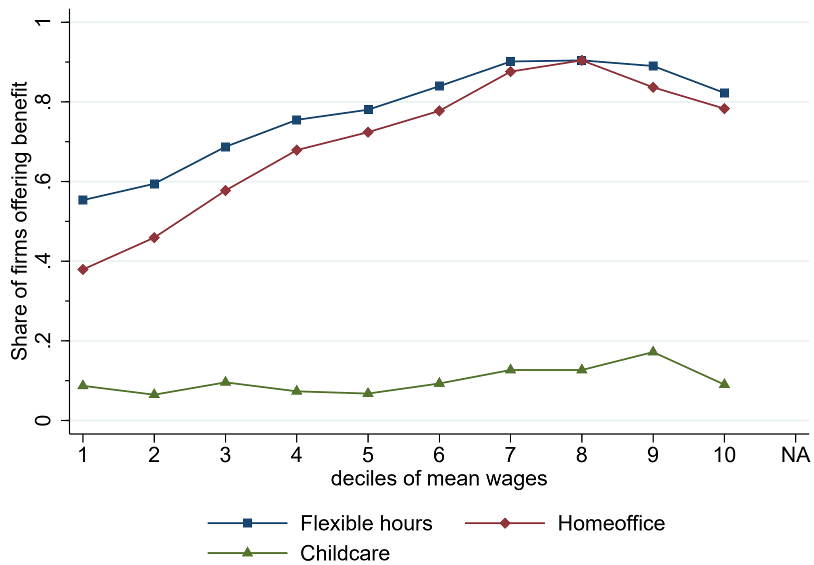
Figure 11: Balance May

	0	1	2	3	4	5	6	7	p-value
Share in Zurich	0.198	0.195	0.192	0.192	0.197	0.198	0.198	0.197	0.807
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	
Share in Switzerland	0.518	0.509	0.507	0.505	0.506	0.504	0.510	0.506	0.459
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	
Share in Germany/France/Italy/Austria	0.057	0.056	0.055	0.062	0.057	0.059	0.061	0.057	0.275
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
mobile	0.574	0.581	0.576	0.578	0.583	0.570	0.575	0.570	0.449
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	
desktop	0.410	0.403	0.405	0.404	0.400	0.411	0.402	0.413	0.368
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	
Language: DE	0.837	0.834	0.838	0.834	0.833	0.841	0.838	0.844	0.313
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	
Hour of the first session: 8-14	0.367	0.364	0.373	0.370	0.368	0.363	0.366	0.377	0.457
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	
Hour of the first session: 14-20	0.338	0.340	0.331	0.334	0.341	0.333	0.344	0.334	0.418
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	
Probability of opening an ad cond. on impression	0.053	0.057	0.052	0.056	0.061	0.059	0.058	0.055	0.901
	(0.003)	(0.005)	(0.003)	(0.005)	(0.005)	(0.004)	(0.006)	(0.003)	
Probability of applying for an ad cond. on view	0.127	0.120	0.120	0.113	0.142	0.114	0.121	0.092	0.291
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)	(0.010)	
Number of Users	11,223	11,010	11,417	11,369	11,301	11,483	11,285	11,215	
Number of users active in Feb	391	385	373	366	404	419	373	350	

4 Distribution of Amenities across Firm Wages

Next, we provide descriptive statistics about the number of available job benefits and the distribution of specific benefits across firms with different pay. To this end, we sort firms into different deciles of average wages offered at the firm according to the wage reviews on the employer review platform. For each decile, we compute the share of firms offering a particular benefit. We define firms offering a particular benefit if at least 20% of reviewers confirm its availability at the firm on the employer review platform.

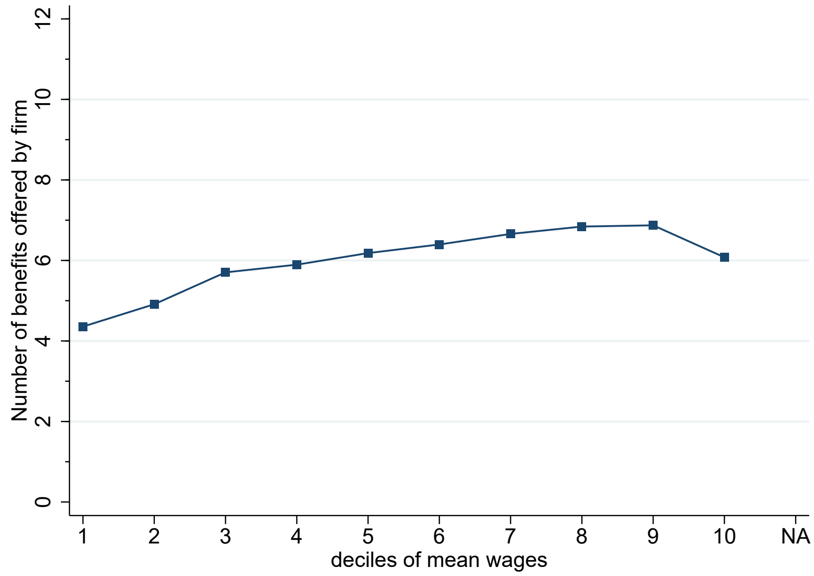
Figure 12: Share of firms offering time flexibility, home office, and childcare



Notes: The figure shows the share of firms offering flexible hours, home office, or childcare in each decile of the average wage offered at the firm.

Figure 12 shows that the likelihood that a firm offers either flexible working hours or the option to work from home both increase strongly with the average wage paid at the firm up until the 7-th decile and plateau thereafter. At the 7-th decile, there is roughly a 90% chance that these benefits are available at the firm. This chance is roughly 2.3 (for flexible hours) or 1.5 (for home office) lower for firms at the bottom of the wage distribution. Furthermore, Figure 13 shows that firms at the top of the wage distribution also offer several benefits more than those at the bottom. For instance, according to reviewers from the employer review platform firms at 7-th decile of average wages and above offer on average about seven of the benefits while firms at the bottom offer only about four.

Figure 13: Better-paying firms offer more benefits



Notes: The figure shows the number of benefits offered at the firm by decile of the average wage offered at the firm.

These results parallel similar findings by Sockin (2022) and Roussille and Scuderi (2023). Since we can measure which benefits are available directly from reviewers on the employer review platform, our analysis is not affected by the otherwise common assumption in the literature ((e.g., Bonhomme and Jolivet, 2009; Sorkin, 2018; Taber and Vejlin, 2020; Sullivan and To, 2014; Lamadon et al., 2022)). that workers' moves to lower-paying firms can only be rationalized by unobserved, positive changes in the availability of (compensating) job amenities. Contrarily, our results highlight that most job amenities are positively correlated with pay. This finding runs counter to the notion that firms' wage premia compensate for unfavorable job characteristics (Sorkin (2018); Rosen (1986) and instead supports more-productive firms offering improved amenities Lamadon et al. (2022); Mortensen (2003).

5 Value of Job Benefits

5.1 Econometric Model

To estimate the value of fringe benefits to job seekers looking for jobs on the job platforms of jobchannel, we run the following regression based on the sample of XX impressions that appeared on the screens of jobs seekers during the experiment period from March 6 to May

31, 2023:

$$y_{ij} = \phi_j + \pi_r + \gamma_w T_{ij}^w + \beta_w \log(\tilde{w}_{ij}) \times T_{ij}^w + \sum_{f=1}^{F} \gamma_f T_{ij}^f + \sum_{f=1}^{F} \beta_f FB_{ij}^f \times T_{ij}^f + \epsilon_{ij} \tag{1}$$

In our main specification, we estimate the regression based on a linear probability model. However, as a robustness test, we also use a poisson model.

In most specifications, y_{ij} is the likelihood that job seeker i opens vacancy j conditional on seeing it on the screen. In some specifications, we also use the likelihood that job seeker i performs an action on the open ad as outcome (e.g., printing, sharing, saving, applying through the platform).

The vacancy fixed effect ϕ_j controls for all constant (observed and unobserved) ad-specific factors that affect the likelihood to open an ad. Thanks to the control group and the within-ad variation in wages and benefits we can estimate this effect together with the effects of wages and benefits. π_r is a rank fixed effect that controls for the position of an ad on the list of search results.

T_{ij}^w is an indicator whether vacancy j that appears on the screen of job seeker i contains wage information. Job seekers in the control group never see information on wages and even in the experiment arms where wages are shown, there are also some ads without wage information. $\tilde{w}_{ij}$ is the specific wage displayed to job seeker i on vacancy j. It corresponds to the mean or median wage (depending on the experiment arm) paid by the firm posting vacancy j for jobs with the same job title. The (log) wage has been centered around its mean value (6224 CHF).

γ_w is thus an estimate of the effect of displaying the mean wage (6224 CHF) on a job ad compared to showing no wage information at all. $\beta_w/100$ is an estimate of the effect of a 1% change in the wage displayed on a job ad. In our baseline specification, β_w is identified by within-ad variation in wages (sometimes we display mean and sometimes median wages) and by across-ad wage variation. Since we control for the effects of all constant ad-characteristics by means of the ad fixed effect, β_w can be interpreted as the effect of varying the wage on a given vacancy, holding the general attractiveness of the vacancy constant. This accounts for the fact that firms or ads that are more attractive in some (unobserved) dimensions might pay higher wages. We also report a specification in which we identify the effect of the wage exclusively by the within-ad wage variation due to the random assignment of job seekers to experiment arms in which they see either the mean or the median wage on the same job ad. The results are very similar to our main specification.

Now we describe the variables and coefficients related to the effects of the fringe benefits:

T_{ij}^{f} is an indicator whether whether vacancy j appearing on the screen of job seeker i contains any information ($T_{ij}^{f} = 1$) on fringe benefit f. Job seekers in the control group never see information on fringe benefits. But also in experiment arms where benefits are shown, there are some ads without fringe benefit information. FB_{ij}^{f} indicates whether job seeker i sees that fringe benefit f is available ($FB_{ij}^{f} = 1$) or not ($FB_{ij}^{f} = 0$) at the firm posting vacancy j. In most treatment arms, a fringe benefit is reported to be available if at least 20% of reviewers on the employer rating platform report that the benefit exists at the firm. However, for three benefits (Flexible working hours, Home office, Childcare facilities) we sometimes change the threshold above which a benefit is reported to be available to 50%, which generates within-ad variation in benefit availability.

Since we estimate separate effects for T_{ij}^{f} and FB_{ij}^{f}, γ_f is an estimate of the effect of showing that fringe benefit f is not available at the given firm compared to showing no information on fringe benefit f at all. β_f is an estimate of the effect of showing that fringe benefit f is available at the firm posting vacancy j compared to showing that it is not available. Since the ad fixed effect controls for all constant ad characteristics that affect the outcome, β_f can also be interpreted as the effect of varying fringe benefit f on a given vacancy. We also report a specification in which we identify the effects of the three benefits, for which we apply different thresholds, using only the benefit variation within the same vacancy. The results are very similar to our main specification. For better interpretability of the fringe benefit effects, we transform β_f into an estimate of the willingness-to-pay for fringe benefit f by dividing β_f by $\beta_w/100$.

ϵ_{ij} is the error term. In all specifications, we cluster standard errors on the user times month level.

5.2 Value of Job Amenities

Now we turn to the question of how much job seekers value certain job benefits. Figure 14 shows our willingness to pay estimates based on equation (1). The Figures report the ratio of the benefit effect and wage effect, i.e. β_f/β_w, and associated standard errors using the delta method. This measures how much a firm can lower wages by additionally offering a certain job benefit, keeping the click and applications probability constant. It is clearly visible that many job benefits are highly valued by job seekers. The highest valued job benefit is home office, which we estimate a willingness to pay of 20 percent of wages. The job benefit with the second highest valuation is company car, with a willingness to pay of about 15 percent of wages. This is perhaps not surprising if the usage of the company car can substitute the usage, or even the ownership of a private car, which entails then a large monetary benefit. Child care is also highly valued with 10 percent of wages. Having a parking lot is also priced highly by job seekers, we estimate a willingness-to pay of around 10 percent of wages. We also find positive willingness to pay estimates in the range of around five percent for public transport, health measure, but these are not precisely enough estimated to rule out a zero effect size at conventional confidence levels. Food allowance, Coaching, employee events do not seem important to job seekers. The Figure further shows that it does not matter whether we use our baseline specification, or a poisson regression with session fixed effects.

So far, we have exploited two types of variation in our experiment: (1) variation in wages and benefits across vacancies, holding the general attractiveness of the vacancy constant through a vacancy fixed effect, and (2) the experimental variation of wages and benefits within vacancies due to the fact that we sometimes show mean and sometimes median wages, and have also variation in the cut-off used for benefits.

Therefore we reestimate our baseline regression, but we only use experimental variation within vacancies. Here we only not use our control group, but rather the treatment arms with median versus mean wages. For the benefits we have only one treatment are available with a different threshold, these cover the home office, child care and flexible hours job benefits. Table 4 compares the estimates derived from the regression using all variation in column (1) with only experimental variation within vacancy (column 2 and 3). It shows that at least for the effect of wages and child care, we find virtually the same effects if we only use experimental variation within vacancies.

5.3 Heterogeneity

Figure 15 explores whether the willingness-to-pay differ across certain occupations and language regions. The top left panel shows that job seekers in higher wage occupations tend to have a higher willingness-to-pay for job benefits. In occupations with a high female share home office is valued higher, but company car is valued lower. Furthermore, female intensive occupations have a much lower valuation for child care. Given that many females typically work part-time in Switzerland, it seems natural that a on-site child care facility is less valuable if working part time. We also find that child care is valued higher in German speaking regions.

Table 4: Exploiting experimental variation in April

	(1) All	(2) Wage	(3) Benefit
Log Wage	.015***	.016***	.016***
	(.0034)	(.0043)	(.0038)
Flexible hours	-.00044	0	-.00018
	(.00061)	(.)	(.00073)
Home office	.0031***	0	.0029***
	(.0006)	(.)	(.00075)
Childcare	.00037	0	-.00081
	(.00082)	(.)	(.001)
Wage shown	.0095***	.0087***	.011***
	(.0011)	(.0013)	(.0012)
Benefits visible	.00044	0	.00044
	(.0006)	(.)	(.00083)
Mean dependent variable	.044585	.04367	.044952
Ad fixed effects	Yes	Yes	Yes
Rank fixed effects	Yes	Yes	Yes
Observations	2,571,069	990,811	1,597,312

Notes: The table shows estimates of our baseline regression model for the wage and benefit treatment arms in April. Estimates in column 2 are based on a sample that only includes the two wage treatment arms (mean wage and median wage). Estimates in column 3 are based on a sample that only includes the four benefit treatment arms (Average Wage + Flexible Working Hours, Home Office, Childcare (>=20%); Average Wage + Flexible Working Hours, Home Office, Childcare (>=50%); Median Wage + Flexible Working Hours, Home Office, Childcare (>=20%); Median Wage + Flexible Working Hours, Home Office, Childcare (>=50%)).

6 Wage inequality versus Job value inequality

The high willingness-to-pay estimates of many job benefits show that job seekers value more aspects of jobs than purely wages. But how much do these benefits quantitatively matter in practice? To answer this question we compute the value of the jobs advertised during our experiment period taking the offered benefits and their valuations into account. For each vacancy where we have wage information from the employer rating platform, we compute the job value, which is the sum of wages and the CHF value of the benefits for which we find a statistically significant willingness-to-pay. Table 5 shows the distribution of wages and job values. On average, a vacancy offers 1660 CHF worth of job benefits, which constitute a 24 percent increase over pure wages. How much do these willingness-to-pay estimates affect our understanding of inequality? We find that job value inequality is significantly higher

Table 5: Comparison of Wages and Job Values

	Mean	SD	P10	P50	P90	P90/P10	P50/P10	GINI
Wage (CHF)	6691	2129	4483	6083	9658	2.15	1.36	0.173
Job Value (CHF)	8354	2942	5184	7784	12346	2.38	1.50	0.194

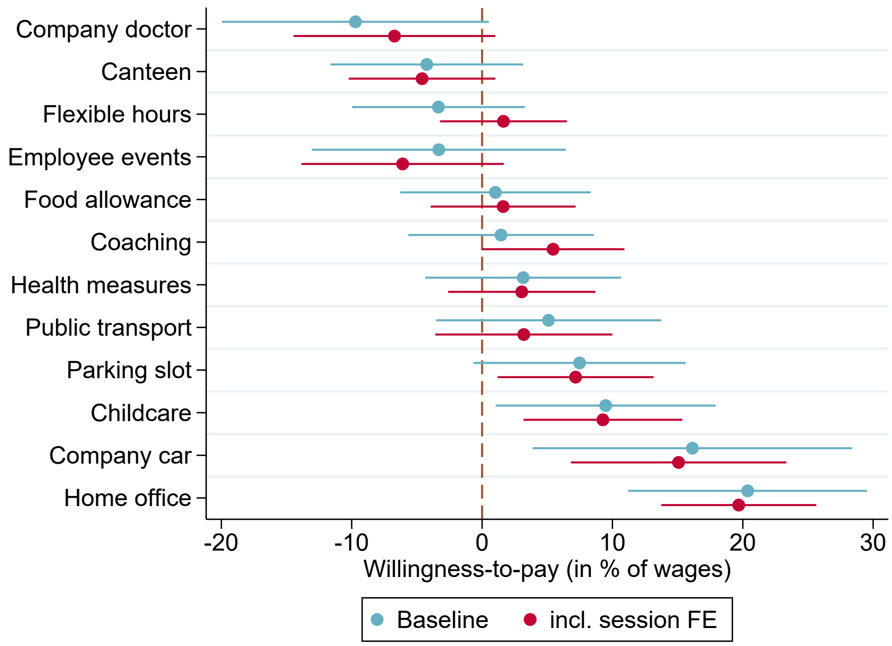
compared to wage inequality. The standard deviation of job values is 40 percent higher than the standard deviation of wages. The Gini coefficient for job value inequality is 0.194 compared to 0.173 for wages, and the P90/P10 ratio of job values is 2.4 compared to 2.15 for wages. The reason behind this is, as we discussed earlier, high wage vacancies typically also offer more benefits. Summarizing, our paper provides experimental evidence that job benefits not only affect the search behavior of job seekers, but also affect our understanding of inequality across workers.

7 Conclusion

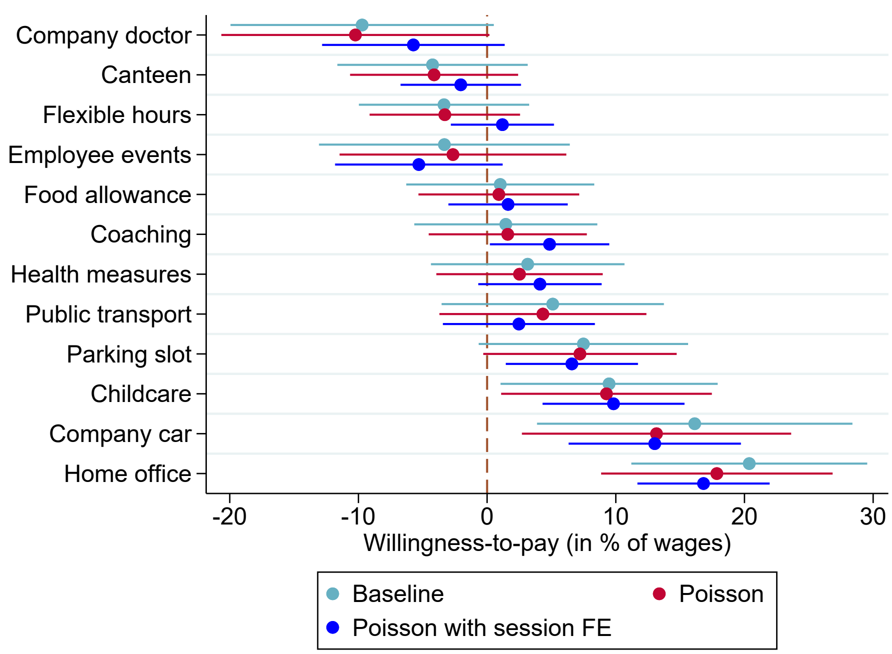
This paper studies the role of job benefits in job search behavior. We use wage and benefit data from a market-leading employer review platform and run a large scale randomized control trial on an online job board to estimate the willingness to pay of job seekers for job amenities. We find that many job benefits are highly valued by job seekers: Home office is valued around 20 percent of wages, company car with 15 percent, company provided child care and parking spots with around 10 percent of wages. The average vacancy offers job benefits worth of 27 percent of wages. We further document that higher paying firms typically offer more amenities. Taking the distribution and valuation of job benefits into account, we show that job value inequality is significantly higher than wage inequality. Summarizing, our paper provides experimental evidence that job benefits not only affect the search behavior of job seekers, but also affect our understanding of inequality across workers.

Figure 14: Willingness-to-pay for benefits

(a) Linear model



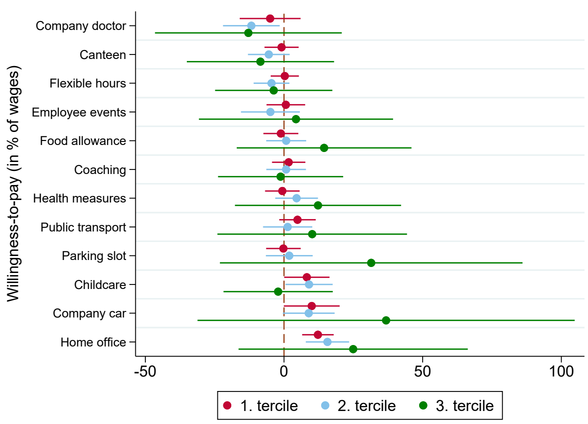
(b) Linear model vs poisson model



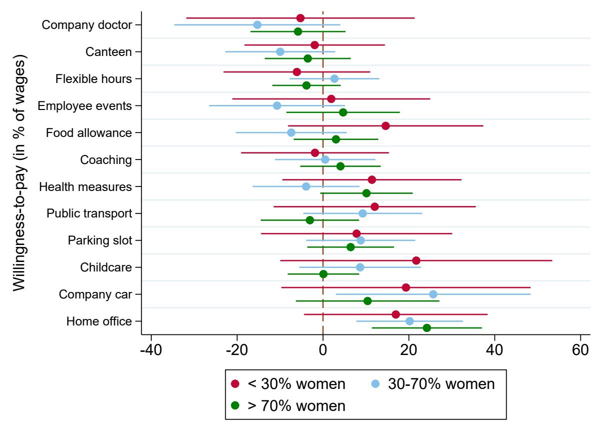
Notes: The figure displays the willingness-to-pay for different fringe benefits. Panel a plots the results based on a linear model and panel b compares them with results from a poission model

Figure 15: Willingness-to-pay for benefits

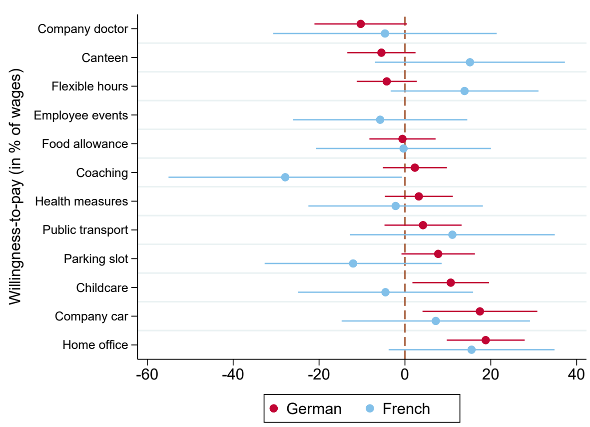
(a) Linear model



(b) Linear model vs poisson model



(c) Linear model vs poisson model



Notes: The figure displays the willingness-to-pay for different fringe benefits.

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A Data cleaning

B Additional Tables and Figures

Figure B1: Snapshot of the benefit review on the employer review website

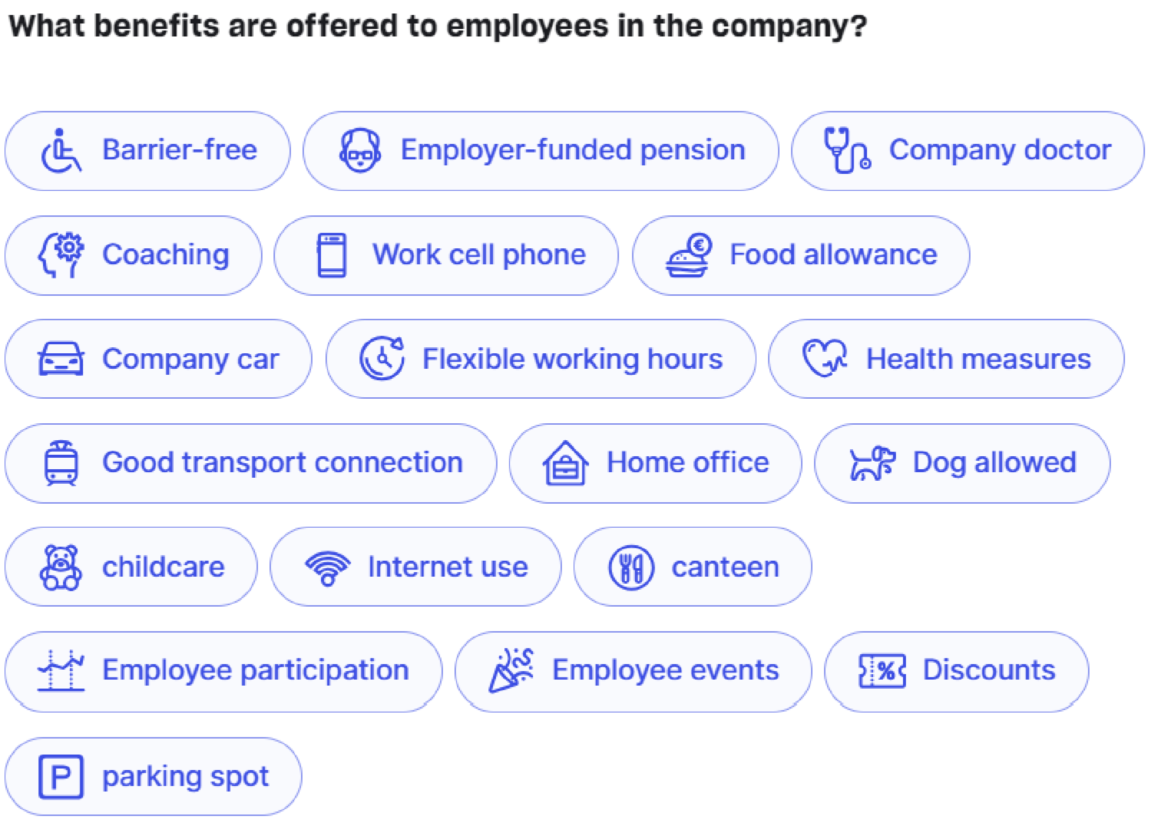

Figure B2: Snapshot of the wage review on the employer review website

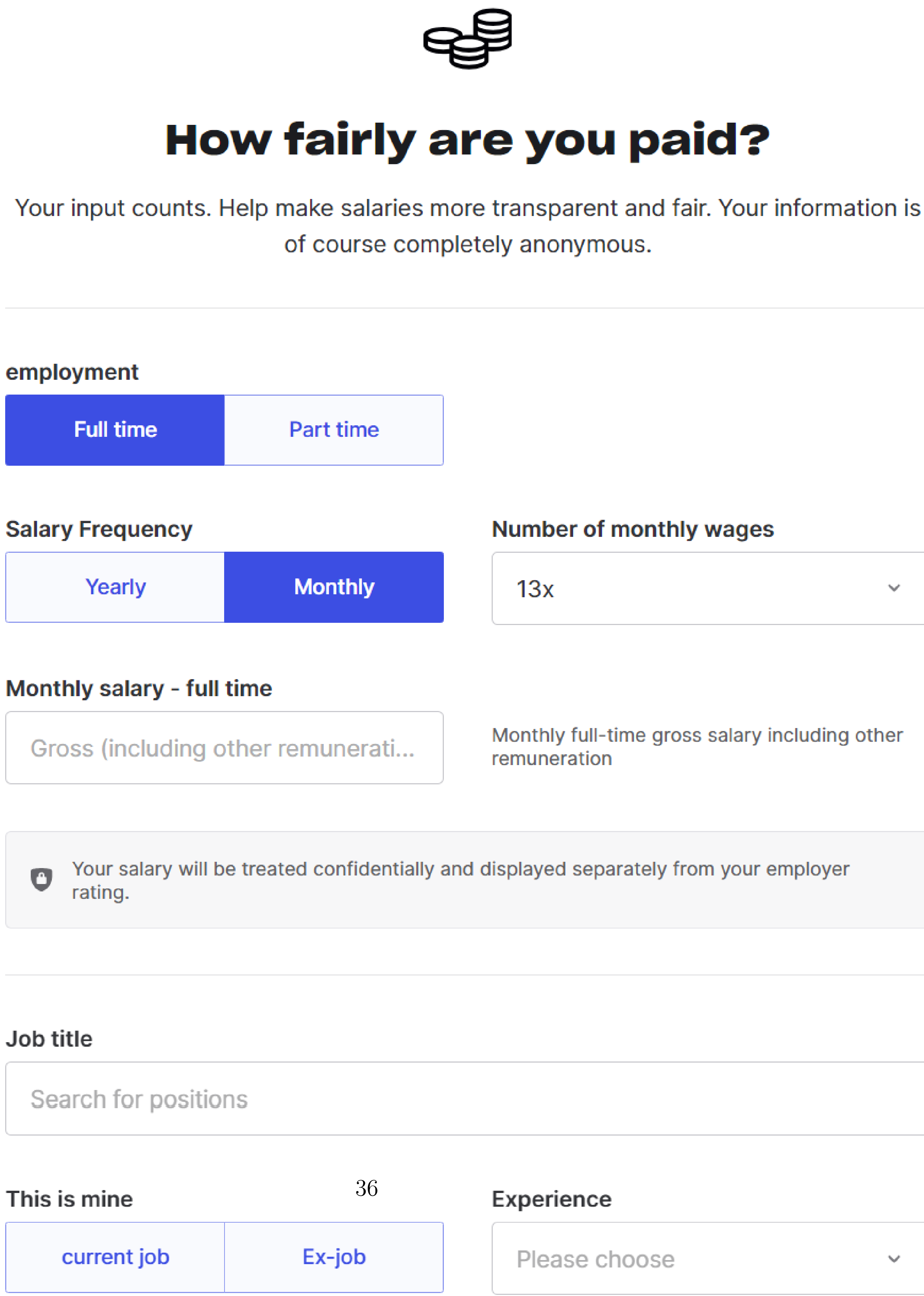

Figure B3: Mean wage among job ads viewed in the experiment vs official mean wages (Federal Statistics, 2018), by ISCO 2-digit occupation code

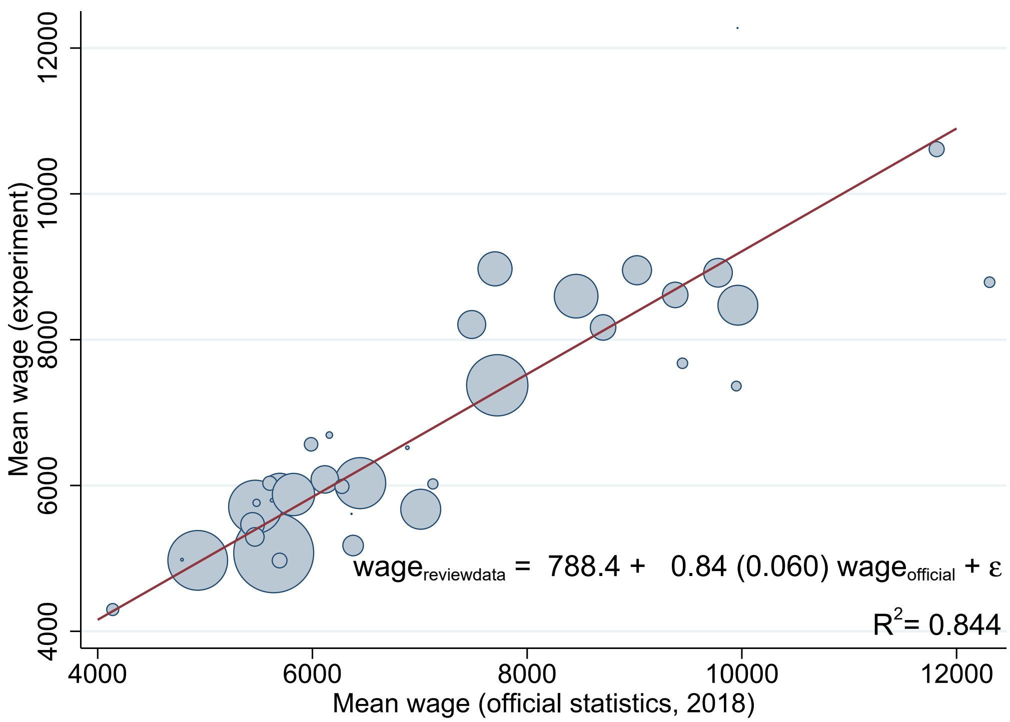

Figure B4: Mean wage among job ads viewed in the experiment vs official mean wages (Federal Statistics, 2018), by industry

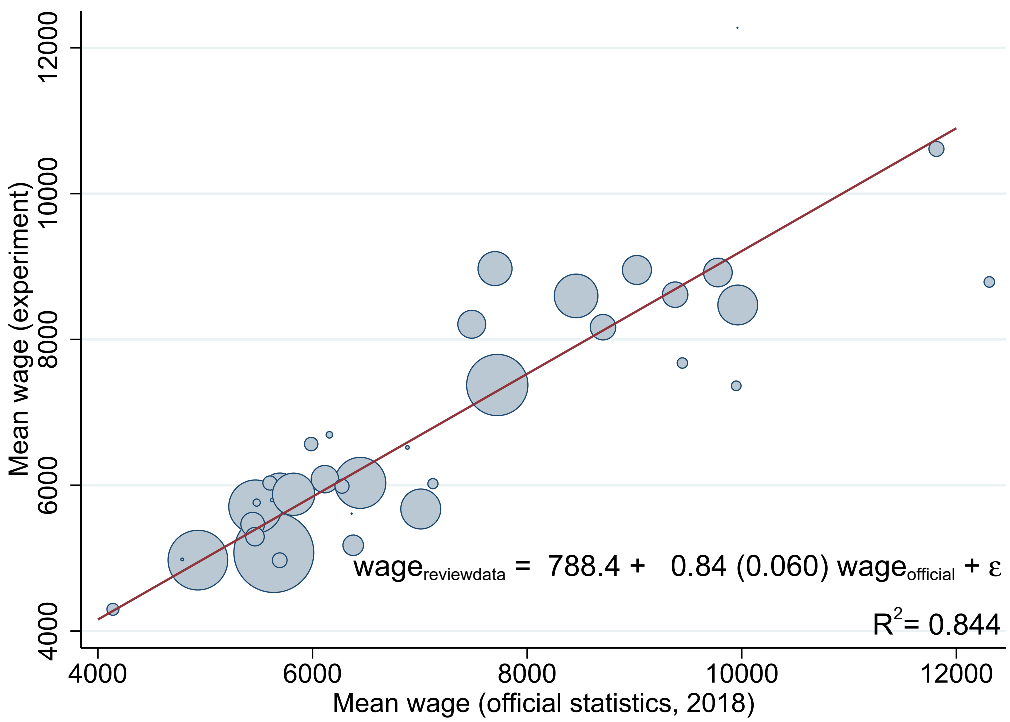

Figure B5: Job ads viewed during experiment vs. job openings in Switzerland on March 31, by industry