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IZA DP No. 16845

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ABSTRACT

Do Recruiters Penalize Men Who Prefer Low Hours? Evidence from Online Labor Market Data*

Part-time work is a popular way to reconcile work and family responsibilities. This study investigates how easy it is for men and women to get part-time jobs. To assess this question, I first analyze the hiring decisions of recruiters who screen jobseekers on an online recruiting platform and estimate contact penalties for men and women seeking part-time jobs. Second, I relate the number of hours advertised in online job postings to firms' confidentially reported gender preferences. I find that recruiters prefer full-time over part-time workers, and that part-time penalties are more pronounced for men than for women. Differences in job or workplace characteristics cannot explain these results. Instead, the preponderance of evidence points to bias due to gender stereotypes.

JEL Classification: J16, J23, M51

Keywords: recruitment, part-time, gender equality, hiring, online labor markets

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1 Introduction

The gap between men and women in the labor market has narrowed along several dimensions in recent decades (Goldin, 2014). However, significant differences remain, in particular an unequal distribution of paid and unpaid work. These gender gaps in hours worked on the job and hours spent on domestic work are closely related to gender gaps in other labor market outcomes (Blau and Kahn, 2017; Denning et al., 2022). Thus, a more equal division of paid and unpaid work between men and women is crucial for achieving greater gender equality. However, in order to take on more domestic tasks, men will most likely have to reduce their hours in paid work, for instance by working more often part-time.[1] But how easy is it to find a part-time job? How flexible are firms concerning the number of hours a jobseeker wants to work? Does it make a difference whether a man or a woman is looking for a part-time job? While we know a lot about workers' preferences for part-time or full-time jobs (Mas and Pallais, 2017), little is known about recruiters' preferences for full-time or part-time workers.

I address this gap by investigating whether recruiters prefer full-time or part-time workers and how these preferences depend on the gender of the jobseeker. I draw on large-scale observational data from Job-Room, the online job and recruitment platform of the Swiss Public Employment Service (PES). This platform combines two functionalities: jobseekers can search for job opportunities by navigating through job ads, and employers can browse profiles of jobseekers registered with the PES to find suitable candidates for their vacancies. I draw on three unique datasets generated by both functionalities.

First, I analyze click data from 43,352 recruiters screening the profiles of 313,566 jobseekers on Job-Room between March and December 2017. In total, 17.4 million jobseeker profiles appeared on recruiters' screens during the observation period.[2] The profiles contain information on various jobseeker characteristics, including gender and the number of hours a jobseeker wants to work. Since every click of a recruiter is recorded, I know which profiles they look at, how long they do so, and who they end up trying to contact. Because the data can be linked to the unemployment register, I have even more information about jobseekers than recruiters. I use two complementary identification strategies to estimate the causal effect of a jobseeker's preferred number of hours on the likelihood of being

[1] A greater popularity of part-time work among men could also mitigate the existing downsides of part-time work, such as occupational downgrading (Manning and Petrongolo, 2008), a lower likelihood of promotion (Francesconi, 2001), and lower social security benefits (Doran et al., 2019), which have so far mainly affected women.

[2] In Hangartner et al. (2021), we use the same data to assess ethnic and gender discrimination.

contacted by a recruiter, and how this effect depends on a jobseeker's gender. Following Hangartner et al. (2021), I take advantage of the fact that I have information on all jobseeker characteristics displayed to recruiters on Job-Room and apply a conditional-on-observables identification strategy. In particular, I use the post-double-selection method (Belloni et al., 2012, 2014) to ensure that I control for all jobseeker characteristics that are systematically correlated with the contact likelihood, gender, and the jobseeker's preferred number of hours. I estimate a linear probability model that includes search fixed effects, implying that all effects are identified by comparing jobseekers who appear on the same results list and are evaluated by the same recruiter. Assuming that only jobseeker characteristics visible to recruiters can influence their decision to contact a jobseeker, the estimated coefficients have a causal interpretation. Placebo tests support the validity of this assumption. The second identification strategy exploits the fact that more than 3,900 jobseekers on Job-Room changed their preferred number of hours during the observation period. By running within-jobseeker regressions, the identification of the causal effect of the preferred number of hours is based on comparing the contact probability of the same jobseeker before and after changing the preferred number of hours. Both identification strategies lead to very similar results.

Second, I analyze data on 563,444 job openings posted by employers on Job-Room between July 2018 and June 2021. The data contain information on several ad characteristics, including the number of working hours expressed in full-time equivalents (FTEs).[3] Companies posting ads on Job-Room also have the option to confidentially indicate a jobseeker's preferred gender.[4] 29,150 vacancies (5.2%) contain such information. Based on this data, I can test whether part-time jobs are less likely to be associated with a preference for men than for women. While the first dataset allows me to evaluate recruiter behavior based on a revealed-preferences approach as in Hangartner et al. (2021), the second dataset allows me to apply a stated-preferences approach similar to Kuhn and Shen (2023) and Card et al. (2021). Moreover, while the recruiter click data are from a recruiter-initiated search setting, the job ad data allow me to test whether the results also hold in a setting of worker-initiated search.

Third, starting in June 2020, I also observe if, when, and by whom a job ad was

[3]FTEs express the number of working hours as a percentage of a full-time job. For example, a 50% job requires half the working hours of a full-time job. In Switzerland, FTEs are the standard way to express the number of hours for a job.

[4]This information is not published on the platform. It will only be visible to PES staff assisting registered jobseekers with their job search. Note that Job-Room only provides a binary option (male/female) for the preferred gender. The same applies to the gender self-identification when jobseekers register on Job-Room.

opened. This allows me to study the relationship between supply and demand for part-time and full-time jobs at the market level, and to learn about the job search behavior of jobseekers looking for part-time or full-time jobs.

The analyses lead to several findings. Recruiters screening jobseeker profiles on the platform show a strong preference for jobseekers seeking full-time jobs over observationally identical jobseekers looking for part-time jobs. The size of the part-time penalty is inversely related to the preferred number of hours, and it is large relative to the reduction in contact probability caused by a lack of work experience, language skills, or educational credentials. This suggests that firms are rather inflexible when it comes to accommodating workers' wishes regarding working hours. Companies also post far more full-time jobs than part-time jobs on Job-Room. As a result, the share of jobseekers looking for part-time jobs is much larger than the share of part-time jobs offered by companies, leading to more competition for part-time jobs.

Second, the part-time penalty is much more pronounced for men than for women. An analysis of the search and selection behavior of recruiters on the platform shows that men looking for a part-time job are contacted 22% less often than men with identical characteristics who appear on the same list and are looking for a full-time job. Women, on the other hand, face an average part-time penalty of 10%. While the female part-time penalty increases linearly as the preferred number of hours decreases, the male part-time penalty rises sharply when male jobseekers seek a job with slightly fewer hours than a full-time position. The analysis of the job posting data supports this finding. Companies are about four times more likely to look for a woman than a man to fill a part-time position. Differences in gender preferences across industries, occupations, or firms cannot explain this gender gap. On the other hand, firms advertising full-time positions are more likely to prefer men than women.

I explore several mechanisms that could rationalize these findings. A firm's production technology could explain why it prefers full-time to part-time workers if some features, such as high fixed costs per worker, make hiring part-time workers more expensive than hiring full-time workers. This explanation is consistent with the inverse relationship between a jobseeker's preferred number of hours and the part-time penalty. However, I find no evidence that the part-time penalty in an occupation is related to technological features that are often associated with full-time work.[5] More importantly, technological features cannot explain the gender differences in the part-time penalty, as these differences

[5]Such as the degree of time autonomy or decision making freedom, the incidence of shift work, or the incidence of overtime

persist even when comparing jobseekers who are evaluated by the same recruiter in the same occupation and who are most likely competing for the same job.

Other explanations relate to theories of signaling and statistical discrimination (Spence, 1978; Arrow, 1973; Phelps, 1972). Given incomplete information, recruiters may use the number of hours a jobseeker wants to work as a signal of a worker's disutility of work, her motivation, or her productivity (Landers et al., 1996). Moreover, recruiters may interpret this signal differently depending on the gender of the jobseeker. However, when comparing jobseeker and worker characteristics that are unobserved by recruiters but are likely to be related to productivity, I find no evidence that jobseekers seeking part-time work have less favorable characteristics than jobseekers seeking full-time work, let alone evidence of a gender gap. This speaks against statistical discrimination based on accurate beliefs as an important source of the gender gap in the part-time penalty.

Instead, I provide suggestive evidence that bias due to gender stereotypes is one reason for the larger part-time penalty for men compared to women. First, using the outcome of a popular vote on extending paternity leave as an indicator of the importance of traditional gender norms in a region, I show that the disadvantage of men in seeking part-time employment relative to women is more pronounced in regions with more traditional gender norms. Second, I find that recruiters who tend to recruit gender-typically, i.e., by favoring the majority gender in an occupation, penalize men seeking part-time work more than recruiters who tend to recruit gender-atypically. Since gender-typical recruitment strategies are likely to be associated with more traditional gender norms, this finding also suggests that gender norms play a role in explaining gender differences in the part-time penalty. Thus, gender norms may not only affect the decisions of jobseekers and workers (Fernández, 2013; Fernández et al., 2004; Bertrand et al., 2015), but also the decisions of employers.

This study contributes to several literatures. First, it adds to the literature on the effects of low working hours on various outcomes such as promotions (Francesconi, 2001), labor market segregation (Manning and Petrongolo, 2008), wages (Garnero et al., 2014), or social security benefits (Doran et al., 2019). So far, however, there is little evidence on how the preferred number of working hours affects a jobseeker's likelihood of finding a job. One exception is Goos et al. (2019). In assessing the impact of automation on unemployed jobseekers in Belgium, they also report a negative effect of a preference for part-time work on the job finding likelihood.

Second, the study contributes to the extensive literature on gender gaps in the labor market in general (for overviews see Bertrand, 2011; Blau and Kahn, 2017) and to the

growing literature emphasizing the important role of gender differences in hours worked in particular (Goldin, 2014; Denning et al., 2022; Gicheva, 2013). While this literature attributes the gender gap in hours worked mainly to different preferences of male and female workers, my study focuses on the role of firms in determining the number of hours worked by men and women. Consistent with my results, other studies find that men who prefer part-time work experience greater difficulties in the workplace.[6] Similar to Delfino (2021), this study highlights the importance of also examining the barriers that men face in entering female-dominated domains in order to better understand the causes of gender gaps in the labor market.

Third, this study adds to the literature showing that workers cannot freely choose their preferred number of hours due to hours constraints imposed by firms (Labanca and Pozzoli, 2022; Johnson, 2011). If individuals are not free to adjust the number of working hours at the intensive margin, labor supply adjustments occur primarily at the extensive margin. This has implications for the design of welfare programs (Saez, 2002), but also for macroeconomic modeling. The findings of this study support macroeconomic models based on indivisible labor (Hansen, 1985; Rogerson, 1988).

This study is structured as follows. Section 2 provides a brief overview of the situation of part-time work in Switzerland. Section 3 describes the data sources. Sections 4 and 5 present the results of the empirical analyses of the the recruiter click data and the job ad data, respectively. Section 6 discusses possible mechanisms and Section 7 concludes.

2 Part-time work in Switzerland

As in other OECD countries, women in Switzerland devote a much larger share of their total working time to unpaid work than men (see Figure B.1 in the Appendix), even though their employment rate is relatively high by international standards. According to the Swiss Labor Force Survey, about 80% of all women aged 15 to 64 were in the labor

[6] Becker et al. (2019) conduct a correspondence study in Germany, Switzerland, and Austria to examine whether callback rates of men and women vary by family status. Although not the focus of their study, they report lower callback rates for men applying for part-time jobs than for men applying for full-time jobs, while no such difference exists for women. Van Osch and Schaveling (2020) find that part-time working men report less career goal progress, less professional ability development, and less promotion speed than their full-time working counterparts. Again, they find no differences between part-time and full-time working women. Noonan et al. (2005) examine the gender gap in lawyer earnings and find that men are penalized more than women for working part-time. Pedulla (2016) examines the effect of a history of part-time work on the likelihood of being invited to a job interview for men and women. He finds a negative effect for men but not for women. Backes-Gellner et al. (2011) find that part-time work puts men—but not women—at a disadvantage in accessing employer-provided training.

force in 2019 (compared to 88% of all men in this age group). However, many of them work part-time. After the Netherlands, Switzerland has the second highest share of part-time workers in Europe, most of whom are women (BFS, 2019). While 60% of employed women work part-time, only 18% of employed men do so (Swiss Labor Force Survey 2019). Part-time work means working less than the 40 to 42 hours per week normally required for a full-time job.[7] The most important reason for women to work part-time is child-care, followed by other family responsibilities (BFS, 2019).[8] In Switzerland, social security contributions for part-time employees are not higher than for full-time employees, as is the case in some other countries (Boeri and van Ours, 2021). On the contrary, employers do not have to pay contributions to the second pillar of the Swiss pension system for part-time jobs that generate an income of less than 21,510 Swiss francs per year (2021), which makes such work arrangements even more financially attractive for companies compared to full-time jobs or higher-income part-time jobs.

3 Data sources

This study draws on data from Job-Room, the online job and recruitment platform of the Swiss Public Employment Service. Job-Room features a job posting platform where jobseekers can search for vacancies, and a platform with jobseeker profiles where recruiters can search for candidates to fill their open positions. I use three datasets generated from both functionalities to investigate whether recruiters prefer full-time or part-time workers and whether their preferences depend on the gender of a jobseeker. Table 1 provides an overview of the three data sources.

3.1 Recruiter click data

The main data source for this study is the recruiter click data from Job-Room's candidate-search platform. It provides employers with the profiles (online CVs) of jobseekers registered with the Swiss Public Employment Service. Employers can access the platform in order to search for candidates to fill their vacancies. Jobseeker characteristics visible on the platform are entered by PES caseworkers. Registered jobseekers can opt out of having their profile displayed on the platform, but only about 20% choose to do so.

[7] In 2021, employees in Switzerland worked an average of 41.7 hours per week in a full-time job (Source: Federal Statistical Office).

[8] Governmental subsidies for external childcare are very low in Switzerland, making it relatively expensive for parents to send their children to daycare (Stern et al., 2015).

Table 1: Overview of the data sources

	Recruiter clicks on Job-Room	**Job ads directly reported to Job-Room**	**Jobseeker clicks on Job-Room**
Time period	March–Dec 2017	July 2018–June 2021	June 2020–May 2021
Linked to	Unemployment register		Unemployment register Job ad data
Information	Recruiters' search criteria Recruiters' search lists Recruiters' profile views Recruiters' contact clicks Jobseekers' preferred hours Jobseekers' gender Other jobseeker charact.	# hours of the job Firm's preferred gender Other ad characteristics	Jobseekers' ad views* # hours of the job Jobseekers' preferred hours Other jobseeker charact.
Unit of obs.	Jobseeker profile on result list	Job posting by firm	Job ad view by jobseeker*
# of obs.	17,399,496	563,444	8,095,300
Additional stats	43,352 recruiters 452,729 search requests 313,566 jobseekers	75,625 firms	134,894 jobseekers* 910,379 job ads 524,456 ads with a view
Occupations	38/40 ISCO-2**	39/40 ISCO-2**	38/40 ISCO-2**

The table shows key characteristics of the datasets used in this study.
* Only registered jobseekers.
** Without armed forces. In the recruiter click data, "subsistence farmers, fishers, hunters and gatherers" and "food preparation assistants" are not covered. In the job posting data "street and related trades and service workers" are not covered. In the jobseeker click data "subsistence farmers, fishers, hunters, and gatherers" and "street and related trades and service workers" are not covered.

Recruiters looking for candidates on Job-Room must first enter search criteria that jobseekers should meet. Typical entries are occupation and location. They can also specify whether they are looking for full-time or part-time workers. Gender cannot be entered as a search criterion. Figure A.1 in the Appendix shows a screenshot of this first selection step and Table B.1 in the Appendix reports summary statistics on the search criteria entered by recruiters other than occupation.[9]

Second, recruiters get a list of at most 100 candidates that match the criteria. Figure A.2 in the Appendix shows a screenshot. Only exact matches are shown. On average, 38 jobseekers appear on a list. Each entry contains a fairly limited amount of information about a jobseeker: Desired weekly hours (in FTE), gender, canton of residence, whether the jobseeker is immediately available or not, and possible additional skills if the jobseeker has entered this information.[10] Only additional skills are entered as unstructured text.

[9]Occupational coverage will be discussed later.
[10]E.g., "Experience in long-term care, experience in Alzheimer and dementia care".

All other information is presented in a structured (tabular) way. The textual information about additional skills has been encoded using a simple text mining algorithm.[11] 61% of all candidates make use of the option to enter additional skills.

Third, recruiters can click on candidates appearing in the results list to access their profiles (see Figure A.3 in the Appendix for a screenshot). Recruiters open 23% of the profiles that appear on the lists. The profiles comprise information about the occupations in which the candidates are looking for jobs, the corresponding level of work experience, educational qualifications, language skills, gender, place of residence, desired work region, driving licenses, and the number of hours a jobseeker wants to work.[12] The preferred number of working hours is expressed in FTE and ranges from 10% (about 4 hours per week) to 100% (about 41 hours per week). 100% corresponds to a full-time job. All information about jobseekers is entered by PES caseworkers. To invite a candidate for an interview, recruiters must click on a contact button at the bottom of the candidate's profile to access the candidate's contact information or the contact information of the regional employment office responsible for the candidate. It is not possible to contact a candidate without clicking on a contact button. Linking the recruiter click data to the unemployment register, Hangartner et al. (2021) show that a contact attempt by recruiters on Job-Room increases the likelihood that jobseekers will find a job within the next few months.

Between March and December 2017, every click made by recruiters screening candidates on Job-Room was recorded. Column 1 of Table 1 reports the most important information about the resulting data set. It contains information about the search criteria specified by recruiters, the characteristics of all jobseekers who appear in the results lists, the order of the lists, which of the jobseekers were selected for full profile view, how long the recruiters viewed the profiles, and who they finally tried to contact by clicking on the contact button. Since the data can be linked to the unemployment register, they include not only jobseeker characteristics visible to recruiters, but also some characteristics that are not visible to recruiters on Job-Room (e.g. age or the last insured wage).

After cleaning the data,[13] the final dataset contains 452,729 searches performed by

[11] See Hangartner et al. (2021) for more details.

[12] Private recruitment agencies registered on Job-Room can also see a candidate's nationality. In addition, if jobseekers agree, they can see their contact information—including their names—and contact them directly. All other recruiters must contact candidates through the regional employment agencies. The names of jobseekers have been classified according to their ethnic origin. See Hangartner et al. (2021) for more details. Registered recruiters account for 30% of all users but are responsible for 73% of all search requests on Job-Room.

[13] Searches by automated bots that crawl the platform to gather information about jobseekers are

43,352 different recruiters, who screened the profiles of 313,566 different jobseekers. Since many jobseekers appear on multiple lists, the total number of profiles appearing on the lists is 17,399,496, of which 4.03 million are selected by recruiters for full profile view. Nearly 1.8 million contact attempts are reported. Recruiters spend an average of 9.1 seconds on a profile before clicking on the contact button or leaving the profile. The data contain little information about recruiters other than an anonymous identifier, whether they are registered with Job-Room, and the search criteria they use to filter the results. Although the data cover a broad set of occupations, lower-skilled occupations are over-represented on Job-Room. However, as Table B.2 in the Appendix shows, there is still a decent number of recruiters searching in occupations that typically require a higher skill level, such as (technicians and associate) professionals. The table shows not only the occupations in which recruiters are looking for candidates on Job-Room, but also the occupations in which registered jobseekers are looking for jobs. Craft and related trades workers are over-represented in recruiters' search queries compared to jobseekers' preferences, primarily due to the large number of searches for construction workers. Most other occupational groups are under-represented, especially service and sales workers.

3.2 Data on job postings

Job-Room is also one of the largest job boards in Switzerland. It contains ads reported directly to Job-Room as well as vacancies added from other large job boards, recruitment agencies and large companies. In total, it contains close to the universe of online job postings in Switzerland. I use data on 563,444 job postings directly reported to Job-Room between July 2018 and June 2021, originating from 76,625 different companies.[14] Column 2 of Table 1 reports key features of the data.

Directly reported ads account for 28% of all job ads published on Job-Room.[15] They cover all but one of the ISCO-2 occupations.[16] However, as Table B.3 in the Appendix shows, occupations that typically require lower skill levels, such as elementary occupations or service and sales occupations, are over-represented among the ads directly reported to

dropped. The same goes for searches where no search criteria are specified (1.8% of all observations) and searches that take place within less than 10 seconds to the next search (3.4% of the remaining observations). In most of these cases, recruiters do not select a candidate, but go back to re-specify the search criteria.

[14]The same data were used in a policy report by Bamert et al. (2021) to evaluate the implementation of the job vacancy notice obligation in Switzerland.

[15]This figure refers to the period from January 2020 to May 2021, for which I have data on all job ads published on Job-Room (directly reported ads and ads added from other sources).

[16]Only street and related trades and service workers are not covered.

Job-Room. But there are still a significant number of ads in occupations that typically require a higher level of qualification. For example, about 18% of all job ads are for managers, professionals, or technicians and associate professionals.

Much of the information in directly posted job ads has been coded, e.g., occupation, industry, location, firm size, type of contract (limited/unlimited), whether the job has special working conditions (night work, shift work, work from home, work on Sundays and public holidays), language skills, work experience, educational certificates, and driving licenses required, as well as the number of working hours expressed in FTE. Importantly, when reporting directly to Job-Room, firms can also indicate the preferred gender of a jobseeker.[17] This information is not published on the platform. It is only visible to PES caseworkers. 29,150 of the job ads submitted to Job-Room during the observation period (5.2%) contain information about the preferred gender. Since the information about the preferred gender is crucial to answering my research questions, I have to restrict most analyses to ads reported directly to Job-Room. For some analyses, however, I use the entire sample of job ads published on Job-Room, but I have to restrict these analyses to January 2020 to May 2021 due to data availability.

3.3 Jobseeker click data

In June 2020, the Swiss Public Employment Service started to record all clicks on job ads published on Job-Room. Therefore, for the period June 2020 to May 2021, I have data on all clicks by registered jobseekers on job ads published on Job-Room (both those reported directly to the platform and those added by external sources). Registered jobseekers are not obliged to search for jobs on Job-Room. However, about 40% do (SECO, 2023). As column 3 of Table 1 shows, 134,894 different jobseekers clicked on 524,456 different job ads (out of 910,379 ads posted on the platform) during the observation period, resulting in 8,095,300 job ad views. Since I can link the data to the unemployment register, I have detailed information on the characteristics of the registered jobseekers, including their gender and preferred number of working hours. I also have information on some of the ad characteristics, including the job location, occupation, job title, and number of weekly working hours, that are prominently displayed on the list of job ads a jobseeker sees after entering the search criteria (see Figure A.4 in the Appendix for a screenshot).

[17] Job ads added from other sources do not contain this information.

4 Analysis based on recruiter click data

Observing the selection behavior of recruiters as they navigate through the profiles of jobseekers with different hours preferences allows me to estimate the causal effect of a jobseeker's preference for a certain number of hours on the contact likelihood. It also allows me to assess how this effect depends on a jobseeker's gender. Since I have the same—and even more—information about jobseekers as recruiters, I can control for everything that influences a recruiter's decision to contact a jobseeker.

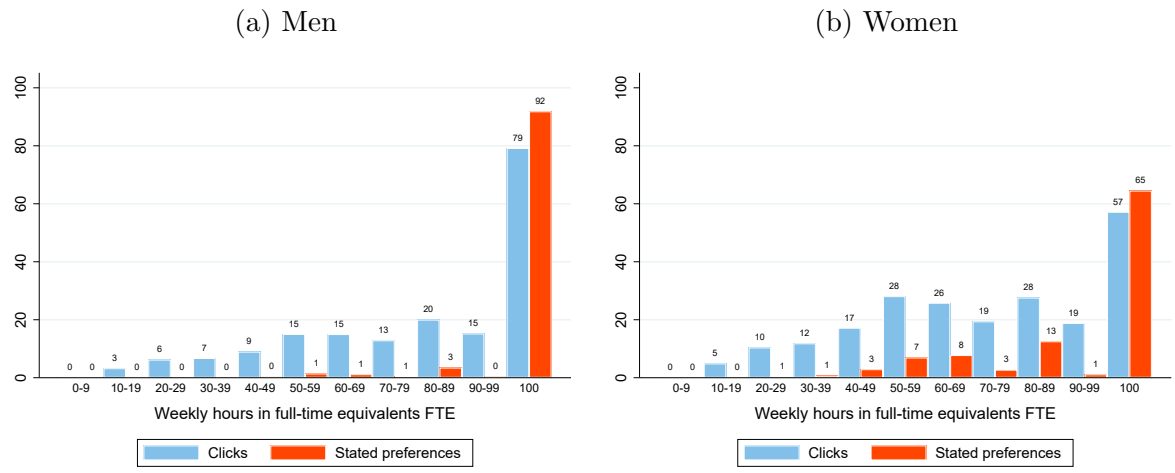
4.1 Descriptive statistics

Every jobseeker who registers with the Swiss Public Employment Service has to indicate how many hours (s)he wants to work. The red bars in Figures 1a and 1b show the distribution of these preferences for men and women.[18] While 92% of the male jobseekers say they are looking for a full-time job, only 65% of female jobseekers do. A significant proportion of women are looking for jobs between 50% and 80% FTEs. However, the preferences reported to the PES do not necessarily reflect the true preferences of jobseekers. The blue bars in Figures 1a and 1b therefore show the distribution of clicks by male and female jobseekers on job ads with different number of hours. The share of clicks on part-time job ads is much higher than the share of jobseekers who say they want a part-time job. This is true for both men and women, but the discrepancy between stated preferences and click behavior is greater for men. This may indicate that hours preferences expressed to caseworkers underestimate actual preferences for part-time work, especially among men.

Do male and female jobseekers looking for part-time work on Job-Room differ from jobseekers looking for full-time work? Table B.4 in the Appendix shows descriptive statistics on jobseeker characteristics by gender and hours preferences. Jobseekers looking for part-time work are more often Swiss than those looking for full-time work. This is true for both men and women. In terms of occupational and regional mobility, there is no significant difference between jobseekers looking for part-time work and those looking for full-time work. This is also true for men and women. Women looking for part-time jobs have more work experience but are less likely to hold a tertiary degree than women looking for full-time jobs. The opposite pattern is observed for men. Men with a preference for

[18] For consistency with the jobseeker click data (blue bars), I restrict the sample period to June 2020 to May 2021. However, Figure B.2 in the Appendix shows that the distributions look very similar when we consider the period from March 2017 to December 2017, for which we have recruiter click data.

Figure 1: Distribution of jobseeker preferences over different # of working hours by gender



Notes: Panel a plots the distribution of job ad clicks (in blue) and stated hours preferences (in red) of male jobseekers across different levels of weekly working hours (expressed in FTE). Panel b does the same for female jobseekers. The sample period is June 2020 to May 2021.

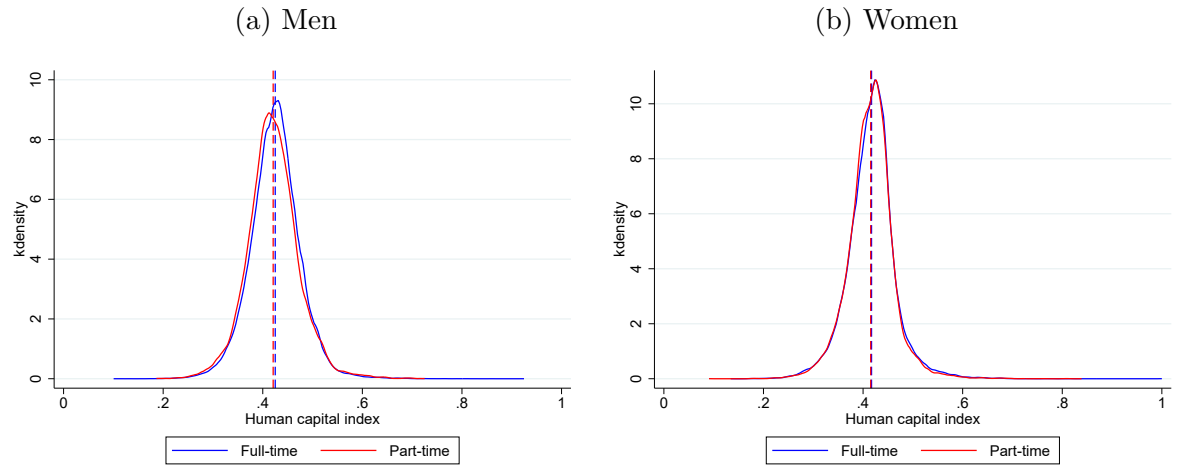
part-time work are on average better educated than those with a preference for full-time work, but have slightly less work experience. They also report better language skills than men looking for a full-time job. The relationship between language skills and preference for working hours is less clear for women. In sum, it remains unclear whether jobseekers seeking full-time jobs or those seeking part-time jobs have more favorable characteristics.

Hence, to better compare the human capital endowments of the two groups, I construct an index that captures the occupation-specific valuation of human capital-related characteristics of jobseekers by recruiters.[19] Figure 2 shows the distribution of this metric for male and female jobseekers looking for full-time and part-time jobs. On average, male and female jobseekers looking for part-time work exhibit slightly less favorable characteristics than those looking for full-time work, but the difference is very small and the distributions look very similar.

Finally, as Table B.4 in the Appendix shows, there are some differences in the occupational composition between jobseekers looking for a part-time job and those looking for a full-time job. While the share of jobseekers looking for part-time work is particularly

[19]I construct the index as follows: I randomly split the sample into a 50% training sample and a 50% test sample. In the training sample, I regress the contact likelihood on all human capital-related variables visible to recruiters on Job-Room (work experience, level of education, origin of education certificate, language skills, other reported skills, and driver's license categories) interacted with occupation dummies (ISCO-1 level), while controlling for other jobseeker characteristics. The estimated coefficients can be interpreted as a measure of the occupation-specific valuation of these variables by recruiters. I use the estimated coefficients to predict the contact likelihood for all jobseekers in the test sample and use these predictions as a composite measure of their human capital.

Figure 2: Distribution of the human capital index by preference for full-time and part-time work and gender



Notes: Panel (a) plots the (demeaned) density functions (solid lines) as well as the means (dashed lines) of the human capital index for male jobseekers searching for full-time (blue) and part-time (red) jobs. Panel (b) does the same for women.

high in education, health, and arts occupations, jobseekers in manufacturing, craft, and construction occupations are predominantly looking for full-time jobs. The pattern is very similar for men and women.

4.2 Research design

I apply two different identification strategies to estimate the effect of the preferred number of working hours on the contact likelihood. First, like Hangartner et al. (2021), I apply a selection-on-observables strategy exploiting the fact that I observe all candidate characteristics visible to recruiters on Job-Room. The assumption is that only characteristics that are visible to recruiters can influence their decision whether or not to contact a jobseeker, while variables that are not displayed on Job-Room cannot. In section 4.3 I provide evidence to support this assumption.

I model the recruiter's decision to contact a jobseeker as a linear function of all jobseeker characteristics visible to recruiters on Job-Room that are systematically correlated with the outcome, the desired number of hours, or gender:

$$y_{i,s} = \beta_k hours^k_{i,s} + \beta_{k,f} hours^k_{i,s} * female_i + \rho female_i + \gamma X_{i,s} + \delta_s + \epsilon_{i,s} \quad (1)$$

$y_{i,s}$ is the probability that the recruiter in search s clicks on the contact button at the bottom of jobseeker i's profile. Conditional on appearing on a results list, this probability

is 10 percent. Hangartner et al. (2021) show that a click on this button significantly increases the probability that a jobseeker will leave unemployment within the next 3 months compared to other jobseekers on the same list who were not contacted.

$hours^k_{i,s}$ is a categorical variable representing the number of hours jobseeker i wants to work, expressed in FTE. It ranges from k=<50% to k=100%. 100% corresponds to a full-time job, while 50% corresponds to a part-time job with half the working hours of a full-time position. $hours^k_{i,s} * female_i$ interacts the variable with a dummy indicating whether jobseeker i is female. Thus, $\beta_{k,f}$ shows the differential effect of the number of preferred hours on the contact likelihood for women compared to men.

The vector $X_{i,s}$ contains all characteristics of jobseeker i visible to the recruiter in search s. It also includes second moments of continuous variables and all first-order interactions that are systematically correlated with the outcome, the number of preferred hours, or gender. To select these first-order interactions, I apply the post-double-selection method (Belloni et al., 2012, 2014): Based on a 20% random sub-sample[20] of all search queries, I use lasso regressions to select interactions that predict a click on the contact button. Then, I use lasso regressions to select interactions that predict gender or preferred number of hours. The union of the interactions selected in these steps is then included in the model as covariates. The final model contains 2,307 covariates (out of 6,768 possible covariates when all possible interactions are considered). $X_{i,s}$ also contains flexible controls for a candidate's rank on the search list, although the ranking does not follow any predetermined rules.[21] Note that most of the information on Job-Room is presented in a structured (tabular) way, which makes it relatively easy to control for it in a statistical model.

The model also includes search fixed effects δ_s. They account for all characteristics that are constant within a given search request, such as occupation or recruiter characteristics. Hence, I only compare jobseekers on the same search list who all meet the criteria entered by the recruiter. As a result, searches in which recruiters use the number of hours as a selection criterion do not contribute to identifying the effect of the preferred number of hours on the contact likelihood because there is no variation in the number of hours within search. Therefore, I restrict the sample to the 73% of searches that do not

[20]The sample is restricted for computational reasons and to facilitate replication.

[21]I include controls for a jobseeker's absolute and relative rank on the list. Since the total number of entries varies from search to search, a given absolute rank has different implications. For example, if a search list contains 15 entries, the 15th entry is the last one on the list. If the list contains 100 entries, the 15th entry would still be in the top 20%. Hence, in addition to detailed indicators for the absolute rank, I also include dummies for each decile of the relative rank (= rank of a candidate divided by the total number of search results).

use the number of hours as a selection criterion.[22]

The second identification strategy exploits the fact that some jobseekers change their preferred number of hours during the observation period. By replacing the search fixed effects from Equation 1 with jobseeker fixed effects, the identification of the effect of the preferred number of hours on the contact likelihood is based solely on within-jobseeker variation:

$$y_{i,s} = \beta_k hours^k_{i,s} + \beta_{k,f} hours^k_{i,s} * female_i + \gamma X_{i,s} + \delta_i + \epsilon_{i,s} \quad (2)$$

The main difference from Equation 1 is the subscript of δ. By replacing the search fixed effects with jobseeker fixed effects, I implicitly control for all time-invariant jobseeker characteristics (observed and unobserved) that influence the recruiters' decisions.[23] I include the same set of covariates in the model as in Equation 1 because some jobseeker characteristics visible to recruiters may change simultaneously with the hours preferences. This analysis is based on the entire sample, including the 24% of searches that use working hours as a selection criterion.

4.3 Validation of the research design

Both identification strategies are based on the assumption that I can control for all factors that are correlated with a contact button click, the preferred number of hours, and gender. A crucial condition for the validity of this assumption is that only jobseeker characteristics visible to recruiters can influence their decision whether to contact a jobseeker. In this section, I test this assumption by conducting two placebo tests.

First, I exploit the link between the click data and the unemployment register to estimate the effect of a jobseeker's age and last wage on the likelihood that a recruiter clicks on the contact button. Both variables are not displayed on Job-Room but would most likely affect the decision to contact a jobseeker if they were known to recruiters.[24] Second, I exploit the sequential nature of the selection process on Job-Room to estimate the effect of work experience and the origin of the educational credential on the likelihood that recruiters open a jobseeker's profile. Both variables are not visible in the results list, i.e. when recruiters decide whether or not to open the profile. They are, however, visible

[22] As a robustness check, I also estimate the model based on the full sample. The results don't change.

[23] Since a jobseeker's gender does not vary over time, its direct effect on the contact likelihood cannot be estimated with this identification strategy.

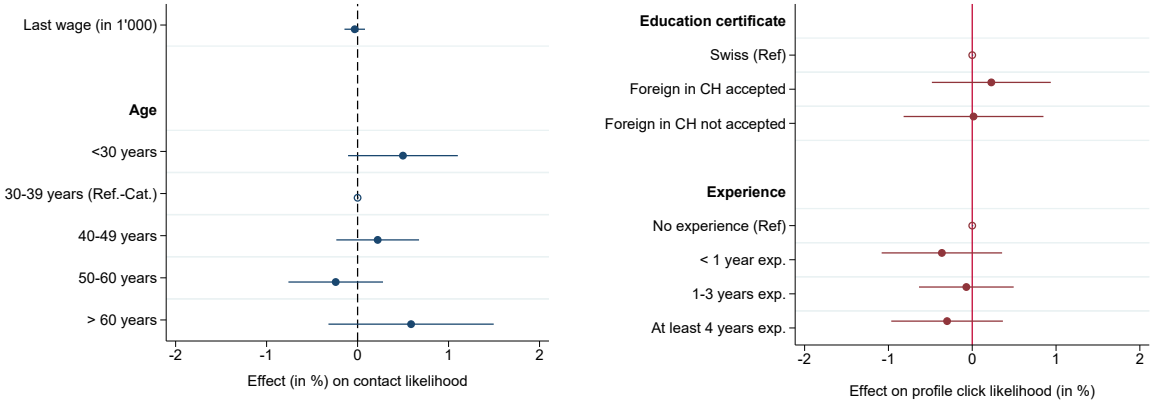
[24] There is ample evidence that age affects the hiring chances of jobseekers (Neumark, 2020, 2018). And assuming that the last wage partly reflects productivity differences across jobseekers, we would also expect it to affect hiring decisions if it were known.

once the profile has been opened and have a large and significant effect on the contact likelihood conditional on profile view (see Figure B.3 in the Appendix).

Figure 3: Effects of characteristics not visible to recruiters on Job-Room

(a) Not visible on Job-Room

(b) Not visible on results list



Notes: Panel (a) plots the effects, and associated 95% confidence intervals, of age and last insured wage on the probability that a recruiter clicks on the contact button. Both characteristics are not visible on Job-Room. Coefficients are normalized with the mean contact rate. The sample includes all jobseeker profiles that appeared in search results lists between March and December 2017, in searches where recruiters did not use working hours as a selection criterion. Standard errors are clustered at the recruiter level. Panel (b) plots the effects, and associated 95% confidence intervals, of the origin of the education certificate and work experience in the occupation in which a recruiter is searching for applicants on the likelihood that a recruiter clicks on the corresponding entry on the results list. Both characteristics are not displayed on the results list, but only on the full profile. Coefficients are normalized with the mean of the dependent variable. The sample includes all jobseekers who do not report any additional skills and who appear on the results lists between March and December 2017. Standard errors are clustered at the recruiter level.

If these placebo tests were to fail, other unobserved variables that correlate with the contact likelihood and the preferred number of hours could also influence recruiters' decisions and bias the estimates. However, as panel (a) of Figure 3 shows, neither last salary nor age has a significant effect on the contact likelihood. And panel (b) shows that neither work experience nor the origin of the education certificate has a significant effect on the likelihood that a recruiter opens the profile of a jobseeker who appears on the results list.[25] Thus, both tests support the assumption that variables not visible to recruiters on Job-Room do not affect their selection decisions. Conditional on controlling for all visible characteristics that are correlated with the contact likelihood, preferred number of hours, or gender, I should therefore be able to identify the causal effect of the preferred number of hours and gender on the contact likelihood.

[25]Note that the sample is restricted to jobseekers who do not report any additional skills, because the unstructured text field that presents jobseekers' additional skills may contain information about a candidate's work experience or education.

4.4 Results

How does the preferred number of hours affect the likelihood of being contacted by a recruiter on Job-Room and does this effect depend on the gender of the jobseeker? In a first step, I report estimates based on Equation 1 without the interactions between gender and the preferred number of working hours. In a second step, I add the interactions to assess whether the preferred number of hours affects the contact likelihood differently for men and women. As noted above, I restrict the sample for these estimates to the 73% of searches that do not use the number of hours as a selection criterion, since the remaining searches show no variation in the preferred number of hours.[26] Since the vast majority (90.5%) of the excluded search requests restrict the candidate pool to jobseekers looking for a full-time job, the estimates tend to underestimate the disadvantage of seeking part-time work. In a third step, estimates based on the within-jobseeker regression described in Equation 2 are reported. Unlike the estimates from steps 1 and 2, these estimates are based on all searches.

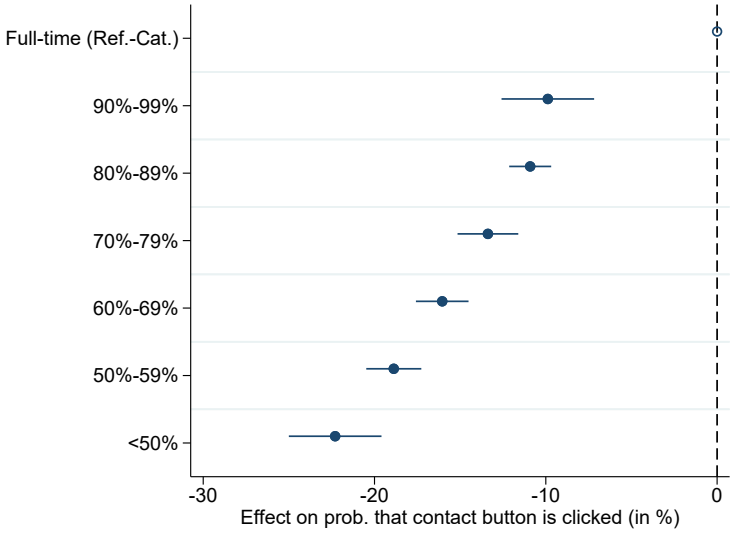
4.4.1 Overall part-time penalty

Figure 4 plots the coefficients, and associated 95% confidence intervals, of the preferred number of hours (expressed in FTE bins) on the contact likelihood. For ease of interpretation, all coefficients are normalized with the mean contact rate. Hence, they represent the effect in percent rather than in percentage points. The reference category are jobseekers looking for full-time jobs.

The figure shows that a preference for part-time work significantly reduces the contact likelihood compared to a preference for full-time work. The lower the preferred number of hours, the lower the contact likelihood, ceteris paribus. Looking for a 90% part-time job instead of a full-time job—a difference of only 4 hours per week—reduces the contact likelihood by 10%. The penalty increases to 22% for jobseekers looking for part-time jobs with less than 50% FTE. Thus, even recruiters who do not a priori restrict the pool of job candidates to jobseekers looking for full-time jobs have a strong preference for full-time workers. The effects are large. Figure B.3 in the Appendix compares the estimates of the part-time penalty with the estimates of the effects of other jobseeker characteristics visible to recruiters on Job-Room. Neither educational qualifications, work experience, language skills, nor soft- or IT skills have similar effects on the contact likelihood as the preference for part-time work.

[26] As a robustness check, I also estimate the model based on the full sample.

Figure 4: Effect of the preferred number of hours on the contact likelihood



Notes: The figure plots the coefficients, and associated 95% confidence intervals, of the preferred number of working hours on the likelihood that recruiters click on the contact button. The model is the same as the one described by Equation 1 without the interaction between the number of working hours and gender. All coefficients are normalized with the average contact rate (9.4%). The reference category are jobseekers looking for full-time jobs. Column (1) of Table B.5 in the Appendix shows the underlying numerical estimates. The sample includes all jobseekers who appear on the results lists of searches where recruiters do not use working hours as a search criterion. It covers the period from March to December 2017. Standard errors are clustered at the recruiter level.

As Figure B.4 in the Appendix shows, part-time penalties are not limited to specific occupations. In all occupations, jobseekers looking for full-time jobs have an advantage over jobseekers with the same characteristics seeking part-time jobs. However, there is considerable heterogeneity in the size of the part-time penalty across occupations, ranging from 3% for protective service workers to 40% for other clerical support workers. Managerial occupations exhibit rather large part-time penalties, while the part-time penalty for (health/legal/social/cultural) professionals is relatively small. Otherwise, there is no clear pattern with respect to the skill level of an occupation.

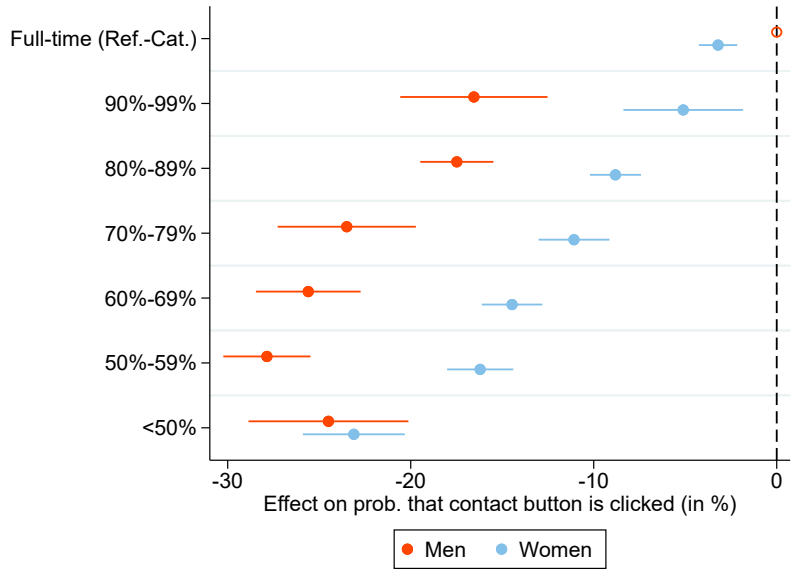
4.4.2 Gender differences in the part-time penalty

Next, I assess whether the preferred number of working hours has a differential effect on the contact likelihood for men and women by estimating Equation 1. Figure 5 plots the respective coefficients, again normalized with the mean contact rate, and the associated 95% confidence intervals. Male jobseekers seeking full-time jobs are the reference group.

The figure shows that women looking for full-time jobs are 3.2% less likely to be contacted than men seeking full-time work. However, as soon as jobseekers express a

preference for part-time work, men are less likely to be contacted than women. For example, seeking a 70% part-time job instead of a full-time job reduces the contact likelihood for men by 23.5%. Women with the same hours preference experience a penalty of only 7.9% compared to women looking for full-time jobs (and 11.1% compared to men looking for full-time jobs). When all part-time categories are combined, the part-time penalty is 10% for women[27] and 22% for men.

Figure 5: Effect of the preferred number of hours on the contact likelihood by gender



Notes: The figure plots the coefficients, and associated 95% confidence intervals, of a preference for different levels of part-time work on the likelihood that recruiters click on the contact button. The estimation model is outlined in Equation 1. All coefficients are normalized with the average contact rate (9.4%). The reference category includes male jobseekers looking for a full-time job. Column (2) of table B.5 in the Appendix shows the underlying numerical estimates. The sample includes all jobseekers who appear on the results lists of searches where recruiters do not use working hours as a search criterion. It covers the period from March to December 2017. Standard errors are clustered at the recruiter level.

Not only the size, but also the pattern of the part-time penalty differs between men and women. Women's contact penalty increases linearly as the preferred number of hours decreases—from 2% for a 90% FTE part-time job to 23.5% for a part-time job of less than 50% FTE. For men, however, the relationship is highly non-linear. Their contact likelihood drops sharply as soon as they want slightly fewer hours than in a full-time job. Men looking for a 90% part-time job already experience a 16.5% penalty compared to men looking for a full-time job, even though the difference in the number of hours is only about 4 hours per week. Thus, while the part-time penalty for women is proportional to

[27]This is the relative disadvantage compared to women seeking full-time work. The penalty is 13% if we compare the contact likelihood with men looking for full-time jobs.

the desired reduction in hours, men seeking part-time work appear to suffer an additional penalty unrelated to the preferred reduction in hours that kicks in once they deviate from seeking a full-time job. The gender gap in the part-time penalty remains constant for jobseekers seeking part-time jobs between 50% and 90% FTE. However, it is insignificant for part-time jobs below 50% FTE.

Are the gender differences exacerbated by the fact that male and female jobseekers look for jobs in different occupations with different average part-time penalties? This is not the case. First, the effects are estimated by comparing jobseekers on the same results list. This means that they are evaluated by the same recruiter in the same occupation and are most likely competing for the same job. Second, as Figure B.5 in the Appendix shows, there is only a weak and insignificant (at the 5% level) relationship between the part-time penalty in an occupation and the share of male jobseekers in the results list.[28] Third, the relative disadvantage of male jobseekers searching for part-time jobs is not limited to a few occupations. Figure 6 shows the ratio of the female to male part-time penalty in all ISCO-1 occupations. Coefficients below 1 indicate a lower part-time penalty for women than for men. The figure shows that the part-time penalty is lower for women than for men in all occupational groups.[29]

How robust are the estimates shown in Figure 5 to different specification choices? Figure B.7 in the Appendix shows that the results are robust to including searches in which recruiters use the number of hours as a selection criterion (Panel a), to restricting the sample to candidates who do not report any additional skills (Panel b),[30] and to including detailed occupation fixed effects instead of search fixed effects (Panel c).

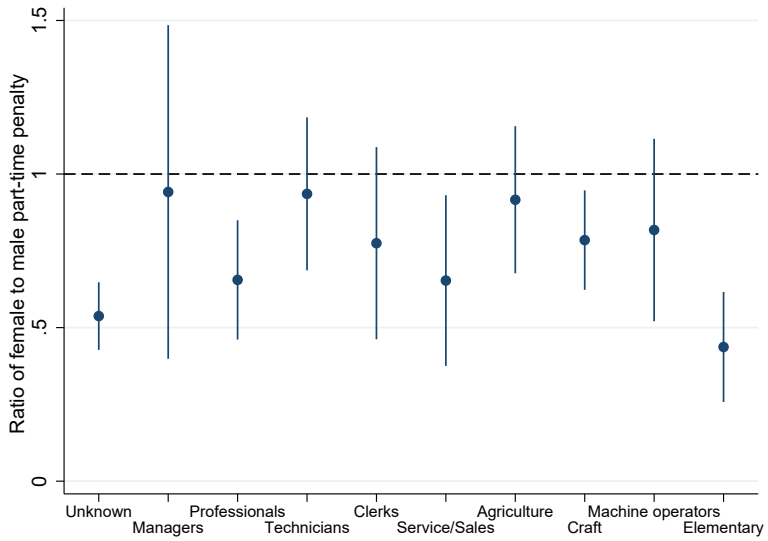
An alternative way to investigate whether men have a harder time finding part-time work than women is to estimate the effect of gender on the contact likelihood for searches in which recruiters explicitly look for part-time workers. Column 3 of Table 2 reports the respective estimates. As a benchmark, columns 1 and 2 report estimates for the effect of being female on the contact likelihood in the baseline sample, i.e., for search

[28]Since the estimates in some occupations are noisy due to the small number of observations, panel (a) shows the linear relationship based on weighting each occupation with the number of observations, and panel (b) shows the coefficients after applying empirical Bayes shrinkage to shrink the estimated coefficients to their overall mean (Koedel et al., 2015; Herrmann et al., 2016).

[29]Figure B.6 in the Appendix shows that the picture looks very similar if we use a more detailed occupational classification. I apply again empirical Bayes shrinkage and report both the shrunken and the original coefficients. The ratio is less than one for the vast majority of ISCO-2 occupations, and none of the ratios greater than one are significantly different from one.

[30]The unstructured text used to report additional skills might contain information correlated with the contact likelihood, gender, and the preferred number of hours. If the algorithm used to code this text does not capture all relevant information, the results may be biased. To rule out such bias, I restrict the sample to the 39% of profiles that do not contain additional skills.

Figure 6: Ratio of female to male part-time penalty by occupation group



Notes: The figure plots the ratio, and associated 95% confidence intervals, of the female to male part-time penalty by ISCO-1 occupation. The regression model is the same as model 1 except that $hours^k_{i,s}$, $female_i$, and $hours^k_{i,s} * female_i$ are interacted with occupation. In addition, the six part-time categories are aggregated into one. The reported coefficients show the ratio of the female part-time penalty for a given occupation ($\beta_k hours^k_{i,s} * occupation_o + \beta_{k,f} hours^k_{i,s} * female_i * occupation_o$) and the male part-time penalty for the same occupation ($\beta_k hours^k_{i,s} * occupation_o$). The associated standard errors are calculated based on the delta method.

requests where recruiters do not restrict the candidate pool to jobseekers seeking full- or part-time work. Consistent with the previous findings, column 3 shows that recruiters trying to fill a part-time position have a strong preference for women. They are 12% more likely to contact a woman than a man with otherwise identical characteristics. In contrast, recruiters who do not restrict the candidate pool ex ante to full-time or part-time workers show a slight preference for men (see columns 1 and 2). Somewhat surprisingly, recruiters who explicitly look for full-time workers also prefer women, but the effect is relatively small (see column 4).

The second identification strategy applied in this section exploits the fact that 3,901 jobseekers changed their preferred number of hours during the observation period. By replacing the search fixed effects in Equation 1 with person fixed effects, I compare the contact rates of the same jobseeker before and after the change, thereby controlling for all time-invariant characteristics. Since jobseekers may also modify other information in their profiles when they change their preferred number of hours, I include the same set of covariates as in Equation 1 to flexibly control for any characteristics that are correlated with the contact likelihood, the preferred number of hours, or gender. The

Table 2: Effect of being female on the contact likelihood for search requests where recruiters (do not) restrict the candidate pool to part-time or full-time jobseekers

	(1) Not restricted	(2) Not restricted	(3) Only part-time	(4) Only full-time
Men	ref.	ref.	ref.	ref.
Women	-3.25***	-1.23**	12.1**	3.24**
	(.53)	(.5)	(4.9)	(1.5)
Part-time	-21.7***	-14.7***		
	(.92)	(.6)		
Part-time*Women	11.8***			
	(.86)			
Mean dep. Var.	0.09	0.09	0.04	0.14
Observations	13,561,699	13,561,699	237,247	3,570,426

Notes: This table shows the effect of being female on the contact likelihood for searches in which recruiters do not use hours as a selection criterion (columns 1 and 2), for searches in which recruiters restrict the candidate pool to jobseekers looking for a part-time job (column 3), and searches in which recruiters restrict the candidate pool to jobseekers looking for a full-time job (column 4). Unlike the model in column 2, the model in column 1 includes an interaction between gender and the part-time dummy. The part-time effect and its interaction with gender can only be estimated if hours is not used as a selection criterion. The other covariates are the same as those reported in Equation 1. All coefficients are normalized with the mean contact rate in the respective sample.

effect of the preferred number of hours on the contact likelihood is now identified only by the 3,901 jobseekers who change their hours preference during the observation period.[31] To address the associated loss of statistical power, I aggregate the six part-time levels into three. Figure 7 plots the corresponding coefficients and associated 95% confidence intervals.

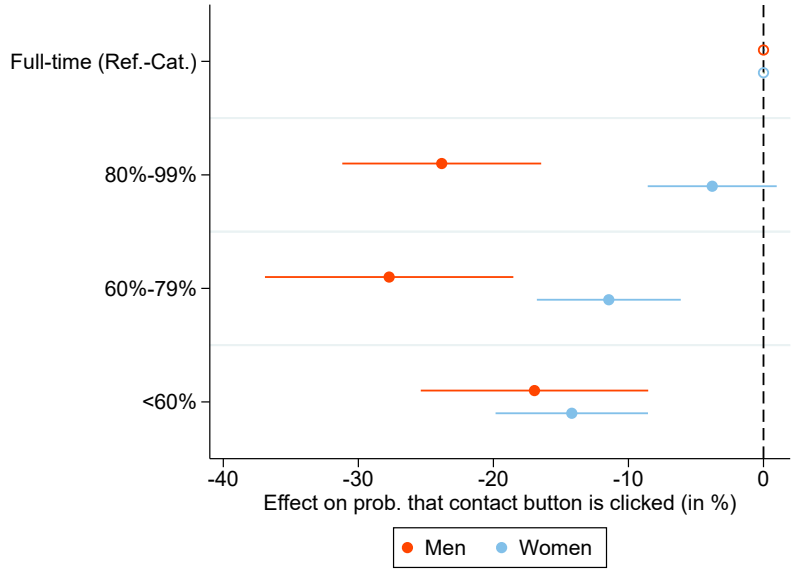
The results look very similar to those based on Equation 1. A preference for part-time work reduces the contact likelihood considerably. This part-time penalty is much more pronounced for men than for women, except when jobseekers want to work very few hours (less than 60% FTE).

5 Analysis based on job ad data

In this section, I complement the analysis of the recruiter click data with an analysis of the public and confidential information contained in the job ads reported directly to Job-Room (see Column 2 of Table 1). One objective is to test whether the findings from the previous section also hold in a setting of worker-initiated search. The analysis of the job ad data also allows me to apply a complementary methodological approach:

[31] Because jobseekers do not change their gender, the baseline gender effect is not identified.

Figure 7: Effect of the preferred number of hours on the contact likelihood by gender, with jobseeker fixed effects



Notes: The figure plots the coefficients, and associated 95% confidence intervals, of the preferred number of hours (expressed in FTE) on the contact likelihood when estimating Equation 2. Since jobseekers do not change their gender during the observation period, the baseline gender effect is not identified. Therefore, in the reference category are men and women searching for a full-time job. The dependent variable is the likelihood that a recruiter clicks on the contact button. All coefficients are normalized with the mean of the dependent variable. The sample includes all jobseeker profiles that appear in a results list between March and December 2017. Standard errors are clustered at the recruiter level.

While I analyze the recruiter click data based on a revealed-preferences approach (as in Hangartner et al., 2021), I analyze the job ad data based on a stated-preferences approach similar to Kuhn and Shen (2023) and Card et al. (2021). Finally, combining the job ad data with the jobseeker click data (see Column 3 of Table 1) allows me to analyze how supply and demand for part-time jobs jointly affect the hiring prospects of jobseekers seeking part-time employment.

5.1 Full-time versus part-time jobs

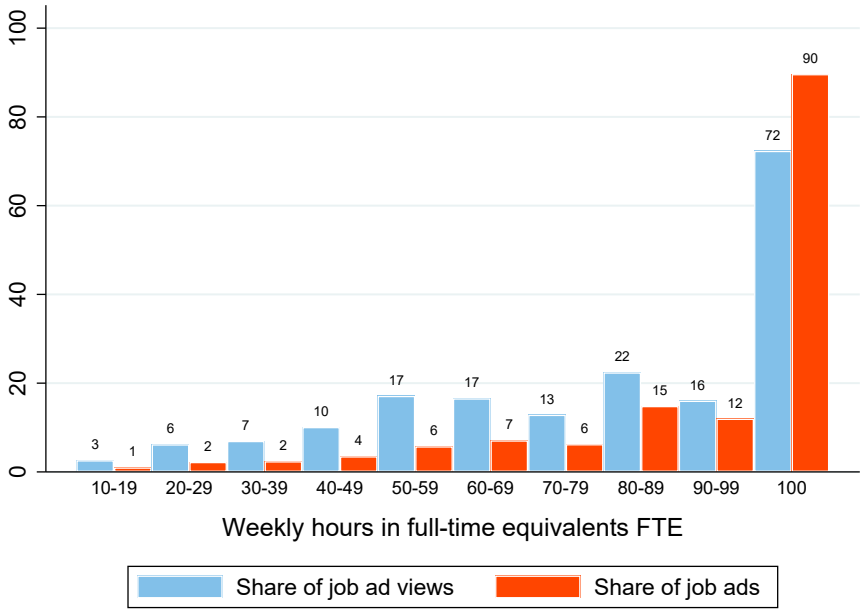
This subsection looks at the supply and demand for part-time jobs. Since the confidential gender preferences are not needed for this analysis, it is based on all ads published on Job-Room between January 2020 and May 2021 (the directly reported ads and those added from other sources).[32]

Between January 2020 and May 2021, 79% of all jobs posted on Job-Room were full-

[32]However, the results hardly change if the analysis is limited to ads reported directly to Job-Room between July 2018 and June 2021. Hence, they also apply to the period before the Corona pandemic.

time positions (=100% FTE), 10% were part-time positions and 11% specified a range of working hours that included both full-time and part-time positions. The red bars in Figure 8 show the distribution of job ads that cover a given number of working hours.[33] 90% of the jobs can be done on a full-time basis, while only 15% can be done with an 80% part-time workload. Among part-time jobs, jobs with a higher workload (50% FTE or more) are more common than jobs with low weekly hours.

Figure 8: Share of job ads and share of job ad views covering a certain level of FTE



Notes: The orange bars show the share of job ads on Job-Room between June 2020 and May 2021 that cover a certain level of weekly working hours, expressed in FTE. The sample consists of 910,379 job postings. The blue bars show the share of job ad views for a given FTE level during the same period. No job ad views were recorded before June 2020. Jobseekers opened 524,456 job ads during the observation period. Job ads with a range of hours may appear in multiple categories.

Whether the small number of part-time vacancies leads to greater difficulties in finding a job for part-time jobseekers also depends on the number of other jobseekers looking for part-time work. Therefore, I add the distribution of job ad views to Figure 8. It shows that the supply of jobseekers looking for part-time work, indicated by clicks on part-time ads, is greater than the demand for part-time workers, indicated by part-time job postings. The share of clicks on full-time ads is 18 percentage points lower than the share of full-time ads posted on Job-Room. On the other hand, the share of clicks on part-time ads is consistently higher than the share of part-time job postings. As a result,

[33]To be consistent with the sample of ad views, the sample is restricted to job ads visible on the platform between June 2020 and May 2021.

the average number of clicks on part-time ads is higher than on full-time ads, as shown in Figure B.8 in the Appendix. This suggests that the competition for part-time jobs on Job-Room is fiercer than the competition for full-time jobs. Because women are much more likely than men to seek part-time work, they suffer more than men from the fierce competition for the few part-time jobs that are available.

Table B.6 in the Appendix shows that the mismatch between supply and demand for part-time workers is particularly large in occupations with a low share of part-time jobs. For example, the share of clicks on part-time jobs is more than twice as high as the share of part-time job ads for craft and related trades workers and more than five times as high for plant and machine operators and assemblers. However, in all occupational groups, the supply of jobseekers looking for part-time work exceeds the demand for part-time workers.

5.2 Gender differences

Do companies that advertise part-time jobs tend to prefer women over men? To answer this question, I take advantage of the fact that companies reporting vacancies directly to Job-Room can confidentially indicate their gender preference. This information is not published on the platform and is only visible to PES caseworkers. Hence, social desirability should not strongly influence the reporting behavior.[34] Since this analysis relies on the confidential gender preferences reported by companies, I have to restrict the analysis to directly reported ads (see column 2 of Table 1 for an overview of the data).

29,150 job ads, 5.2% of all ads directly reported to Job-Room, contain a gender preference during the observation period. 52% of these ads contain a preference for men and 48% for women. Table B.7 in the Appendix compares the characteristics of firms that never specify the preferred gender during the observation period with those that specify the preferred gender at least once. There are some differences, but they are not large.[35] A descriptive analysis suggests that recruiters prefer women when filling a part-time position. Only 1.4% of firms that advertise a part-time position state a preference for men, while more than four times as many, 6.1%, prefer women. Firms that advertise

[34]However, since the information is visible to the caseworkers, social desirability bias cannot be completely ruled out. Moreover, attitudes behind gender preferences may be implicit (Bertrand et al., 2005; Hangartner et al., 2021) and therefore not reflected in these explicit statements. This is a drawback of the stated-preference approach compared to the revealed-preference approach applied in Section 4.

[35]E.g., firms operating in the accommodation and food services sector are over-represented among firms that report a preferred gender. The opposite is true for private employment agencies. Smaller firms are slightly over-represented among employers who report a gender preference, but the differences in the firm size are rather small. The same is true for legal status.

a range of hours, including full-time and part-time positions, are also more likely to state a preference for women than for men (3.2% versus 1.7%). The opposite is true for firms advertising full-time positions, although the gender gap is smaller than for part-time positions. 3.2% of the firms advertising full-time positions prefer men and only 1.4% state a preference for women.

To assess whether this gap can be explained by factors other than the gender of a jobseeker, I regress a dummy equal to one if firms indicate an explicit preference for men on a categorical variable indicating whether the job is part-time, has a range of hours including full- and part-time positions, or is full-time, and several sets of fixed effects. Table 3 reports the results. The model without any controls (column 1) shows that firms advertising a part-time job are 1.8 percentage points less likely to explicitly search for men than firms advertising a full-time job. This difference is large, given that 3.2% of the firms advertising a full-time position indicate a preference for men. Firms that advertise a range of hours, including full-time and part-time positions, are 1.5 percentage points less likely to (explicitly) search for men than firms that advertise full-time jobs. Controlling for job ad characteristics such as firm location, firm size, required education, or experience does not reduce the difference in the likelihood of firms seeking male applicants between full-time and part-time jobs (column 2). The same holds when we add industry fixed effects (column 3). Adding occupation fixed effects (column 4) reduces the gap somewhat, but it remains large and highly significant. Thus, even within the same occupation and the same industry, firms advertising a part-time position are significantly less likely to explicitly look for men than firms advertising a full-time position. Column (5) shows that this conclusion holds even when we add firm fixed effects, i.e., when we compare job ads posted by the same firm in the same occupation. Table B.8 in the Appendix regresses the likelihood that firms prefer women on the indicators for full-time and part-time jobs. It shows the mirror image of Table 3. Recruiters advertising a part-time job are significantly more likely to indicate a preference for women than recruiters advertising a full-time job.

A limitation of the analysis is that it relies solely on the 5.5% of job ads that contain an explicit gender preference. Although a descriptive analysis of firm characteristics did not reveal major differences between firms that specify a gender preference and those that do not, the external validity could be limited. Another limitation is that only firms that report their vacancies directly to Job-Room can be included in the analysis.

To address these limitations, I apply an alternative approach to categorize all vacancies on Job-Room (ads reported directly to the platform and those added from other sources) according to the gender preference of the firm. I take advantage of the fact

Table 3: Regression of a preference for men on working hours and different fixed effects

	(1)	(2)	(3)	(4)	(5)
Full-time job	ref.	ref.	ref.	ref.	ref.
Full- or part-time job	-.015***	-.016***	-.016***	-.01***	-.0071***
	(.0011)	(.0011)	(.0012)	(.0012)	(.00087)
Part-time job	-.018***	-.022***	-.024***	-.016***	-.0088***
	(.00082)	(.00082)	(.001)	(.001)	(.00089)
Job ad characteristics	No	Yes	Yes	Yes	Yes
Industry	No	No	Yes	Yes	Yes
Occupation	No	No	No	Yes	Yes
Firm fixed effects	No	No	No	No	Yes
Mean dependent variable	0.027	0.027	0.027	0.027	0.026
Observations	559,556	559,556	559,556	558,853	524,546

Notes: The table reports results of ordinary least squares regressions of a dummy equal to one if the job ad states a preference for men on various sets of fixed effects, some ad specific controls, and a categorical variable indicating whether the job is part-time job, a job with a range of working hours including full-time and part-time positions, or a full-time job. The latter is the reference category. Columns refer to different models with different control variables. The controls for job ad characteristics include the location of the firm (canton), a dummy for a temporary job, dummies for special working conditions (night work, shift work, working from home, working on Sundays and public holidays), a categorical variable for the required experience, a categorical variable for the required education, and firm size. Standard errors (in parentheses) are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

that job titles in German, French, and Italian are often gender-specific. This means that the grammatical form of a job title can be masculine, feminine, or both genders can be addressed.[36] I use the grammatical gender of a job title as an indicator of the gender preference of the firm advertising the job. This signal is somewhat noisy, because historically it has been common to use the masculine form even in situations where both male and female persons are meant (the so-called generic masculine). However, the use of the generic masculine has declined in recent decades, and alternatives such as explicitly mentioning both genders or using inclusive spellings such as 'MalerIn' with internal-I or the gender star 'Maler*in' have gained popularity (Fennert, 2022; Friedrich et al., 2021). Hence, while some masculine job titles may be the result of firms sticking to the old habit of the generic masculine, others are likely to signal a preference for men. In contrast to the masculine form, the exclusive use of the feminine form is always likely to indicate a preference for women. I categorize job titles according to their grammatical gender by applying a simple algorithm to the most common grammatical rules that determine

[36] I.e., "Maler" is a male painter, "Malerin" is a female painter and "MalerIn" or "Maler*in" addresses both men and women.

whether a word has a masculine or feminine form in German and French.[37] 63% of all job titles could be categorized (24% as masculine, 3.2% as feminine, 35.3% as explicitly gender-neutral).

I repeat the previous analysis, but using the grammatical form of the job title as an indicator of the preferred gender and based on all vacancies posted on Job-Room between January 2020 and May 2021. The results are reported in Tables B.9 and B.10 in the Appendix. They confirm the previous findings. A part-time ad is significantly less likely to contain a job title that indicates a preference for men than a full-time ad. This holds even in the most restrictive specification with firm fixed effects. However, as expected due to the noisier signal, the size of the coefficient relative to the mean of the dependent variable is smaller than in the analysis presented in Table 3. However, for females, the magnitude of the effect is similar to the previous analysis. A part-time ad is significantly more likely to contain a job title signaling a preference for women than a full-time ad, even within the same location, occupation, and company.

In summary, the analysis of the job ad data confirms—based on a different methodological approach and a different dataset—the conclusions drawn from the recruiter click data. A firm advertising a part-time position is much more likely to be looking for female candidates than male candidates. The opposite is true for full-time positions. These results also hold when comparing job postings from the same company in the same occupation. It is therefore more difficult for men to get a part-time job than for women. However, combining the job ad data with the jobseeker click data shows that the competition for part-time jobs is fiercer than for full-time jobs. This is particularly bad for women, who are more likely than men to look for part-time jobs.

6 Mechanisms

How can these findings be rationalized? I first discuss possible explanations for the general disadvantage of jobseekers looking for part-time jobs compared to jobseekers looking for full-time jobs. I then discuss possible reasons for the gender differences.

6.1 Possible explanations for the overall part-time penalty

Several studies challenge the canonical labor supply model's assumption that workers are free to choose their preferred number of working hours (Labanca and Pozzoli, 2022;

[37] I disregard the Italian job titles due to their small number.

Johnson, 2011; Altonji and Paxson, 1988). Most of the studies assume that firms constrain this choice because their production technology requires workers to work a certain number of hours. Similarly, some features of a production technology, such as high fixed costs per worker or high coordination costs, could explain why recruiters prefer full-time to part-time workers. Fixed costs per worker, including administrative costs of maintaining records for each worker, costs of workplace infrastructure, or costs of hiring and firing, lead to a disproportionate increase in total labor costs when working hours are increased at the extensive instead of the intensive margin (Garnero et al., 2014). As a result, firms have incentives to increase the number of hours worked per employee as much as possible by hiring full-time instead of part-time workers.[38] Part-time work could also lead to higher coordination costs if it is costly to hand over customers to co-workers (Briscoe, 2007) or to transmit information to colleagues (Goldin, 2014).[39]

The assumption that features of the production technology explain the part-time penalty is consistent with the inverse relationship between the part-time penalty and the preferred number of hours documented in Section 4.4.1. With (high) fixed costs per worker, the total cost per worker increases the lower the number of hours per worker. A similar logic applies to coordination costs. They are also likely to increase if more workers with low hours need to be coordinated.

However, the empirical literature on the relationship between labor costs and part-time work yields ambiguous results (e.g., Edwards and Robinson, 2004; Kelliher and Anderson, 2010). Moreover, I find no evidence that the part-time penalty per occupation is related to indicators of technological features that are often associated with full-time work: The share of workers with a high degree of time autonomy, the share of workers with a high degree of decision freedom, the incidence of shift work, and the incidence of overtime. Table C.1 in the Appendix summarizes the reasons for these associations. Section C in the Appendix discusses the results.

Thus, while theoretical considerations provide plausible reasons for technology as a driver of the part-time penalty in hiring, the empirical evidence is less clear. In the next section, I show that technology is certainly not the only explanation for the part-time

[38]The opposite logic applies when firms face a decline in demand: In the presence of high fixed costs per worker, firms tend to adjust their labor demand by reducing the number of workers rather than the number of hours worked per worker (see Boeri and Bruecker, 2011).

[39]However, Goldin and Katz (2016) show that these technological features are not set in stone, but can be adapted to make a workplace more suitable for part-time work. For example, in the pharmaceutical sector, technological and organizational changes, in particular the extensive use of information technology and the standardization of products and services, have increased the substitutability among workers and thereby contributed to a reduction in the pay penalty for part-time work.

penalty, as it cannot explain the large gender gap.

6.2 Possible explanations for the gender difference

Several reasons speak against a technological explanation for the gender gap in the part-time penalty. Most importantly, the analyses of the recruiter click data and the job ad data show that the gender gap is not due to differences between industries, occupations, firms, recruiters, or jobs. E.g., the effect of the preferred number of hours on the contact likelihood shown in Figure 5 is identified by comparing jobseekers with different hours preferences on the same results list. Hence, they are being evaluated by the same recruiter in the same occupation, meet the same search criteria, and are likely to be competing for the same job. Thus, technological factors should affect all jobseekers on the list equally. Moreover, technological explanations for the part-time penalty in hiring often imply a smooth (negative) relationship between hours worked and cost per worker, especially when the number of hours is high. For example, a production function with fixed costs per worker would in most cases yield a smooth curve of costs per hour worked, assuming that productivity does not depend on hours.[40] This does not fit the pattern of a sharp, nonlinear increase in the part-time penalty for men when they deviate slightly from a full-time job. Allowing productivity to vary with the number of hours, the pattern of the male part-time penalty would imply a sudden increase in output per hour once the threshold of 36 hours per week (about 90% FTE) is reached. This seems arbitrary and is not supported by empirical studies.[41]

Another possible explanation for the documented gender bias in the part-time penalty is related to theories of signaling and statistical discrimination (Spence, 1978; Arrow, 1973; Phelps, 1972). Given incomplete information, recruiters might use the number of hours a jobseeker is willing to work as an indicator of some valuable but unobservable characteristics.[42] For example, Landers et al. (1996) argue that a preference to work few hours could signal a higher disutility of work. Thus, recruiters might interpret a preference for part-time work as a sign of a jobseeker's low commitment, motivation, or

[40] There may be some special cases where the production technology exhibits a discontinuous jump at a given level of hours. For example, assembly-line technologies where all workers must be present at the same time for any output to be produced.

[41] On the contrary, several studies examining the relationship between hours and productivity find a decreasing rather than increasing marginal productivity of hours above a certain threshold (Collewet and Sauermann, 2017; Pencavel, 2015; Shepard and Clifton, 2000). However, the estimates are derived from very specific settings that may not be representative of other contexts.

[42] Similar to Tô (2018), who argues that parental leave take-up might provide employers with a signal about future labor market choices or worker productivity.

ambition.[43] There is also evidence that a person's gender can matter for the interpretation of a signal. For example, Sarsons (2017a) shows that gender influences how physicians interpret information about surgeon performance. And Sarsons (2017b) shows that the gender of an economist affects the signal of a co-authored paper about individual ability.

But why should the signal to look for a part-time job depend on the gender of the jobseeker? Women are still the primary caregivers in many households, and part-time work is one of the most popular ways to reconcile work and family life (Blau and Kahn, 2013). Thus, recruiters may interpret a woman's preference for part-time work as necessary to reconcile work and household responsibilities without drawing conclusions about her commitment or motivation. On the other hand, men are still the main breadwinners in many households. Hence, a preference to work part-time is more likely to be interpreted as a sign of low commitment, low ambition, or some other deficiency that leads to difficulties in finding a full-time job. There is evidence along these lines. For example, Eagly and Steffen (1986) found that part-time work among women is interpreted as a commitment to domestic duties, while part-time work among men indicates difficulty in finding full-time employment. Other studies have found that part-time working men are perceived as less competent (Etaugh and Folger, 1998) or less agentic (Eagly and Steffen, 1986) than their full-time working counterparts, while this is not (or to a lesser extent) the case for women. Such differences in the perceptions of men and women seeking part-time work may explain why the former face more resistance from employers than the latter.

Differences in the interpretation of a signal due to a jobseeker's gender can be caused by actual differences in the distribution of unobserved characteristics or by inaccurate beliefs (Bohren et al., 2019). Suppose that statistical discrimination based on true beliefs is the reason for the different treatment of male and female jobseekers looking for part-time jobs. In this case, jobseekers looking for part-time jobs should have worse unobserved characteristics than those looking for full-time jobs, and this gap should be larger for men than for women. Unobserved characteristics may include ambition, motivation, or (future) firm attachment. Since most of the characteristics are unobserved not only by firms but also by researchers, it is difficult to assess these hypotheses directly. However, I have some information about jobseekers and workers that is not observed by recruiters but may be related to productivity.

[43] Recruiters might also interpret the preferred number of hours as a productivity signal. According to Sousa-Poza and Ziegler (2003), productive individuals are often perceived as hardworking, since many people believe that workers who like their jobs and work a lot tend to be good at them.

Panel A of Table 4 reports a jobseeker's age, adjusted insured monthly earnings prior to registering with the PES,[44] and the share of jobseekers with an unemployment spell in the 1.5 years prior to (re-)registering with the PES. All these characteristics are not visible to recruiters on Job-Room. Jobseekers looking for part-time jobs are on average older than jobseekers looking for full-time jobs. As there is evidence that firms prefer younger jobseekers (Neumark, 2020, 2018), this could be a reason why recruiters on Job-Room refrain from hiring jobseekers looking for a part-time job. However, this age difference is larger for women than for men. Thus, it cannot explain why the part-time penalty is more pronounced for men than for women. Last job earnings or prior unemployment could also be indicators of (unobserved) productivity. However, adjusted monthly earnings in the last job are even higher for jobseekers looking for part-time work than for jobseekers looking for full-time work.[45] The former are also less likely to have been unemployed in the 1.5 years prior to registering with the PES than the latter. This is true for both men and women.

Is there evidence that jobseekers looking for part-time work are less motivated to find a job than jobseekers looking for full-time work? And if so, is this more the case for men than for women? We have already seen that there is no significant difference in terms of occupational and regional mobility between jobseekers looking for a part-time job and those looking for a full-time job (see Table B.4 in the Appendix). However, this information is visible on Job-Room and is taken into account when estimating the part-time penalty. But Panel B of Table 4 reports some descriptive statistics on the unobserved search behavior of jobseekers on Job-Room's job platform using the data presented in column 3 of Table 1. Men and women seeking part-time work are significantly more likely to actively search for jobs on Job-Room. Conditional on using the platform, there is no significant difference in terms of search intensity. As a result, the average number of ad views in the first month after registration is significantly higher for men looking

[44] I standardize insured monthly earnings by converting them to a full-time equivalent wage. Since the number of hours worked in the last job is unknown, I assume that it is equal to the number of preferred hours that jobseekers report when they register with the PES. I discuss possible implications of this assumption below.

[45] Because I approximate hours worked in the last job with the number of preferred hours that jobseekers report when registering with the PES, I might underestimate the last adjusted earnings of jobseekers looking for full-time work, as some of them may have actually worked fewer hours. It is also possible that I am overestimating the adjusted earnings of jobseekers looking for a part-time job with very few hours because some of them may have worked more hours before. However, both of these concerns apply to a much lesser extent—if at all—when I compare jobseekers looking for full-time jobs to those looking for a 90% part-time job. In this case, however, the gap becomes larger rather than smaller, and even unadjusted insured monthly earnings are not significantly higher for jobseekers looking for a full-time job.

for part-time jobs than for men looking for full-time jobs. For women, the difference is also positive but not significantly different from zero. Thus, using search behavior on the platform as an indicator of motivation, men looking for part-time jobs appear to be even more motivated than men looking for full-time jobs.[46]

Finally, is there any evidence that part-time workers are less committed to their work? As Panel C of Table 4 shows, the slightly higher absenteeism of part-time employees compared to full-time employees is offset by the higher likelihood of working overtime. Consequently, the share of actual hours in normal hours is the same. This holds for both men and women. What about investment in skills? While full-time workers are more likely to participate in professional training, part-time workers are more likely to participate in extra-professional training. Again, the pattern is the same for men and women. Thus, even if participation in professional training is weighted more heavily than participation in extra-professional training, the higher participation of full-time employees in professional training cannot explain the higher part-time penalty for men. The finding that the differences between full-time and part-time workers are rather small is in line with results of a meta-analysis of 38 studies (Thorsteinson, 2003). It found very little difference in terms of job satisfaction, organizational commitment, and intention to leave the company, regardless of the workers' gender. Only in terms of job involvement were full-time workers found to be more involved than part-time workers.

Taken together, the evidence presented in Table 4 does not support the notion that jobseekers looking for part-time work are less motivated, less committed to their jobs, or less productive than jobseekers looking for full-time work. Moreover, they do not point to any gender differences that could explain the differences in the part-time penalty. Thus, it seems unlikely that statistical discrimination based on accurate beliefs is the main cause of this gender gap.

However, people may hold inaccurate beliefs about the distribution of unobserved characteristics of a group. They can be caused by a lack of information or by stereotypes (Bohren et al., 2019). In fact, there are a number of studies showing that gender stereotypes can lead to unequal treatment.[47] Role congruity theory (Eagly and Karau, 2002)

[46]However, we do not know whether jobseekers looking for a full-time job search more intensively on other platforms. But a priori there is no reason to assume that this is the case.

[47]For example, Sarsons (2017a) shows that differences in the treatment of male and female surgeons by physicians cannot be explained by gender differences in surgeons' abilities, but are likely due to gender stereotypes. And studies from social psychology suggest that violations of traditional gender roles are the reason why men experience greater difficulties than women when making their caregiving responsibilities salient in the workplace (Rudman and Mescher, 2013; Allen and Russell, 1999; Butler and Skattebo, 2004).

Table 4: Unobserved characteristics of men and women seeking full-time and part-time jobs

	Women			Men		
	(1) Full-time	(2) Part-time	(3) Difference	(4) Full-time	(5) Part-time	(6) Difference
A. Jobseeker characteristics						
Age	37	42	4.6***	39	41	1.7***
Insured monthly earnings adj.	4,786	5,253	467***	5,649	5,862	214***
Unemployed before March 1, 2017	.312	.226	-.086***	.253	.181	-.0724***
B. Jobseeker search behavior						
Share active on Job-Room	.19	.211	.0212***	.244	.277	.0325***
# ad views in 1st month (if active)	19.6	18.4	-1.24	19.8	18.7	-1.04*
# ad views in 1st month	3.73	3.89	.157	4.83	5.19	.355**
C. Worker characteristics						
Absences (in % of normal hours)	0.04	0.05		0.05	0.06	
Overtime (in % of normal hours	0.02	0.04		0.01	0.03	
Actual hours (in % of normal hours	0.98	0.98		0.96	0.97	
Participation in professional training	0.69	0.61		0.67	0.59	
Participation in extra-prof. training	0.22	0.26		0.32	0.34	

Notes: The table shows characteristics of jobseekers seeking full-time and part-time jobs (panels A and B) and of full-time and part-time workers (panel C) by gender. The jobseeker characteristics reported in Panel A come from the unemployment register and are not visible to recruiters on Job-Room. Insured monthly earnings refer to a registered jobseeker's earnings before becoming unemployed up to a threshold of 12,500 CHF per month. I convert it to a full-time equivalent wage. As I do not have information on the number of hours worked in the last job, I assume that it corresponds to the number of preferred hours reported when registering with the PES. Adusted insured monthly earnings have been winsorized to 12,500 CHF per month (the value of the maximum insured earnings) and, following the practice of the Swiss Statistical Office, to 2125 CHF per month (1/3 of the median). The variable "Unemployed before March 1, 2017" indicates the share of newly registered jobseekers between March and December 2017 who were unemployed at least once in the previous 1.5 years. Panel B reports some key figures on the search behavior of jobseekers registered with the PES who search for jobs on Job-Room between June 2020 and May 2021 (see Table 1 column 3 for a brief description of the data). Panel C reports information on male and female workers who had a part-time or full-time job in 2017. Data on absenteeism, overtime, actual hours worked and normal hours worked are taken from the Federal Statistical Office's work volume statistics. Data on participation in non-formal professional and extra-professional training come from the Swiss Adult Education Survey, a survey conducted by the Federal Statistical Office every five years, and refer to the year 2016. Since I only have aggregated data in Panel C, I cannot compute a t-test for the difference in the means.

provides a theoretical foundation for the notion that gender stereotypes may influence recruiters' beliefs about men and women seeking part-time work. The theory posits that people evaluate gender role congruent behavior more favorably than gender role incongruent behavior.[48] Men who seek part-time work deviate from the male breadwinner norm and do therefore not conform to stereotypical male behavior.[49] The opposite is true for part-time working women. This could explain why recruiters refrain from hiring men seeking part-time work but not from hiring women.

Since I have little information about individual recruiters, let alone their beliefs, it is difficult to directly test this claim. However, I provide indirect evidence on the relation-

[48]This evaluation may be conscious or unconscious. In fact, stereotypes can have important implicit modes of operation that can lead to implicit biases (Greenwald and Banaji, 1995; Chugh, 2004).

[49]Several studies show that the male breadwinner norm is still prevalent and that traditional gender norms can affect economic outcomes such as the relative income within households (Bertrand et al., 2015) or the labor supply decisions of women (Fernández et al., 2004).

ship between the gender gap in the part-time penalty and gender norms at the regional level and the level of individual recruiters. Both analyses provide suggestive evidence that gender norms are a driver of the gender differences in the part-time penalty.

First, I test whether regional differences in gender norms are related to gender differences in the part-time penalty in each region. Specifically, I use cantonal variation in the outcome of a popular vote on a law that aimed to extend parental leave for fathers as an indicator of the importance of traditional gender norms in a canton.[50] Since extended paternity leave for fathers contradicts the male breadwinner norm, the outcome of the vote is arguably a valid indicator of the importance of traditional gender norms in a canton. Panel (a) of Figure 9 shows that the gender gap in the part-time penalty is significantly (t-value: 2.33) larger in cantons with a lower share of votes in favor of extending paternity leave for fathers than in cantons with a higher share of yes votes. Thus, the disadvantage for male jobseekers seeking part-time work is more pronounced in cantons with more conservative gender norms.[51] Panel (b) of Appendix Figure B.9 confirms this finding using a different data source: It shows, based on the job ad data, that there is a positive relationship between the share of part-time jobs in a canton with an explicit preference for men and the share of yes votes in the parental leave referendum. That is, in cantons where a higher proportion of people voted in favor of extending parental leave for fathers, firms are more likely to look for men when they post a part-time job. These findings are consistent with the idea that gender norms play a role in explaining men's difficulties in finding part-time work.

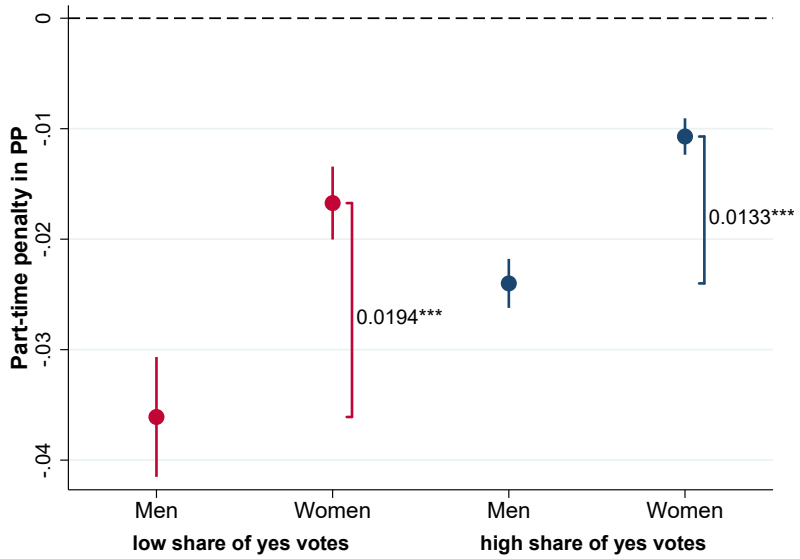
Second, I use information about the selection behavior of recruiters on Job-Room's candidate search platform to construct an indicator of the strength of their gender stereotypes. Studies show that in occupations dominated by one gender, some recruiters or supervisors refrain from hiring or promoting members of the minority gender, arguably because of a perceived "lack of fit" due to gender stereotypes (Clarke, 2020; Heilman, 2012; Hangartner et al., 2021). Therefore, I categorize recruiters, who search for candidates in occupations dominated by one gender, according to whether they select gender-typically, i.e., prefer the majority gender, or gender-atypically, i.e., prefer the minority gender.

[50]There are several other studies that use regional variation in the outcome of popular votes in Switzerland as an indicator of regional differences in norms and attitudes (Lalive and Stutzer, 2010; Janssen et al., 2016; Kuhn and Wolter, 2019). The law I consider aimed to extend paternity leave for fathers from one day to two weeks. As the law was subject to a referendum, Swiss voters had to vote on it on September 27, 2020. It passed with a 62% majority. However, there was considerable heterogeneity among the cantons, with no votes ranging from 18% in the canton of Vaud to 65% in Appenzell Inner Rhodes.

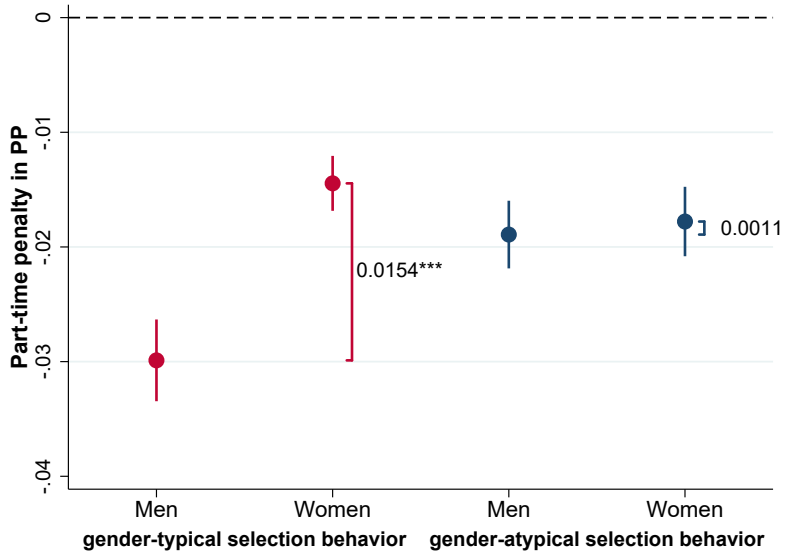
[51]Panel (a) of Figure B.9 in the Appendix examines this relationship in more detail by plotting the share of yes votes in a canton against the gender gap in the part-time penalty.

Figure 9: Gender norms and the part-time penalty for men and women

(a) Cantons with high/low share of yes-votes in parental leave referendum



(b) Recruiters with a gender-typical or gender-atypical selection behavior



Notes: Panel (a) plots the part-time penalty for men and women in cantons with a low (red) and a high (blue) share of voters in a canton who voted in favor of extending the right to parental leave for fathers. Cantons with an above-average share of yes votes are classified as high. The sample is restricted to the 62 percent of searches where I know the location of the firm. Panel (b) plots the male and female part-time penalty for recruiters with a gender-typical (red) and a gender-atypical (blue) selection behavior. Recruiters are considered to select gender-typically if the proportion of the majority gender is higher in their profile views than in their results lists. I only consider occupations where one gender has an employment share higher than 60%. In addition, only searches by recruiters with at least 5% gender atypical candidates on their lists and with at least 10 profile views in the respective occupations are considered. The coefficients in both figures are the result of estimating a slightly different version of Equation 1: Instead of estimating separate effects for the different part-time categories, I aggregate them into a dummy and interact this part-time dummy, gender, and its interaction with the indicator for a high share of yes votes in a canton and the identifier for a gender-typical recruiter, respectively.

Specifically, recruiters are considered to select gender-typically if the proportion of the majority gender in their profile views is higher than the proportion of the majority gender in their results lists. I only consider occupations that are dominated by one gender, i.e., occupations in which one gender accounts for more than 60% of employment. Recruiters categorized as gender-typical thus reinforce gender segregation in the occupation. The opposite is true for recruiters who select gender-atypically. As Panel (b) of Figure 9 shows, the gender gap in the part-time penalty is much more pronounced for recruiters with gender-typical selection behavior than for those with gender-atypical selection behavior. For the latter, the gap is even insignificantly different from zero. Thus, this analysis also provides suggestive evidence that stereotypes play a role in explaining the gender gap in the part-time penalty.

7 Conclusions

This study draws on large-scale observational data from an online recruitment platform and an online job board in Switzerland to investigate whether recruiters prefer full-time or part-time workers and whether these preferences depend on the gender of the jobseeker. I apply two complementary strategies to assess these questions.

First, I analyze click data from 43,352 recruiters navigating through 313,566 jobseeker profiles on the candidate search platform of Job-Room, the job and recruitment platform of the Swiss Public Employment Service. The profiles contain, among other things, information about a jobseeker's preferred number of working hours. I observe several million recruiters' decisions on whether or not to contact a jobseeker. I estimate the effect of the number of preferred working hours on the probability of being contacted by a recruiter. Since I have all the information about jobseekers available to recruiters, I can flexibly control for all jobseeker characteristics related to the likelihood of being contacted, the gender of a jobseeker, and the preferred number of working hours. This allows me to estimate the causal effect of a jobseeker's preference for part-time work on the contact probability, as well as its interaction with a jobseeker's gender.

Second, I analyze 563,444 vacancies posted directly on Job-Room. All job ads contain information on the number of working hours. In addition, companies can confidentially indicate the preferred gender of a jobseeker. This allows me to assess whether they prefer men or women when advertising a part-time job. As a robustness check, I use the grammatical gender of the job titles as a complementary indicator of recruiters' gender preferences. This allows me to significantly increase the coverage of the data and thus

the external validity of the results.

The analyses consistently show that recruiters prefer full-time workers to part-time workers and that this part-time penalty is more pronounced for men than for women. Differences in job or workplace characteristics cannot explain these results. This finding is consistent with survey evidence for Switzerland, which shows that more men than women would reduce their working hours if they had the opportunity.[52]

Given the research design, the gender differences in the part-time penalty cannot be explained by differences in the production technology. Moreover, when comparing jobseeker and worker characteristics that are unobserved by recruiters but are likely to be related to productivity, I find no evidence that jobseekers seeking part-time work have less favorable characteristics than jobseekers looking for full-time jobs, let alone that there is a consistent gender gap. This speaks against statistical discrimination based on accurate beliefs as the main driver of the gender gap in the part-time penalty. Instead, I provide suggestive evidence that bias due to gender stereotypes is one reason for the larger part-time penalty for men compared to women. Since a stereotypical man is supposed to work full-time to provide for his family, men who seek part-time jobs seem to arouse suspicion and trigger concerns that they lack motivation or ambition, or have some other deficiency that makes it difficult to find a full-time job. On the other hand, women who work part-time conform to traditional gender roles and are therefore likely to face less backlash from recruiters. However, more research is needed to explore the causal mechanisms behind the higher part-time penalty for men in more depth.

The findings of this study have several implications. They support macroeconomic models based on indivisible labor (Hansen, 1985; Rogerson, 1988). The lack of flexibility to adjust the number of hours worked at the intensive margin implies that labor supply adjustments occur primarily at the extensive margin. They also have implications for gender equality. First, a part-time penalty in hiring implies higher search costs and a reduction in the number of potential jobs for jobseekers who prefer part-time work. This mainly affects women as they are more likely than men to look for part-time jobs. However, the few men seeking part-time work experience even greater difficulties than women who look for part-time jobs. The associated stereotype threat (Steele et al., 2002; Hoff and Pandey, 2006; Glover et al., 2017) may partly explain why men are more

[52] According to the 2017 Swiss Labor Force Survey, 38% of employed men prefer to work fewer hours, while only 29% of women do so. Similarly, according to a representative survey by the insurance company Swiss Life, 74% of male respondents with children under the age of 18 said they would like to reduce their working hours, while only 41% of female respondents expressed this wish (Christen and Myohl, 2023).

reluctant than women to seek jobs with fewer hours.[53] Recruiters' reluctance to hire part-time working men is therefore likely to be an additional barrier to a more equal division of paid and unpaid work by gender.

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[53] Consistent with this hypothesis, Vandello et al. (2013) found that although men highly value work flexibility, they are less likely than women to seek such flexibility for fear of the reactions of superiors or colleagues.

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Appendix

A Job-Room screenshots

Figure A.1: Candidate search platform. First step: Specify search criteria

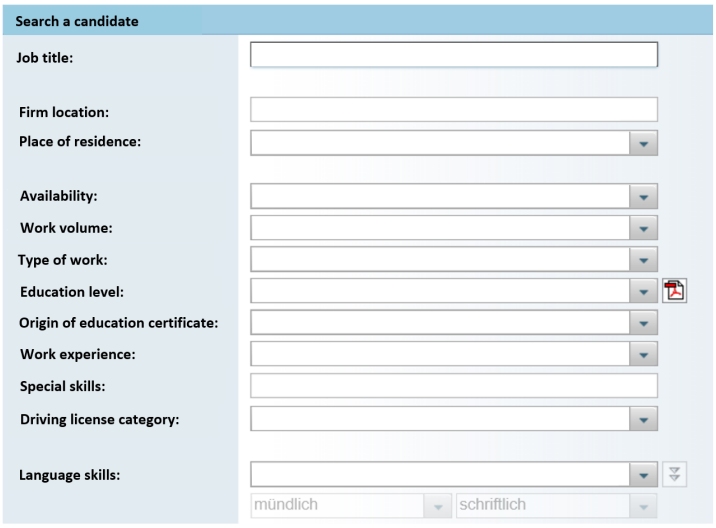


Figure A.2: Candidate search platform. Second step: Select from results list

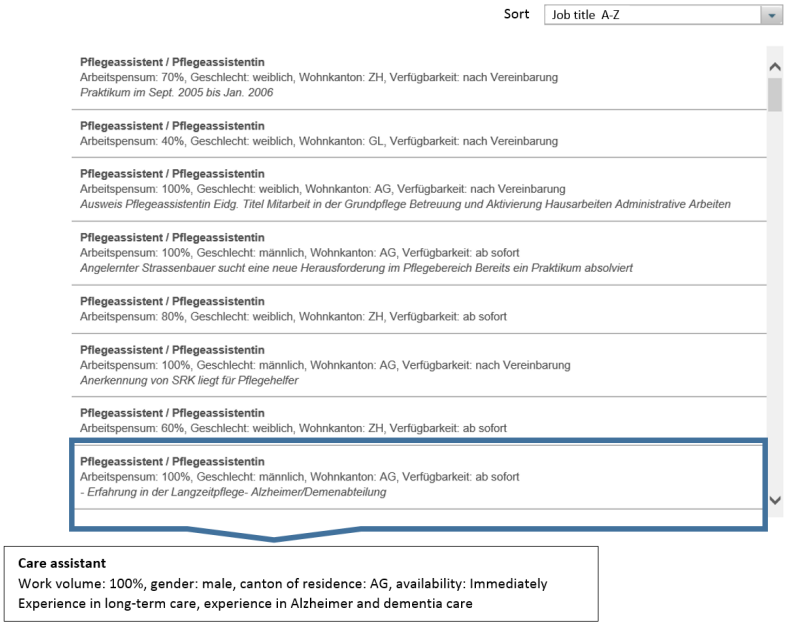


Figure A.3: Candidate search platform. Third step: Screen profile, reveal contact info

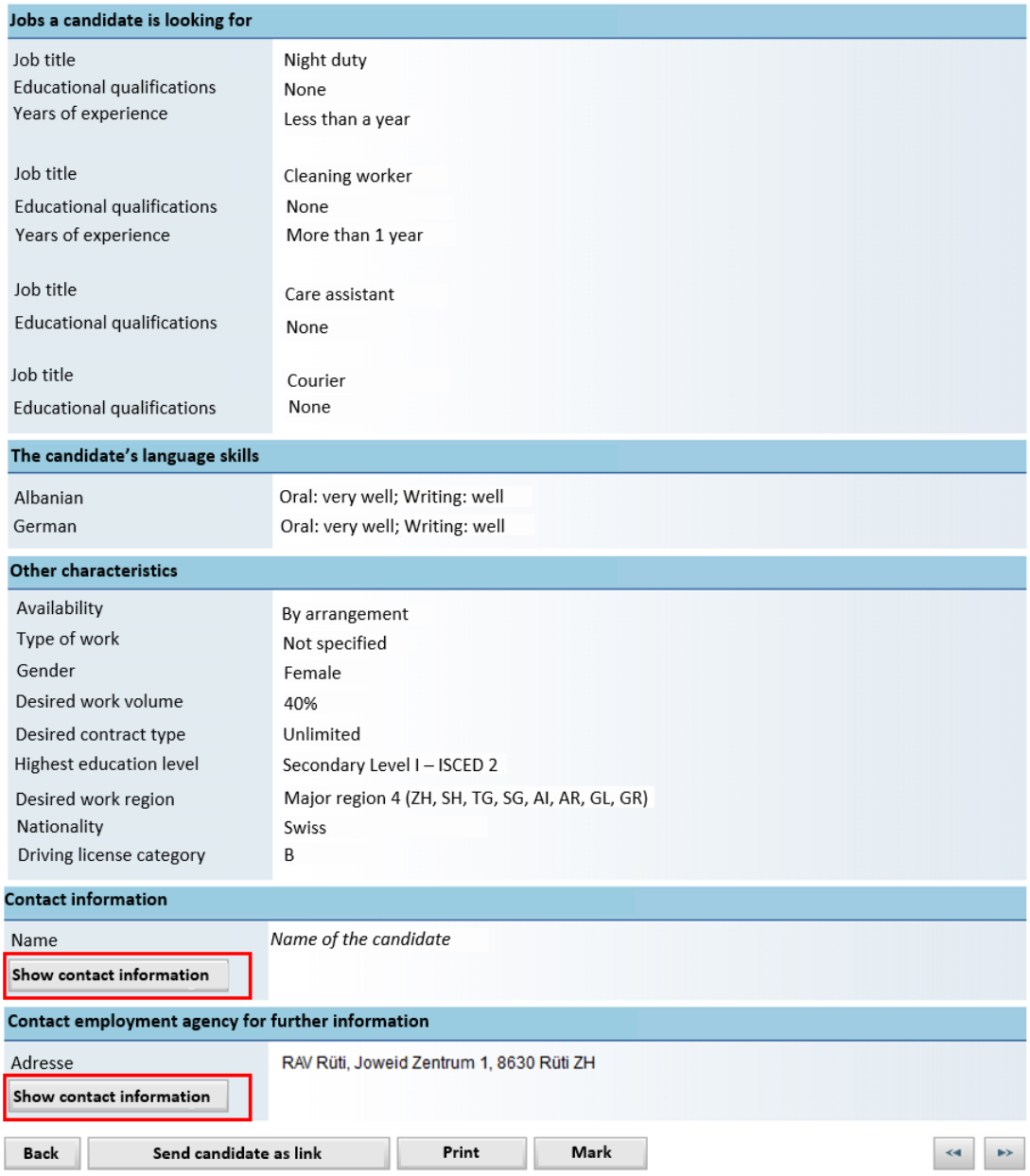
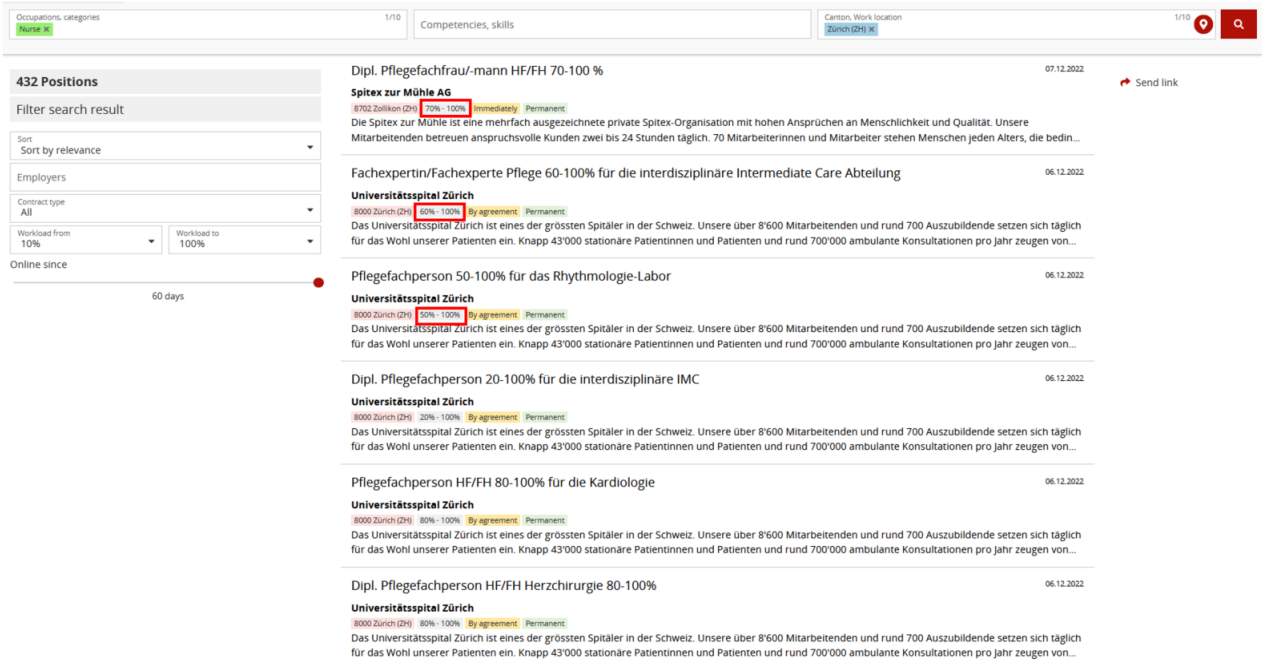


Figure A.4: Job platform. Results list

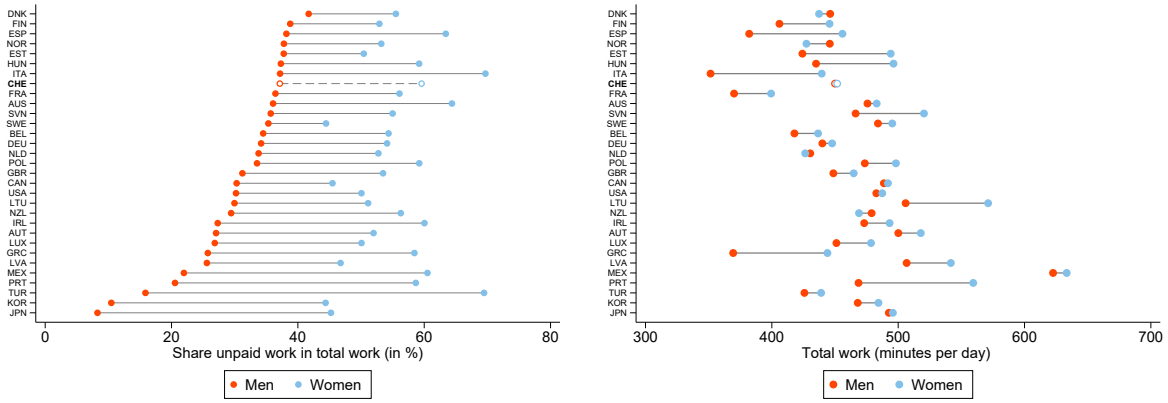


B Additional tables and figures

Figure B.1: Distribution of unpaid work and total work among men and women

(a) Share of unpaid work

(b) Total work in minutes a day



Notes: Panel (a) plots the share of unpaid work in total hours worked for men and women in several OECD countries, including Switzerland (bold label, hollow marker and dashed line). Panel (b) shows the total working time for men and women in the same countries, measured in minutes per day. Data are from the OECD. Only the data for Switzerland are from the Swiss Statistical Office, as the OECD does not report such data for Switzerland. The Swiss data had to be converted from hours per week to minutes per day.

Table B.1: Search criteria specified by recruiters

	(1) Share selected	(2) Share within category
Job title	84.2	
Place of residence of jobseekers	49.8	
Work location	41.4	
Zurich		21.4
Bern		17.5
Argovia		9.8
...		
Origin of diploma	27.4	
CH		68.2
Foreign, recognized in CH		24.7
Foreign, not recognized in CH		5.0
None		2.1
Work volume	26.8	
Full-time		90.6
Part-time 50-90%		7.6
Part-time $< 50\%$		1.8
Language skills	23.0	
German		65.0
CH-German		18.6
French		13.3
English		9.9
...		
Availability	22.1	
Immediately		92.7
By arrangement		7.3
Experience	21.2	
< 1 year		5.0
1-3 years		37.1
> 3 years		58.0
Drivers license	13.3	
Special skills	13.7	
Education level	1.6	
Type of work (night/shift work,..)	1.0	

Notes: The table reports the search criteria (and the main subcategories) entered by the recruiters on Job-Room during the sample period from March to December 2017. For example, in 41.4% of all searches, recruiters enter the work location. As a result, only candidates willing to work in this canton are displayed in the results list. 21.4% of the recruiters who specify the work location are looking for candidates for a company based in Zurich. About 16% of the users do not select any of the predefined job titles. Note that a recruiter can select multiple categories.

Table B.2: Occupations selected by recruiters on Job-Room's candidate search platform and last occupation of candidates

	# recruiters	% searches	% candidates
Craft and related trades workers	15713	46	15
Technicians and associate professionals	8097	9	9.8
Professionals	7954	6.6	12
Plant and machine operators, and assemblers	4619	5.3	4.6
Service and sales workers	6964	5.2	21
Elementary occupations	3837	3.8	9.6
Clerical support workers	3636	2.6	6.6
Skilled agricultural, forestry and fishery workers	1897	2.4	.77
Managers	1561	.85	4.8

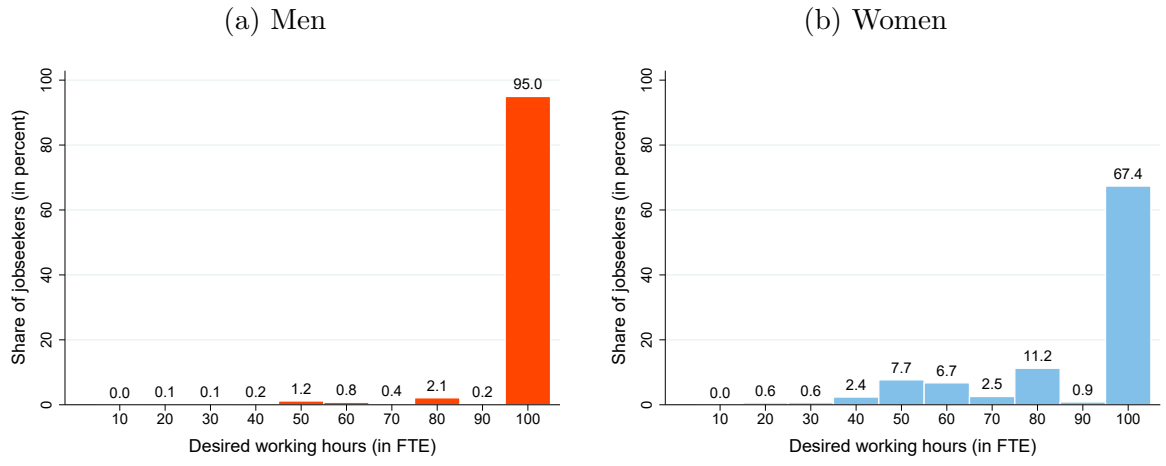
Notes: The table illustrates the occupational coverage of the recruiter click data between March and December 2017. Column 1 shows the number of different recruiters searching for candidates on Job-Room by ISCO 1-digit occupation. Column 2 shows the share of each occupational group in the total number of searches on Job-Room. Note that in 18% of the searches, recruiters do not specify an occupation. Column 3 shows the share of candidates available on Job-Room per occupational category.

Table B.3: Share of occupations in job ads reported directly to Job-Room and in all job ads published on Job-Room

	(1) Ads directly reported 07/2018–06/2021	(2) Ads directly reported 01/2020–05/2021	(3) All ads 01/2020–05/2021
Managers	0.021	0.018	0.024
Professionals	0.086	0.079	0.179
Technicians and associate professionals	0.071	0.073	0.145
Clerical support workers	0.107	0.097	0.093
Service and sales workers	0.216	0.171	0.112
Skilled agricultural, forestry and fishery workers	0.010	0.013	0.016
Craft and related trades workers	0.202	0.233	0.298
Plant and machine operators, and assemblers	0.044	0.057	0.048
Elementary occupations	0.243	0.260	0.086

Notes: Column 1 shows the share of occupations in the job advertisements reported directly to Job-Room between July 2018 and June 2021, the entire sample period of the job posting data. Note that 17.8% of the job ads are assigned to more than one occupation and are counted more than once. Column 2 reports the same figure but based on the period from January 2020 to May 2021, to make the sample consistent with the sample of column (3), which contains the share of all job ads (including those added from other sources) published on Job-Room during this time period.

Figure B.2: Distribution of male and female jobseekers by number of preferred working hours (in FTE)



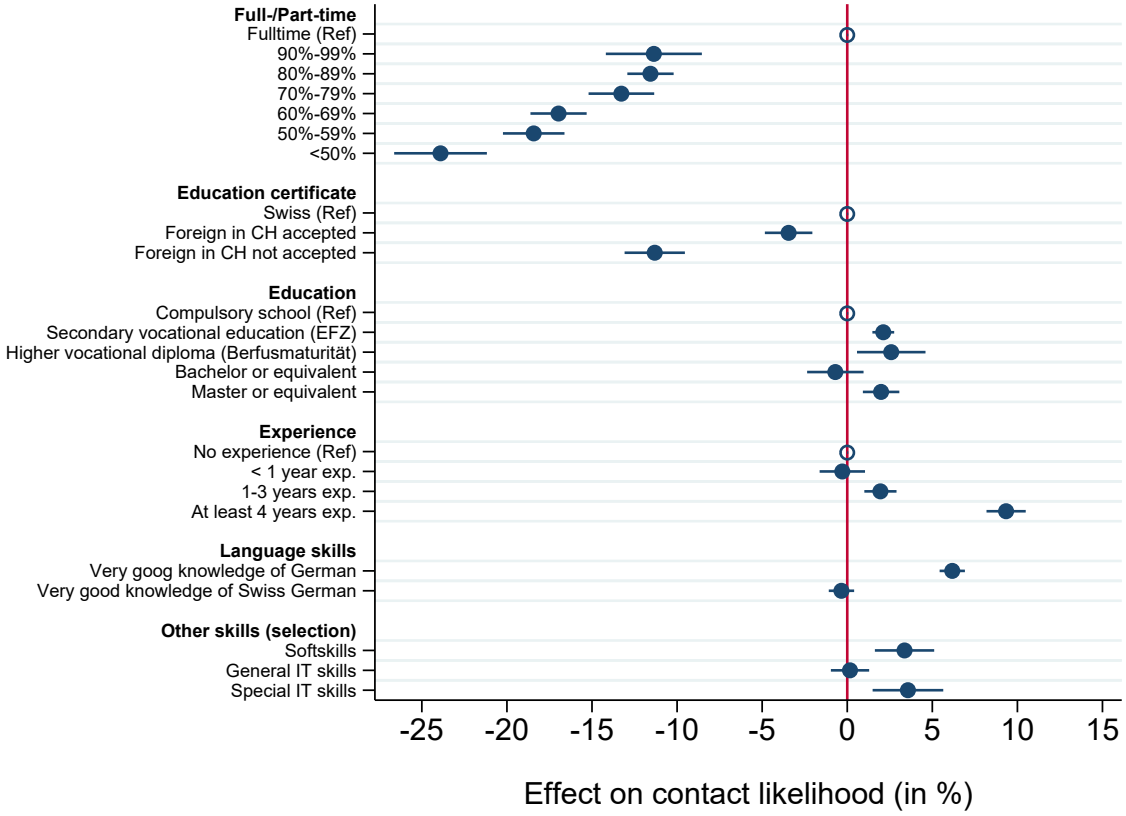
Notes: The figure plots the share of male (panel a) and female (panel b) jobseekers registered on Job-Room by different levels of preferred weekly working hours (expressed in FTE). The sample period is March 2017 to December 2017.

Table B.4: Descriptive statistics by part-time and full-time status and gender

	Women			Men		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full-time	Part-time	Difference	Full-time	Part-time	Difference
Swiss citizen	.55	.69	.14***	.48	.73	.25***
Occup. mobility (No of occupations)	3.1	3	-.0093	3.1	3.1	.0032
Regional mobility (No of cantons)	4.1	4.1	-.031	4.5	4.5	.0086
Work experience						
None	.29	.28	-.016***	.23	.29	.06***
< 1 year	.065	.042	-.023***	.063	.061	-.0017
1-3 years	.17	.12	-.045***	.15	.14	-.0085*
> 3 years	.47	.56	.084***	.55	.5	-.05***
Education						
No information	.045	.045	.000059	.055	.038	-.017***
Primary education	.01	.0088	-.0014*	.011	.0067	-.0047***
Lower secondary education	.2	.16	-.038***	.23	.12	-.11***
Upper secondary education	.52	.57	.051***	.51	.55	.039***
Bachelor's or equivalent level	.1	.12	.02***	.11	.17	.059***
Master's or equivalent level	.1	.078	-.024***	.069	.091	.022***
Doctoral or equivalent level	.023	.016	-.0074***	.017	.023	.0059***
Language skills						
Very good German skills	.46	.57	.1***	.43	.62	.19***
Very good Swiss German skills	.19	.25	.06***	.17	.29	.11***
Very good English skills	.24	.2	-.04***	.19	.26	.072***
Very good French skills	.32	.3	-.02***	.28	.28	.0075
Very good Italian skills	.12	.11	-.0073***	.13	.1	-.031***
Occup. last job						
Agriculture and forestry	.014	.0073	-.0065***	.022	.02	-.0023
Manufacturing and craft	.083	.048	-.036***	.17	.14	-.031***
IT	.03	.019	-.01***	.11	.13	.02***
Construction	.006	.0017	-.0044***	.21	.071	-.13***
Trade and transport	.2	.21	.0074**	.14	.17	.029***
Hotel/restaurant, personal services	.23	.22	-.017***	.12	.1	-.018***
Management, finance, law	.2	.21	.013***	.14	.15	.0086*
Education, health, arts	.16	.22	.062***	.052	.17	.12***
Unclassified	.076	.068	-.0083***	.037	.044	.0073***
Observations	89016	43128	132144	172292	9130	181422

Notes: The table shows descriptive statistics for female (columns 1–3) and male (columns 4–6) jobseekers registered with Job-Room and whose profile appeared at least once in a search list between March and December 2017. It further splits the sample by jobseekers looking for full-time (columns 1 and 4) or part-time jobs (columns 2 and 5). Columns 3 and 6 report the difference between those who look for a full-time and those looking for a part-time job. Stars indicate the result of a t-test for equality of the two values (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). All characteristics presented in the table are visible to recruiters on Job-Room

Figure B.3: Effects of different jobseeker characteristics on the contact likelihood



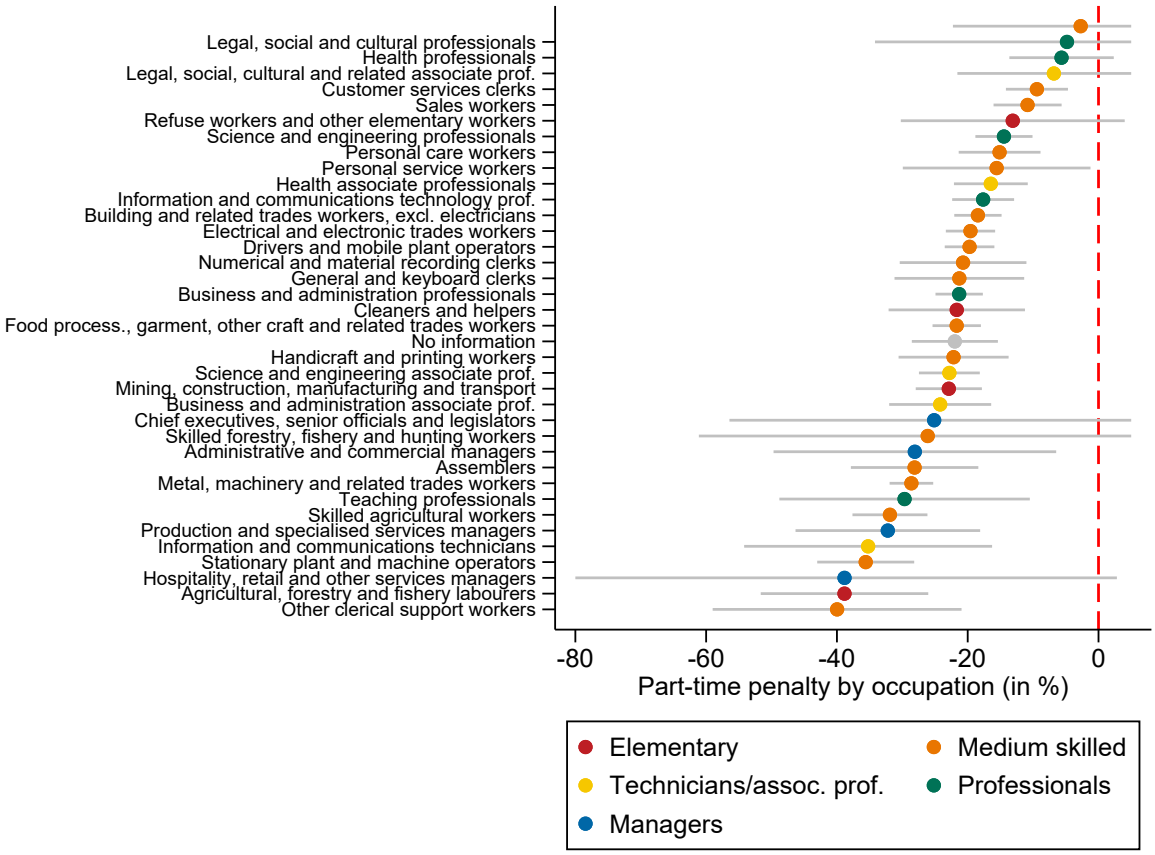
Notes: The figure plots the coefficients, and associated 95% confidence intervals, of different jobseeker characteristics visible to recruiters on Job-Room. Unlike the regression model shown in Equation 1, this model does not contain first order interactions because the main effects of the different variables could not be interpreted if they were also part of some interactions. The dependent variable is the likelihood that a recruiter clicks on the contact button. All coefficients are normalized with the average contact rate (9.4%). The sample covers all jobseeker profiles appearing on the results lists of search queries between March and December 2017, where recruiters did not restrict the candidate pool to jobseekers looking for full- or part-time jobs. Standard errors are clustered at the recruiter level.

Table B.5: Effect of a stated preference for part-time work on the probability of a contact attempt by gender

	(1)	(2)
Full-time	ref.	ref.
90%-99%	-9.88	-16.5
	(1.4)	(2.1)
80%-89%	-10.9	-17.5
	(.63)	(1)
70%-79%	-13.4	-23.5
	(.9)	(1.9)
60%-69%	-16	-25.6
	(.78)	(1.5)
50%-59%	-18.9	-27.9
	(.82)	(1.2)
<50%	-22.3	-24.5
	(1.4)	(2.2)
Female		-3.21
		(.54)
Female # 90%-99%		14.6
		(2.5)
Female # 80%-89%		11.9
		(.99)
Female # 70%-79%		15.6
		(2)
Female # 60%-69%		14.3
		(1.4)
Female # 50%-59%		14.9
		(1.3)
Female # <50%		4.59
		(2.2)
Mean dep. Var.	0.09	0.09
Observations	13,561,643	13,561,643

Notes: The table reports the effects (in %) of indicating a preference for (different levels of) part-time work on the likelihood that recruiters click on the contact button, conditional on appearing in a results list. Column (1) shows the overall effect of part-time work obtained by estimating Equation 1 without the interactions between gender and the part-time categories. Jobseekers searching a full-time job are in the reference category. Column (2) reports the part-time coefficients interacted with gender, obtained by estimating Equation 1. Here, male jobseekers searching for a full-time job are the reference category. Standard errors (in parentheses) are clustered at the recruiter level.

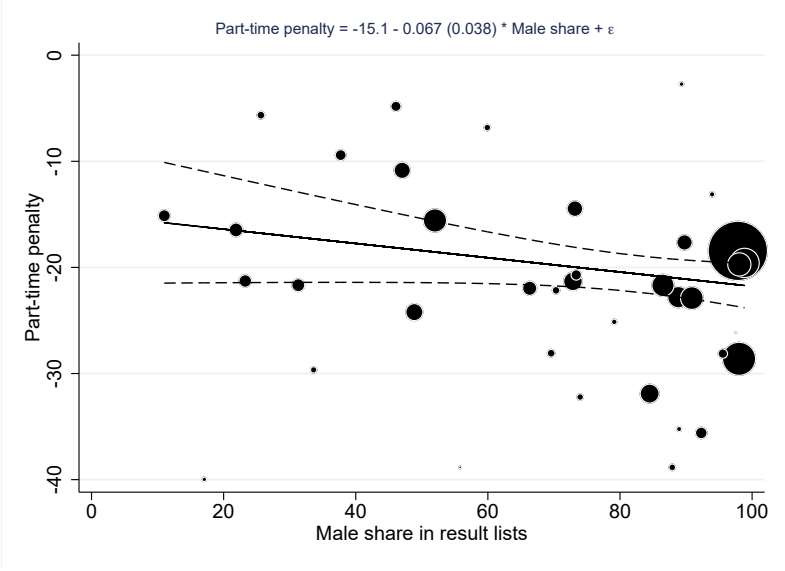
Figure B.4: Overall effect of a preference for part-time work on the contact likelihood by occupation



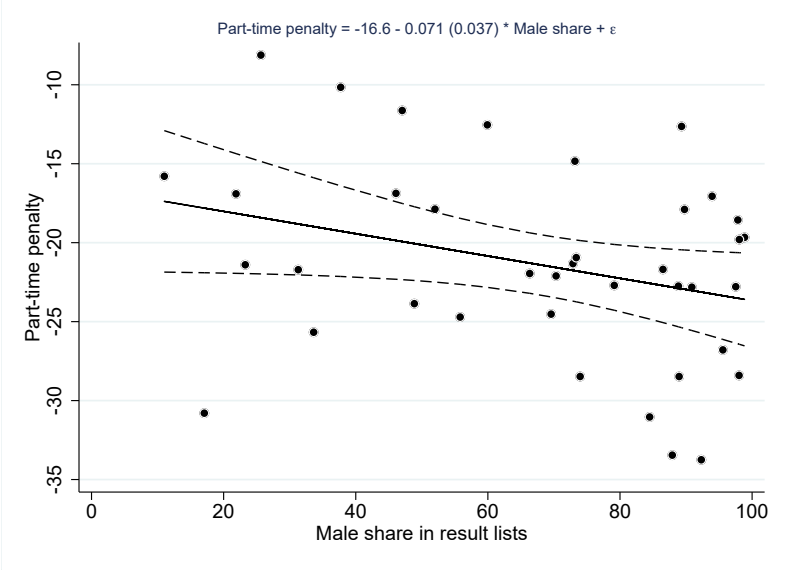
Notes: The figure plots the coefficients of a preference for part-time work, and associated 95% confidence intervals, by occupation (following the ISCO-2 classification). The dependent variable is the likelihood that recruiters click on the contact button. Unlike the regression model shown in Equation 1, this model aggregates the six part-time categories into one part-time dummy, which is not interacted with gender, but instead with indicators for ISCO-2 occupations. The reference category includes jobseekers looking for a full-time job in the same occupation. Coefficients are normalized with the average contact rate in the respective occupation. The colors indicate the skill-level of an occupation (according to the ISCO skill classification). Note that I cut confidence intervals at -80 and +5. The sample covers all jobseeker profiles appearing in the results lists of search queries between March and December 2017, where recruiters did not restrict the candidate pool to jobseekers looking for full- or part-time jobs. Standard errors are clustered at the recruiter level.

Figure B.5: Relationship between the part-time penalty in an occupation and the share of men in the results lists

(a) Raw (weighted) part-time penalties

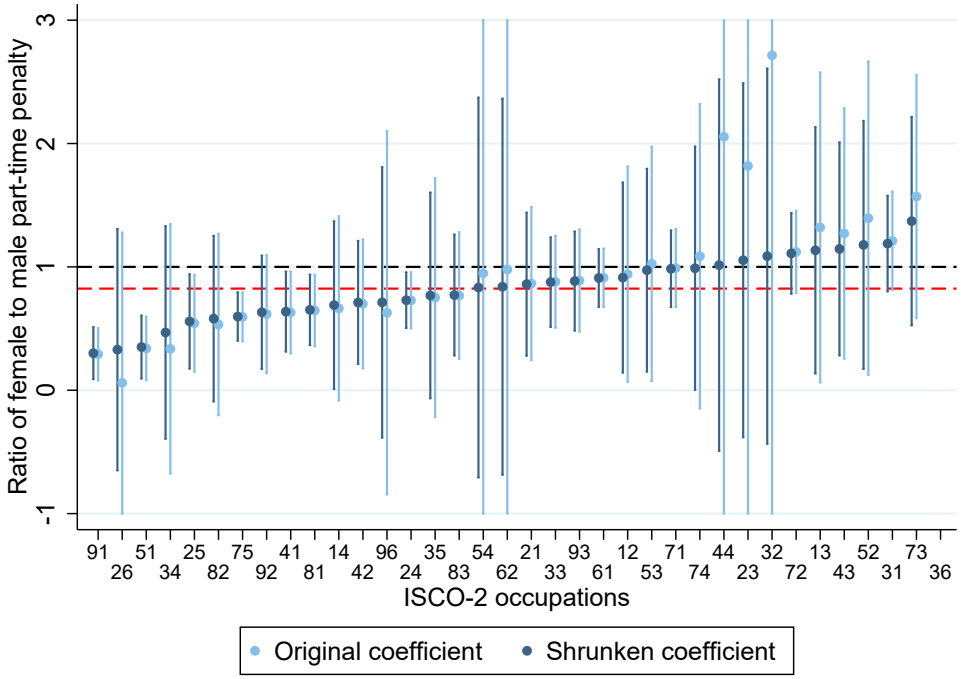


(b) Shrunken part-time penalties



Notes: The figure relates the overall part-time penalty in an ISCO-2 occupation to the share of men in the results lists of the occupation. The part-time penalties are calculated by estimating Equation 1, except that the six part-time categories are aggregated into one part-time dummy. This dummy is not interacted with gender but instead with indicators for ISCO-2 occupations. All coefficients are normalized with the mean of the average contact rate in the respective occupation. Panel a reports the raw coefficients weighted by the number of observations in an occupation. Panel b reports coefficients that have been shrunken towards their mean with empirical Bayes shrinkage (Koedel et al., 2015; Herrmann et al., 2016) because some estimates are noisy in occupations with a low number of hours. The size of the markers corresponds to the number of observations in an occupation. The black solid line indicates the ordinary least squares regression of the estimated part-time penalty against the male share in each occupation. The dashed lines show the associated 95% confidence intervals.

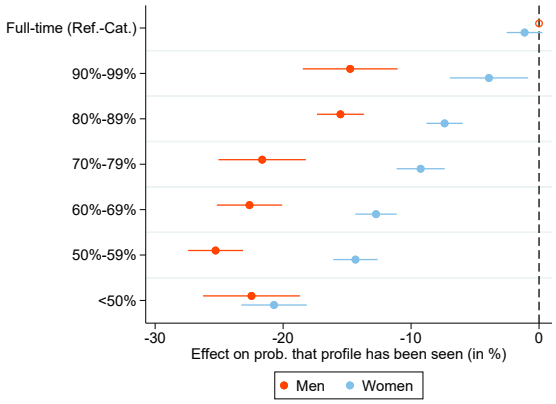
Figure B.6: Ratio of the female to male part-time penalty by ISCO-2 occupation



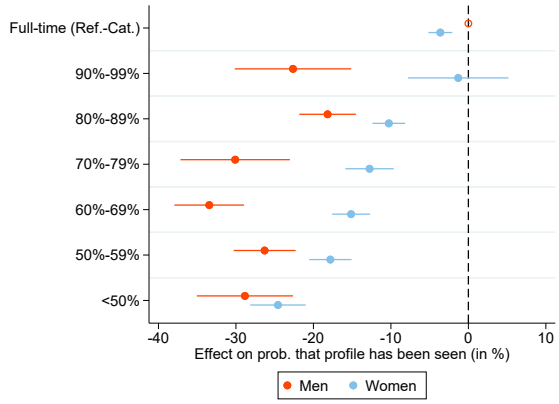
Notes: The figure plots the ratio, and associated 95% confidence intervals, of the female to male part-time penalty by ISCO-2 occupation. The regression model is the same as the one shown in Equation 1 except that the part-time categories ($\beta_k hours^k_{i,s}$), gender ($female_i$) and their interaction ($\beta_{k,f} hours^k_{i,s} * female_i$) have been interacted with occupation (i.e. $occpation_o$). In addition, the six part-time categories are aggregated into one. The reported coefficients are calculated by dividing the female part-time penalty in an occupation ($\beta_k hours^k_{i,s} * occpation_o + \beta_{k,f} hours^k_{i,s} * female_i * occpation_o$) by the male part-time penalty in the same occupation ($\beta_k hours^k_{i,s} * occpation_o$). The associated standard errors are calculated using the delta method. Since the estimates are noisy in some occupations due to the small number of observations, I apply empirical Bayes shrinkage (Koedel et al., 2015; Herrmann et al., 2016) to shrink the estimated ratios towards their mean (0.817). The light blue coefficients show the original estimates and the dark blue ones the shrunken ones. The dashed horizontal red line indicates the mean of the ratios.

Figure B.7: Robustness

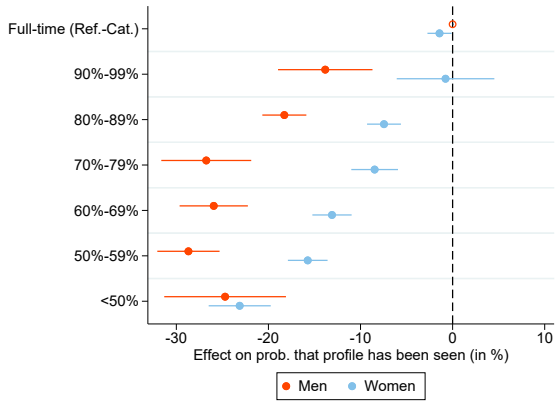
(a) Including searches with hours as a criteria



(b) No profiles with additional skills

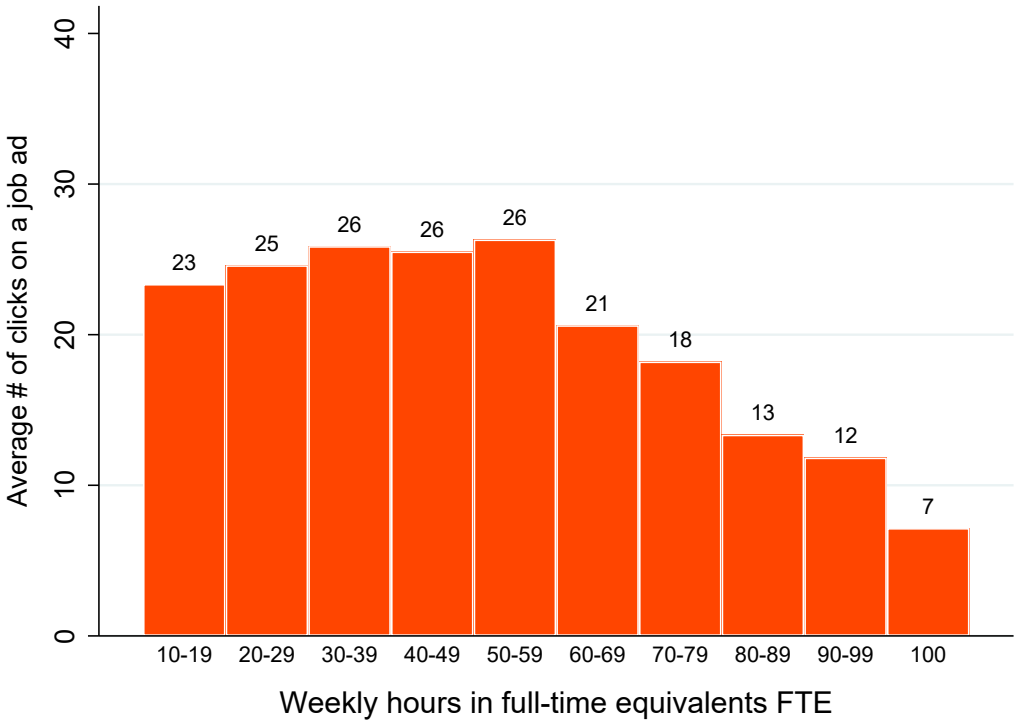


(c) With occupation fixed effects



Notes: The figure shows three robustness tests for the result shown in Figure 5. All three panels show the effect of the number of preferred working hours (expressed in FTE), and associated 95% confidence intervals, on the likelihood that recruiters click on the contact button. All coefficients are normalized with the respective mean of the dependent variable. In the reference category are male jobseekers searching for a full-time job. Standard errors are clustered at the recruiter level. Panel (a) also includes in the sample those search requests where recruiters use hours worked as a selection criterion. Panel (b) reports results for a sample without profiles that report additional skills. Panel (c) shows estimates based on a model with occupation fixed effects instead of search fixed effects.

Figure B.8: Average number of job ad clicks by weekly working hours (in FTE)



Notes: The bars show the average number of clicks on a job ad by number of weekly working hours (expressed in FTE). The sample consists of 910,379 ads published on Job-Room between June 2020 and May 2021. Job ads without a view are included in the sample. Note that some job ads specify a range of possible working hours and therefore may appear in multiple categories.

Table B.6: Share of part-time job ads and share of clicks on part-time job ads by occupational group

	(1) Part-time ads	(2) Part-time clicks	(3) # obs
Managers	.074	.097	20,939
Professionals	.15	.23	163,689
Technicians and associate professionals	.11	.22	129,588
Clerical support workers	.2	.36	81,301
Service and sales workers	.21	.38	95,003
Skilled agricultural, forestry and fishery workers	.016	.075	15,215
Craft and related trades workers	.0091	.03	267,166
Plant and machine operators, and assemblers	.029	.16	45,016
Elementary occupations	.16	.25	78,278

Notes: Column 1 shows the share of part-time job ads on Job-Room between June 2020 and May 2021 by ISCO-1 occupation. Column 2 reports the share of clicks on part-time job ads in the same occupation during the same period. This sample consists of 524,456 job ads. In both columns, I consider only job ads that exclusively cover part-time jobs. Job ads that cover part- and full-time positions are not counted. The number of observations reported in column 3 refer to all job ads posted on Job-Room between June 2020 and May 2021.

Table B.7: Characteristics of firms that never report preferred gender and characteristics of firms that report preferred gender

	(1) never	(2) sometimes
Industry		
Manufacturing	.11	.13
Construction	.051	.061
Wholesale and retail trade	.11	.12
Transportation and storage	.021	.021
Accomodation and food service activities	.17	.26
Information and communication	.023	.0047
Financial and insurance services	.019	.0059
Real estate activities	.011	.0081
Professional, scientific and technical activities	.067	.034
Administrative support activities	.031	.049
Private employment agencies	.22	.17
Public administration	.018	.0093
Education	.014	.0048
Human health and social work activities	.059	.046
Arts, entertainment and recreation	.013	.011
Other service activities	.039	.046
No information	.024	.02
Firm size		
1-9 employees	.43	.5
10-49 employees	.2	.19
50-249 employees	.094	.092
>=250 employees	.014	.017
No information	.26	.2
Legal status		
Private company	.15	.2
Stock company	.5	.47
Limited liability company	.23	.26
Public sector	.034	.017
Other/no information	.088	.05
Observations	74557	13663

Notes: The table reports the distribution of firms across industries, firm size categories, and legal status for firms that never specify preferred gender during the observation period (column 1) and firms that sometimes specify preferred gender (column 2). The sample covers 88,220 different firms posting 563,444 job ads on Job-Room between July 2018 and June 2021.

Table B.8: Regression of expressing a preference for women when submitting a job ad on part-time/full-time status and various fixed effects

	(1)	(2)	(3)	(4)	(5)
Full-time job	ref.	ref.	ref.	ref.	ref.
Full- or part-time job	.018***	.017***	.0093***	.0026**	.006***
	(.0013)	(.0013)	(.0012)	(.0012)	(.001)
Part-time job	.047***	.044***	.034***	.021***	.015***
	(.0018)	(.0016)	(.0015)	(.0014)	(.0013)
Job ad characteristics	No	Yes	Yes	Yes	Yes
Industry	No	No	Yes	Yes	Yes
Occupation	No	No	No	Yes	Yes
Firm fixed effects	No	No	No	No	Yes
Mean dependent variable	0.025	0.025	0.025	0.025	0.023
Observations	559,556	559,556	559,556	558,853	524,546

Notes: The table reports the results of regressing a dummy equal to one if the job ad states a preference for women on several sets of fixed effects, some ad-specific controls, and a categorical variable indicating whether the job is part-time job, a job with a range of working hours including full- and part-time positions, or a full-time job. The latter is the reference category. The different models reported in columns 1-5 differ in the set of controls included in the estimation. The controls for the characteristics of the job ad include firm location (canton), a dummy for whether the job is temporary, dummies for special working conditions (night work, shift work, work from home, work on Sundays and public holidays), a categorical variable for the required experience, a categorical variable for the required education certificate, and firm size. Standard errors (in parentheses) are clustered at the firm level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.9: Regression of a preference for men, as signaled by the job title, on the number of hours and various fixed effects based on the universe of job ads on Job-Room

	(1)	(2)	(3)	(4)
Full-time job	ref.	ref.	ref.	ref.
Full- or part-time job	-.23***	-.23***	-.044***	-.02***
	(.033)	(.033)	(.0083)	(.0056)
Part-time job	-.24***	-.23***	-.04***	-.019***
	(.033)	(.028)	(.0061)	(.004)
Canton fixed effects	No	Yes	Yes	Yes
Occupation fixed effects	No	No	Yes	Yes
Firm fixed effects	No	No	No	Yes
Mean dependent variable	0.246	0.245	0.242	0.244
Observations	1,152,571	1,019,671	1,004,391	975,354

Notes: The table reports results from ordinary least squares regressions of a dummy equal to one if the job title is in the masculine form on various sets of fixed effects and a categorical variable indicating whether the job is part-time, a job that covers a range of working hours including full- and part-time positions, or a full-time job. The latter is the reference category. Job titles are categorized according to their grammatical gender by applying a simple algorithm to the most common grammatical rules that determine whether a word has a masculine or feminine form in German and French. The sample covers all job ads published on Job-Room between January 2020 and May 2021. Standard errors (in parentheses) are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

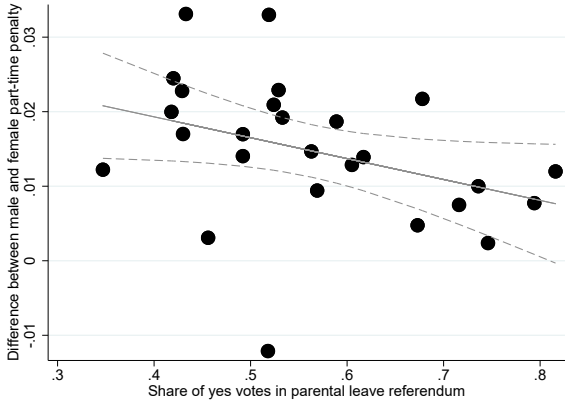
Table B.10: Regression of a preference for women, as signaled by the job title, on the number of hours and various fixed effects based on the universe of job ads on Job-Room

	(1)	(2)	(3)	(4)
Full-time job	ref.	ref.	ref.	ref.
Full- or part-time job	.012***	.0095***	-.0012	-.0049**
	(.0036)	(.0024)	(.002)	(.0023)
Part-time job	.03***	.03***	.0085***	.0055*
	(.0027)	(.0025)	(.0024)	(.0029)
Canton fixed effects	No	Yes	Yes	Yes
Occupation fixed effects	No	No	Yes	Yes
Firm fixed effects	No	No	No	Yes
Mean dependent variable	0.014	0.014	0.014	0.013
Observations	1,152,571	1,019,671	1,004,391	975,354

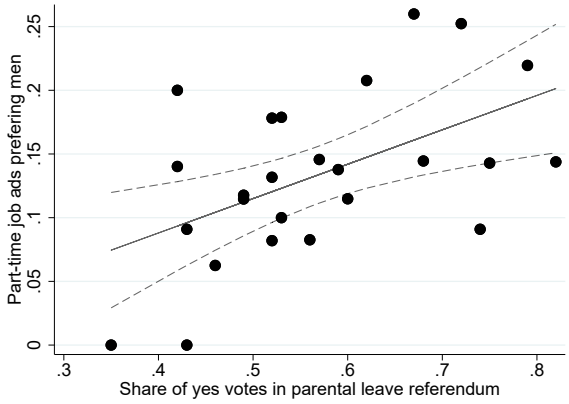
Notes: The table reports results from ordinary least squares regressions of a dummy equal to one if the job title is in the feminine form on various sets of fixed effects, and a categorical variable indicating whether the job is part-time, a job that covers a range of working hours including full- and part-time positions, or a full-time job. The latter is the reference category. Job titles are categorized according to their grammatical gender by applying a simple algorithm to the most common grammatical rules that determine whether a word has a masculine or feminine form in German and French. Standard errors (in parentheses) are clustered at the firm level. The sample covers all job ads published on Job-Room between January 2020 and May 2021. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure B.9: Relationship between the regional share of yes votes in a parental leave referendum and the relative disadvantage of men seeking part-time work

(a) Difference between male and female part-time penalty



(b) Share of part-time ads with an explicit preference for men



Notes: The figures relate the share of voters in a canton who voted in favor of extending parental leave for fathers to two measures of men's relative disadvantage in finding a part-time job: Panel (a) relates it to the gender gap in the part-time penalty in a given canton estimated based on the recruiter click data. The gender gap in the part-time penalty is estimated by aggregating the different part-time categories in Equation 1 into a dummy and interacting this dummy, the gender dummy, and their interaction with indicators for the different cantons. The sample is restricted to the 62 percent of searches for which I know the location of the firm. Panel (b) relates the share of yes votes in a canton to the share of part-time job ads on Job-Room with a preference for men out of all part-time job ads with a gender preference in the respective canton. Recruitment agencies were excluded from the sample. In both panels, the solid lines indicate the ordinary least squares regression of the dependent variable on the y-axis against the share of no votes in the referendum. The dashed lines show the associated 95% confidence intervals.

C The part-time penalty and indicators for technologies that are associated with full-time work

This section explores the relationship between the part-time penalty and indicators of technologies that are often associated with full-time work. Table C.1 proposes four such indicators based on the economic literature: The degree of time autonomy a worker enjoys, the degree of decision freedom, the incidence of shift work, and the incidence of overtime. The table also proposes several measures to operationalize these indicators.

I relate these indicators to the part-time penalty in an occupation by running bivariate regressions of the latter on the former. The respective coefficients are reported in Table C.2. Details on the estimation of the part-time penalties by occupation can be found in the table notes. Column 2 of the table shows the sign of the coefficient that we would expect, based on the theoretical considerations in Table C.1, if the respective technological feature were a main factor for the part-time penalty.

There is no significant relationship between the part-time penalty and the share of workers with very flexible working hours. The same is true for the relationship between the part-time penalty and the share of workers who can take hours off at short notice and the share of workers with autonomy in determining the order of tasks. In fact, the estimated coefficients are negative for all three regressions. This is the opposite of what we would expect if the respective technological feature were a major driver of the part-time penalty. The estimated coefficient has the expected sign when we relate the part-time penalty to the share of workers reporting time pressure. This is also the only coefficient that is statistically significantly different from zero. There is no significant relationship between the part-time penalty in an occupation and the share of workers reporting autonomy in determining the content of their tasks. The same is true for the relationships between the part-time penalty in an occupation and the share of shift workers, the share of workers working overtime, and the share of overtime pay in the total wage bill. Two of the four coefficients even have the wrong sign.

Table C.1: Indicators for production technologies that are associated with full-time work

Indicator	Explanation
Degree of time autonomy	Goldin (2014) argues that jobs where workers have little time pressure and do not constantly have to meet strict deadlines are better suited to work part-time because workers do not have to be present at specific times. The same is true for jobs where workers are free to choose the start and end of their working day and where it is easy for them to take time off at short notice. Moreover, a high degree of time autonomy is a sign that the work process requires little coordination between workers, which makes it easier to work part-time. Therefore, we would expect a smaller part-time penalty in occupations with more time autonomy. I measure the degree of time autonomy using the following four indicators: 1) The share of workers who report being very flexible in determining the start and the end of their working hours. 2) The share of workers who report being able to take one or two hours off at short notice. 3) The share of workers who report that they (very) often suffer from time pressure at work. 4) The share of workers who say they can influence the order of their tasks. Data for all four measures come from the Swiss Labor Force Survey conducted by the Federal Statistical Office.
Degree of decision making freedom	Goldin (2014) states that workers who enjoy a lot of decision-making freedom are less likely to have close substitutes. It is easier to replace one worker with another when workers have to follow clear guidelines and predetermined procedures. When workers cannot be easily replaced by other workers, it becomes more important for them to be present at all times. Therefore, jobs in which workers have a lot of decision-making freedom do not seem to be particularly suitable for part-time work. I measure the degree of decision-making freedom by the share of workers who report that they can influence the content of their tasks. The data source is the Swiss Labor Force Survey.
Incidence of shift work	Fernández-Kranz and Rodríguez-Planas (2021) argue that reducing working hours is more costly for firms in occupations with a high incidence of shift work. Shift work allows firms to produce or provide services 24 hours a day. It is important that shifts are standardized and harmonized, leaving little room to accommodate different work schedules. Therefore, it should be more difficult to accommodate part-time schedules in an occupation with a high incidence of shift work. I measure the incidence of shift work with the share of workers working shifts according to the Swiss Labor Force Survey.
Incidence of overtime	In the absence of fixed costs per worker, it is cheaper for firms to hire new workers at a normal wage rate than to pay an overtime premium to existing workers when they need to expand production. The opposite is true when firms face high fixed costs per worker. Then it pays to pay the overtime premium instead of hiring new workers. Thus, a high incidence of overtime pay in an occupation may indicate a production technology with high fixed costs per worker (Hamermesh, 1996), which makes it more costly to hire part-time workers. I measure the incidence of overtime using two indicators: 1) The share of workers who worked more than their contractual hours in the week prior to responding to the Swiss Labor Force Survey. 2) The share of overtime pay in the total wage bill as reported by firms in the Swiss Earnings Structure Survey. Both surveys are conducted by the Swiss Federal Statistical Office.

Table C.2: Relationship between the part-time penalty in an occupation and indicators of technologies that are often associated with full-time work

	(1) Coefficient (SE)	(2) Expected sign
Share of workers with very flexible working hours	-1.19	+
	(9.5)	
Share of workers who can take hours off at short notice	-7.94	+
	(9)	
Share with autonomy in determining order of tasks	-9.19	+
	(9.5)	
Share of workers reporting time pressure	-51.8**	-
	(23)	
Share with autonomy in determining content of tasks	-4.37	-
	(14)	
Share of workers working shift	4.69	-
	(8.5)	
Share of workers working overtime	.353	-
	(8)	
Share of overtime pay in total wage bill	-2.86	-
	(6.6)	

Notes: The table reports the results of bivariate weighted least squares regressions of the part-time penalty in an occupation on various indicators of technologies that are often associated with full-time work. Column 1 reports the estimated coefficients and standard errors. Column 2 reports the signs of the coefficients that we would expect if the respective technological characteristic were a main reason for the part-time penalty. See Table C.1 for an explanation. Note that the smaller the coefficient on the part-time dummy, the larger the part-time penalty. Thus, a negative coefficient implies a positive relationship between an indicator and the part-time penalty. The part-time penalties by occupation are estimated by aggregating the different part-time categories in Equation 1 into a part-time dummy and interacting this dummy with indicators for the different occupations. The part-time penalties are normalized with the mean of the average contact rate in each occupation. The number of observations per occupation is used to weight the estimates.