# When Does Gender Occupational Segregation Start? An Experimental Evaluation of the Effects of Gender and Parental Occupation in the Apprenticeship Labor Market*

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**Abstract**

The apprenticeship market is the earliest possible entry point into the workforce in developed economies. Since early labor market shocks are likely magnified throughout professional life, avoiding mismatches between talent and occupations – for example due to gender- or status-based discrimination – appears crucial. This experimental study investigates the effects of applicant gender and its interaction with parental occupation on the probability of receiving an invitation to an interview in the Swiss apprenticeship labor market. We find no robust evidence of differential treatment by employers in most cases. Our results have clear and relevant policy implications.

*JEL Classification: C93, J16, J71*

*Keywords: Field Experiment, Correspondence Test, Discrimination, Gender, Parental Occupation.*

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# 1 Introduction

This paper presents a so-called correspondence test based on experimentally sending out fictitious applications to vacancies in the Swiss apprenticeship market, in order to assess the effects of applicant gender and its interaction with parental occupation on employers' callback rates. By and large, we do not find statistical evidence for differential treatment by employers in terms of callbacks, i.e. invitations to an interview, assessment center, or to a trial apprenticeship, with one noticeable exception.

One major motivation for our study is the empirically observed gender occupational segregation between males and females, see e.g. Cortes and Pan (2018) for a recent overview of evidence and preference-based explanations of gendered occupational choice. Because this phenomenon is associated with less favorable labor market outcomes for women as wages in female-dominated professions tend to be lower than wages in male-dominated ones, see Blau and Kahn (1996), its causes are the object of intense scrutiny. The experimental literature (e.g. through correspondence testing) has attempted to uncover evidence of potential demand-side effects. Employers would contribute to gender occupational segregation if they preferably hired women for female-dominated occupations and, vice-versa, men for male-dominated occupations. Although the empirical findings do not speak in unison, it is nonetheless possible to discern an imperfect pattern suggesting that employers indeed favor males in male-dominated professions and females in female-dominated ones, see the literature reviews in Rich (2014) and Bertrand and Duflo (2017). Along the same line, a recent correspondence test including Switzerland by Becker et al. (2019) documents a much higher average callback rate for women relative to men in (female-dominated) secretarial and accounting positions.

In preventing the best match between talent and occupations, demand-side effects are inefficient in addition to being socially unjust. Furthermore, differences in initial conditions in the labor market may matter more for lifetime inequality than do shocks afterwards, see Huggett et al. (2011). Therefore, an important question is whether or not such stereotypical decisions are already present at early stages of labor market participation. While the empirical evidence described above applies to adults, it is the aim of this study to advance research by examining demand-side effects on gender occupational segregation in the apprenticeship market, the earliest point of entry into the labor market in developed economies. For this reason, we experimentally assess how applicant gender affects callback rates in the Swiss

apprenticeship market.

In Switzerland, job applications typically contain very detailed personal information, including a photo and demographic details such as age and marital status, among other elements. Apprenticeship applicants are typically 14 or 15 years of age. Because of their youth, they usually do not yet have that much to say about themselves in their CVs. However, they routinely indicate the profession of their parents. This quite unique feature of the Swiss apprenticeship market allows us to investigate whether parental background affects the labor market chances of offspring, and differently so across applicant gender. This is an important question as equality of opportunity would require such background information not to have an effect on the applicants' labor market outcomes. How closely one's earnings relate to those of one's parents is subject of an extensive literature attempting to estimate the *intergenerational elasticity*, a measure of intergenerational income persistence. To the best of our knowledge, this is the first attempt to investigate labor demand effects in relation to the intergenerational persistence of income in the experimental literature.

To assess whether employers take applicant gender and parental occupation into consideration, we sent out approximately 3000 fictitious applications (containing CVs and educational certificates) via e-mail to open apprenticeship positions across four regions in Switzerland (Basel, Bern, Lausanne, and Zurich) between August and October 2018. In the applications, we randomized demographic characteristics like gender and parental occupation in order to investigate the impact on callback rates by employers, namely invitations to interviews, assessment centers, or trial apprenticeships. The employers' responses to our applicants were recorded up to February 2019. Using applications that signaled a comparable level of productivity and differed only w.r.t. the applicant's gender and/or parental occupation was key for investigating whether employers systematically differ in their treatment of groups with particular demographics.

By and large, we find no robust evidence for discrimination based on applicant gender or parental occupation. For all but one of the investigated combinations of gender and occupational choice, differences in call back rates are not statistically significant at any conventional level when accounting for multiple hypothesis testing. The one exception is stating father's occupation to be a university professor, which boosts callbacks in a statistically and economically significant way for female applicants, but not for males. Our results therefore provide some support for a blind

recruitment procedure. Personal attributes (such parental occupation) should not be communicated to the employer in the first round of an application process, in order to prevent signaling effects and set the callback chances of all applicants on an equal footing.

Point estimates across subsamples suggest that the aforementioned professor effect for female applications is, to a larger extent, driven i) by the German rather than the French speaking sample, ii) by less demanding apprenticeships from the point of view of required qualifications, iii) by more female- rather than male-dominated apprenticeships, and iv) by smaller rather than larger employers in terms of the number of employees. However, due to low statistical power and issues related to multiple hypotheses testing, we abstain from putting strong interpretations on the effect heterogeneities found across subsamples. The findings across subgroups generally back those of the main analysis. Specifically, when excluding the empirically rare case of having a professor as parent from our sample, we find no statistically significantly differential callback rates across gender. Importantly, the asymmetric impact of parental profession on girls relative to boys is not driven by the chances of having a father who is a university professor being much higher for boys compared to girls as highly educated fathers are unlikely outcomes for both genders in reality, as documented below.

The absence of statistically significant gender bias in employers' callback rates goes against well-established regularities in the experimental literature, as discussed above, though those findings pertain to the labor market of adult persons for the most part. Recent evidence for Switzerland in Becker et al. (2019) is a case in point, where the callback rates for females vastly surpass those for males in – female dominated – secretarial and accounting jobs. Nonetheless, the vignette study in Kübler et al. (2018), which focused on the German apprenticeship labor market, similarly finds that the worse average treatment of girls versus boys disappears once the share of women in an occupation is taken into account.

We attribute the different results on gender discrimination for Germany and Switzerland in the apprenticeship labor market as originating in asymmetric labor market regulations across these two countries, as follows. The degree of employment protection in the German labor market is significantly higher compared to the Swiss case. According to the OECD Indicators of Employment Protection,[1] workers in

[1]See e.g. OECD Indicators of Employment Protection, https://www.oecd.org/els/emp/oecdindicatorsofemploymentprotection.htm, consulted online on 23 March 2020. Regarding measures for the Strictness of Employment Protection – Individual

Germany enjoy significantly greater employment protection compared to those in Switzerland. These differences provide rather different incentives for firms to train and, importantly, to *retain* their apprentices (Mühlemann et al. (2010)). Indeed, the apprentice retention rate by German firms is almost twice as high as that of Swiss firms (59% versus 35.5%, Mühlemann (2016)). If retaining apprentices helps firms reduce their hiring and firing costs, we would expect them to regard their apprentices as potential future permanent employees. And for this to happen more so in the country with the more stringent employment protection. Where firms do consider their apprentices as akin to future permanent employees, one would expect the biases that characterize the labor market of adult persons to be moved forward in time to the evaluation of apprenticeship candidates. This appears to indeed be the case in Germany (Kübler et al. (2018)) but not so in Switzerland, where firing (and thus hiring) is much less costly to employers. Our results of gender-neutral treatment of apprentices in the Swiss apprenticeship labor market are additionally corroborated by the recent vignette study of Fossati et al. (2019), focusing on the same market.

From a policy point of view, and answering the questions outlined above, our findings represent rather good news: employers do not appear to gender-discriminate applicants for apprenticeship positions in the Swiss labor market - at least not to a level that we can statistically detect. Gender occupational segregation at the apprenticeship level, therefore, appears to have its roots in the occupational choice of young persons. Fostering occupational diversity thus requires removing educational or cultural barriers currently narrowing the horizons of young persons at the time of their labor market entry.

Our paper is structured as follows. Section 2 reviews the literature on labor market discrimination and correspondence testing. Section 3 provides institutional background information on the Swiss educational system and apprenticeship market. Section 4 outlines the experimental design. Section 5 provides descriptive statistics for our data. Section 6 presents the empirical results. Section 7 concludes.

# 2 Literature Review

Our paper is closely related to the experimental literature aiming at causally assessing the prevalence of discriminatory practices. In economics, asymmetric labor

Dismissals (regular contracts), the corresponding indicator for Germany is 2.6 whereas it is only 1.6 for Switzerland (for an OECD average of 2.0). Data are for 2013, the latest available year.

market treatment of individuals for reasons unrelated to their productivity amounts to *discrimination*. The two main reasons for employers to discriminate offered in the literature originate from tastes (see Becker (1957)), e.g. when employers or customers dislike working with a particular group in the population, or in uncertainty about the true productivity of the candidate employee (see Arrow (1973) and Phelps (1972)). The former is commonly known as *taste-based discrimination* and the latter as *statistical discrimination*.

The preference for one gender over the other as a function of occupation type could have elements of both taste-based and statistical discrimination. Employers may have a preference for candidates with the gender that matches the sex typically expected or encountered in a particular occupation, possibly reflecting stereotypical preference biases. They may also believe that such a gender-based matching is relevant for productivity, see Goldin (2015) and also Weichselbaumer (2003) for a detailed discussion on this matter. An interesting aspect of our experiment is that, due to the young age of apprenticeship applicants, statistical discrimination against females due to fertility concerns appears less likely than for older age groups.

Field experiments (i.e. so-called audit studies and correspondence testing) are experimental methods of data collection which involve sending fictitious applications in response to real job advertisements. In correspondence testing, for example, applications including CVs that are matched in all relevant qualifications, like schooling and job experience, but which differ w.r.t. the demographic characteristics of interest (e.g. gender, ethnicity, age), are sent out in response to job advertisements. If all productivity-related characteristics are comparable, any statistically significant differences in the response rate of employers related to the demographics is indicative of discrimination. For example, the study by Bertrand and Mullainathan (2004) addressed ethnic discrimination and the racial gap in callback rates in the US labor market by implementing a correspondence test in which the crucial element was the choice between White- or African American-sounding names. Experimental methods gained notoriety as they were able to overcome important empirical limitations of previous tools, such as omitted variables bias, see Guryan and Charles (2013) and Bertrand and Duflo (2017) for a discussion. The latest developments in this extensive literature and results have been systematized in recent surveys, see Rich (2014), Bertrand and Duflo (2017), Neumark (2018), and Baert (2018).[2]

[2]Hangartner, Kopp, and Siegenthaler (2019) present an innovative approach to the question of employer search criteria and potential discriminatory practices. They analyze employer behavior in a job portal through machine learning methods. Hangartner *et al.* identify patterns in employer's

Regarding gender discrimination, results are not completely unanimous but it is nonetheless possible to discern an imperfect pattern. The evidence summarized in Riach and Rich (2002) and Rich (2014) suggests that women are discriminated against in male-dominated jobs and, vice-versa, men are discriminated in female dominated occupations, while such results are frequently not found for occupations lacking a clear gender pattern.

The interpretation of gender discrimination (in contrast e.g. to ethnic discrimination) is further nuanced by fertility expectations. One strand of the literature attempts to isolate employers' concerns with fertility related costs which could lead to statistical discrimination of women in fertile age. A strategy often followed in order to separate fertility concerns from other forms of gender discrimination is to contrast callback rates of candidates in fertile age with those of older individuals. The empirical evidence is mixed. Duguet and Petit (2005) and Petit (2007) found no indication of discrimination against older women relative to older men. However, younger females received callbacks significantly less frequently than younger males when applying to highly qualified jobs, which the authors attributed to higher maternity costs in these occupations. Also the results in Bartoš (2015) point to a motherhood penalty, but only for highly qualified positions. Using gender and parental status as a way to reveal potential fertility costs, Bygren et al. (2017) however, did not find discriminatory behavior for different occupations and regions in Sweden.

In order to isolate different facets of fertility costs (maternity leave versus child related chores, for example), Becker et al. (2019) considered a wider range of applicant types in terms of family status (e.g. single and married job applicants, the latter with or without children). Their results suggest that married but childless job applicants are at a disadvantage compared to mothers of older children, when applying to part-time jobs, but not so when full-time positions are considered. Since part-time jobs are traditionally perceived as a way to reconcile family and work in the countries analyzed there, the authors argue that fertility related cues from the applicants – such as being married but (still) childless – provide stronger signals about fertility costs than they otherwise would in the context of applications to full-time jobs. Becker et al. (2019) therefore interpret their results as evidence of fertility discrimination. While fertility-related costs are absent in the context of the apprenticeship market due to the young age of applicants, the work of Becker et al. (2019)

search behavior and on their decision to "click" on a button enabling the disclosure of the candidate's contact information.

is nonetheless a relevant reference point for our results because Switzerland was one of the countries covered in that study. For the female-dominated professions considered there – secretaries and accountants – females had significantly higher callback rates than males.[3]

While most studies consider prime age workers, such that statistical discrimination related to family obligations could partly explain gender differences in callback rates, two vignette studies focused on the apprenticeship market as we do. Kübler et al. (2018) examined the German apprenticeship market while Fossati et al. (2019) focussed on the Swiss apprenticeship market. Kübler et al. (2018) embedded a vignette study in a nationally representative survey of German firms hiring apprentices and found females to be evaluated worse than males, on average. In line with the broad patterns described above, the female disadvantage disappeared with the share of women in an occupation.[4] Fossati et al. (2019) contact employers hiring for apprenticeship positions and ask them to evaluate potential candidates. Their focus is on the question of whether or not employers rely on productivity unrelated information when hiring, and especially so in situations of high uncertainty. Examples of those situations would be cases where some of the academic results point in different directions (for example, when the candidate has a low grade average but a very high score in an independent general test often used by employers to compare candidates outside the schooling system). Their benchmark results (Table 2) align well with ours in that gender is not significant and the same mostly holds for parental background. Indeed, employers react to those demographic indicators only in a very restricted subset of cases when facing uncertainty in the applicants' profiles (Tables 3 and A1). Sharing a common focus on the apprenticeship labor market as Kübler et al. (2018) and Fossati et al. (2019), our paper employs a different methodology and is the first correspondence test on the Swiss apprenticeship market.

Correspondence testing poses one advantage over vignette studies in that it examines real decisions of employers faced with credible job/apprenticeship applications. Despite this formal difference, the data suggest that employers react differently to

[3]Further correspondence tests in Switzerland have focused on ethnicity, see Fibbi et al. (2006), Zschirnt (2019), Zschirnt and Fibbi (2019) for labor market studies. A recent study carried out by the Universities of Geneva, Neuchâtel, and Lausanne on behalf of the Federal Housing Office investigated the impact of having a foreign name on the probability of being invited to a viewing of an apartment, see https://www.swissinfo.ch/eng/discrimination_foreign-names-impact-chance-of-getting-an-apartment-viewing/45019430, accessed in August 2019.

[4]Although parental occupation of the applicants is used as control variable, the relevance of family background is not the focus of the study by Kübler et al. (2018).

gender cues in these two neighboring countries. As mentioned in the Introduction, we rationalize this difference under the light of labor market regulations concerning employment protection.

An extensive literature going back to Becker and Tomes (1979) and Becker and Tomes (1986) has focussed on how the educational attainment – and other later-in-life outcomes – of children relate to the education of their parents as well as to the investments parents made in offspring education. Parents influence their children's outcomes through genetical as well as educational channels, which the literature has labeled as the "nature versus nurture" dichotomy. One of the goals of this literature is measuring intergenerational income persistence, thus the degree to which offspring income is related to parental income.[5] Our experimental setup fits into this literature by allowing us to measure the social status effect of parental background on the employer's selection of an apprenticeship candidate, an instance of "nurture" type effects. The measurement of such effects in an experiment is usually difficult to implement as adult persons normally do not mention parental background in their cvs. However, as described earlier, in the Swiss apprenticeship labor market, young people in their apprenticeship applications typically do.

# 3 The Swiss Education System and Vocational Education

In Switzerland, the constitution broadly defines the general foundations of the educational system, like obligatory free access to primary schooling. However, the core responsibilities in providing education rest with the country's 26 cantons (regional administrative units). For this reason, there is considerable variation in school systems across cantons, although there are also attempts to harmonize key aspects of compulsory schooling through the so-called HarmoS concordate. According to the State Secretariat for Education, Research, and Innovation (2013), the vast majority of students in compulsory education attend public schools, only 5% went to private schools in the academic year of 2012/2013.

According to the Swiss Coordination Centre for Research in Education (2018), compulsory schooling consists of 11 years of education in most cantons (in particular those participating in the HarmoS concordate), including two years of kindergarten

[5]See e.g. Lee and Seshadri (2019) for a version of the Becker-Tomes model allowing for multiple investments stages in children's education calibrated to US data, and Björklund et al. (2017) for an empirical comparison of factors influencing intergenerational income mobility between the UK and Sweden.

attendance that starts at the age of four. After kindergarten, primary schooling typically consists of six years and lower secondary schooling of three. In the last year of primary school, students are assessed and subsequently placed into different tracks of lower secondary education that differ in terms of qualifications. Concretely, this means that classes in grades seven to nine will be taught with varying levels of difficulty, matching the different educational tracks in which students are placed. After finishing lower secondary education, and depending on the qualifications obtained, students follow one of two possibilities. They enter either the vocational education and training (VET) track, typically consisting of a dual apprenticeship system of formal education and training in a company, or the academic track, by attending either a general or specialized high school that prepares students for tertiary education, see the State Secretariat for Education, Research, and Innovation (2018).[6]

The different educational tracks and corresponding lower secondary education qualification levels give rise to three different "tiers" in which occupations in VET are classified. For example, students who wish to apply for a beauty apprenticeship (a 3 year program) are required to have a *Realschulabschluss*, a school degree with comparably lower qualifications. Apprenticeships with similar requirements (e.g., baker, gardener, etc.) constitute the first tier. A *Sekundarschulabschluss*, i.e. a school degree with comparably higher qualifications, possibly combined with a standardized aptitude test, is a typical requirement for second-tier occupations, such as electric technician, mechanic or dental assistant, among others. Lastly, apprenticeships in areas such as informatics or polymechanics make up our third tier and typically require a higher level degree with reasonable grades in math and physics. Please refer to Table 7 in Appendix A for the complete list of occupations targeted in our study and the corresponding tier classification.

In Switzerland, roughly two thirds of all students with completed compulsory education enter the VET track and have around 230 occupations to choose from, see the State Secretariat for Education, Research, and Innovation (2018). Apprenticeships typically take between two to four years, as discussed in Kuhn et al. (2019). Most popular are dual apprenticeship programs, which combine classes at a vocational school with on-the-job training at a host company. Apprentices are employed and

[6]Students typically receive career counseling concerning their professional interests and options at the age of 14. If they choose the VET pathway, then starting the apprenticeship application process is encouraged. At the age of 15 to 16, when students have accomplished compulsory education, they typically start their apprenticeships.

paid a salary which increases with each completed year. However, also (full-time) school-based VET programs exist. They are less common overall, but relatively more popular in the French and Italian speaking regions of Switzerland.

Upon successful completion of the program, apprentices receive a federal VET diploma which not only serves as recognized occupational qualification but is also a precondition for further education and higher qualifications in the chosen occupation. According to the State Secretariat for Education, Research, and Innovation (2018), the VET system is managed as a public-private partnership, with the federal and cantonal governments as well as the employers and professional organizations jointly defining the curricula, skill sets, and standards for occupations. Moreover, the employers cover the costs for on-the-job-training, salaries, and in-house courses. The cantons, on the other hand, fund the vocational schools and career guidance services.

# 4 Experimental Design

Our correspondence test in the Swiss apprenticeship market consisted of a preparatory phase, from October 2017 to July 2018, an experimental phase, from August 2018 until February 2019, and the debriefing of the employers in March 2019.

**Preparatory Phase** In the preparatory phase, we developed all materials required for the production of fictitious applications to open apprenticeships. We first screened apprenticeship advertisements online to learn which documents were required in the application process.[7] Furthermore, we consulted teenagers applying for apprenticeship positions in order to learn how typical applications look like. In addition, we collected CVs and motivation letters (through personal contacts as well as online sources) to use them as templates for our fictitious applications. We also prepared electronic versions (i.e. in pdf format) of school certificates for the fictitious candidates. In order to compare candidates beyond their school credentials, employers may require apprenticeship applicants to take an aptitude test. Whether or not testing is common generally depends on the occupation (with most companies hiring in a given occupation either requesting or not requesting the test results). We thus prepared electronic versions of aptitude test certificates for the fictitious candidates as well.

[7] Such information is, for instance, provided on the websites https://www.berufsberatung.ch and https://www.yousty.ch, which we accessed in late 2017.

A further task was to classify apprenticeship types w.r.t. their relative empirical importance among females and males. We relied on information about the relative popularity of specific occupations across gender provided online by the Educational Office of the Canton of Bern (*Kanton Bern, Erziehungsdirektion*) and the Office for Equality of Males and Females of the Canton of Zurich (*Kanton Zürich, Fachstelle für Gleichstellung von Frau und Mann*).[8] These classifications were further cross-checked with additional online resources on the apprenticeship market.[9] Using these criteria, we categorized occupations into clearly male-dominated, female-dominated, and (more or less) gender neutral types.

As mentioned above, a second classification concerned the level of qualifications attained in terms of lower secondary schooling. We classified apprenticeship types into three levels of requirements (or tiers) and adapted school certificates and aptitude tests accordingly to make applications look appropriate concerning the skills typically expected. For the first tier, which was lowest in terms of requirements, applications contained school certificates reflecting a lower level degree (*Realschulabschluss*) and comparably low scores in the aptitude test, if the latter was required at all. For the second tier, certificates reflecting a higher level degree (*Sekundarschulabschluss*) along with intermediate grades and aptitude test scores were used. For the most demanding third tier, certificates reflecting a higher level degree along with comparably good grades and test scores were included in the application documents.

In total, 30 occupations were selected and included in the experiment, eight of which are gender neutral (e.g. baker, cook, sales assistant, designer), six female-dominated (e.g. hair dresser, dental assistant, medical practice assistant), and 16 male-dominated (e.g. gardener, carpenter, car mechanic, mason, electrician). In selecting these occupations, we took into consideration the need of having sufficiently many observations for all three gender types in the sample, guided by online search-based estimates of how many advertisements would be posted for each type. Please refer to Table 7 in Appendix A for a complete list of occupations considered, together with their gender-type and tier.

[8] See https://www.erz.be.ch/erz/de/index/berufsbildung/grundbildung/kennzahlen_berufsbildung/kennzahlen_berufsbildung2.html and https://ffg.zh.ch/internet/justiz_inneres/ffg/de/bildung/berufswahl/_jcr_content/contentPar/morethemes/morethemesitems/factsheet_die_belieb.spooler.download.1393238737874.pdf/FFG_2013_factsheet_die_beliebtesten_berufe_von_maedchen_und_jungen.pdf, respectively, both accessed in the beginning of 2018.

[9] See for instance the following list of the 10 most popular apprenticeships for females and males in 2015: https://blog.100000jobs.ch/de/2016/09/die-top-10-der-beliebtesten-lehrstellen/, accessed in the beginning of 2018.

Aiming to find an acceptable balance between expected sample sizes and organizational burden in preparing and managing applications, we decided to focus on three agglomerations in the Swiss German-speaking region, namely Basel, Bern, and Zurich, and on one agglomeration in the French-speaking region, Lausanne. We prepared fictitious motivation letters, CVs, school certificates, and aptitude tests as well as two female and male profiles for either language region with varying names, addresses, and photos. Concerning names, we took the most popular choices for first names for either gender in 2004 in the German and French speaking parts, respectively, while the last names corresponded to the most frequent occurrences in the phone book in either language region.

We also picked residential addresses in the four agglomerations for the fictitious candidates. Preparing school certificates that matched these addresses turned out to be more complicated than initially expected. This was so first, because certificates look different in each canton (and even over time) and, second, because of adapting certificates to the qualifications appropriate for the three different tiers of apprenticeships. While applicant addresses and school certificates match in terms of cantonal congruence for Bern and Zurich, this is not the case for Basel and Lausanne. For the latter two agglomerations, it was apparent from the application documents that the respective fictitious candidate had recently moved from a different region.

**Experimental Phase** We aimed at sending out two applications per open apprenticeship position and to only consider one apprenticeship per employer to avoid straining companies excessively with our experiment. In the CVs, the gender of our two applicants was independently randomized, with a 50% probability of being female or male. As a result, application pairs with either two females, two males, or with one female and one male were sent via e-mail to a specific employer. Our design thus required two profiles per gender and language region. We also independently randomized other features like the gender of the applicant's sibling and the gender of the teacher given as a reference person. In contrast, mother's occupation was randomized pairwise among the two applications per open position, implying that these applications had necessarily different values for mother's occupation. The latter was either homemaker or primary school teacher, each with a chance of 50%.

Father's occupation was also randomized pairwise (and independently of mother's occupation) and contained the following options: university professor (with 12.5% probability), an intermediate technical position (37.5%) matching the job type of

the apprenticeship (e.g. mechanic), an intermediate commercial position (37.5%) matching the job type (e.g. sales manager), and an unskilled worker (12.5%). The idea was to consider high skilled, low skilled, as well as intermediate profiles, with the latter being related to the position to be filled. The skill level of intermediate profiles therefore varied depending on the tier and industry of the position. For instance, for a technical apprenticeship in the first, second, or third tier, father's intermediate technical occupation would either be a mechanic, a polymechanic, or an engineer. This implies substantial heterogeneity of educational achievements within the intermediate profiles for the sake of aligning father's occupation well with open apprenticeships. Some other CV features, such as motivational sentences and leisure activities, were also randomized pairwise in order to make sure that the same phrases and hobbies would not be used twice in applications sent to the same vacancy.

Employers advertise apprenticeship positions in specialized job portals, at least if they cannot be filled through professional or personal networks. In total, 3069 applications were sent out between August and mid October 2018 via e-mail to open positions posted on Switzerland's most popular online portal for apprenticeships.

During the data collection process, several issues arose. In August, we accidentally sent out applications to some positions that were from the previous year and thus not relevant for our fictitious candidates. In a few cases, the employers' e-mail addresses provided online contained typos or were not valid such that the applications could not be sent. In total, 129 observations were dropped due to such issues. Furthermore, while most employers received two applications as intended, 397 employers in Lausanne only received one application due to technical issues at the end of the application period (end of September until mid October). However, also in these cases, the application features were correctly randomized as described above.

A more serious concern was that five employers in the German speaking region detected that our applications were not related to existing students, having followed up on the candidates by consulting the schools. Even though these cases were excluded from the analysis, it cannot be ruled out that the information was communicated to other employers. If so, this could bias our results.

We envision several ways in which this may have occurred. One possibility is that employers started ignoring our candidates, thus biasing any effects towards zero. Another possibility is that, once made aware of the experiment, employers decided to invite our candidates to an interview when they otherwise would not have done

so. Such procedure would likewise reduce our ability to identify any empirical links between demographic attributes and acceptance rates. Nonetheless, as described below, our results for the whole experimental period present a very specific pattern whereby one particular parental occupation listed in the candidates profiles led to a great boost in the success rate of our female candidates. This pattern could hardly have been the result of intentional behavior. Robustness checks discussed below, where we restricted the sample to a time period when the detections were more likely to have had an effect in the way companies responded to our candidates, deliver a comparable response pattern as the one for the whole sample. We thus believe that these issues did not affect callback rates on a large scale.

A final incident (also in the German speaking part) concerns a situation where we accidentally sent out four applications to the same employer, resulting in the same applicant's name being sent twice. Even though no reaction by the employer was received, we immediately withdrew our applications when noticing the issue and excluded this employer from the sample, as well. All in all, we dropped 12 observations because of the issues mentioned. Our final evaluation data set thus consists of 2928 observations.

Most of the time, employers responded to our applications by e-mail, though phone calls were also frequent. We never answered the phone directly but regularly checked on the messages left by companies in the voicemail of our fictitious applicants' phone numbers. In 10 out of the comparably few instances when actual letters were sent as replies to our applications, they could not be delivered and were returned to employers, who then wrote e-mails to ask for a correct address. In these cases, we replaced the problematic addresses with new ones (which were then subsequently used for the continuation of the study). We apologized to the companies via e-mail and asked to have the letters sent to the new address or for the possibility to get the message via e-mail instead. These employers are kept in our evaluation sample, albeit excluding them leaves our results virtually unchanged.

If one of our applications received an invitation, which was either for a job interview, an assessment center, or a trial apprenticeship, we declined the offer within several days. In this case, the dependent variable, *employer response*, was coded as one, corresponding to a 'callback'. In the case of a negative response or no reaction on the part of the employer until to February 2019, the dependent variable was coded as zero.

**Ethical Questions and Debriefing** The methodology of correspondence testing raises ethical issues, as it necessarily involves the deception of recruiters assessing the electronic documents of our fictitious applicants. While ethical concerns are of first importance and have been addressed in the literature, see e.g. Riach and Rich (2004), it has also been recognized that carrying out research based on a correspondence testing methodology (or, more generally, on field experiments) requires breaking informed consent, see Blommaert et al. (2013). Indeed, informing participants a priori would invalidate the experiment.

Well-defined exceptions to informed consent have been established in law in a variety of countries (e.g. Sweden, see Bursell (2007), and the USA, see Pager (2007)). In the discussion of ethical issues and correspondence testing, one argument often used in favor of the methodology is the relevance of the research question. Arguably, investigating the prevalence of discrimination is a pursuit worth following whose merits could outweigh the cost of not informing participants beforehand. Indeed, the use of deception has been defended on the grounds of the necessity to evaluate the effectiveness of anti-discriminatory legislation, see Banton (1997). Many courts, including e.g. the US Supreme Court, have endorsed 'tester' methodologies. (For legal practices, it is common to 'test' one company multiple times whereas the practice of correspondence testing addresses many companies and tends to focus on particular employers only once.) Such practices have gained systematic support from US courts over time, see Pager (2007). In Sweden, initial rejections of the methodology from the Swedish Ethics Board were later overturned (thus aligning with many other OECD countries) after the use of testing results in legal proceedings against detected discriminatory practices, which demonstrated the usefulness and social relevance of the methodology, see Carlsson and Rooth (2012) for an example.

Even if an exception to the principle of informed consent is accepted, correspondence testing poses costs to employers, as recruiters spend time on evaluating fictitious candidates. However, if only a small number of applications is sent to each company and if invitations to interviews (or to a follow-up action) are swiftly declined, the time cost can be kept at a comparably small level, as argued in Wood et al. (2009). In this study, we adhered to these practices, e.g. by sending out not more than two applications per employer.

While informing participants about an ongoing experiment would invalidate its results, ethical considerations may suggest informing participants *ex-post*. Debriefing practices nonetheless also have potential downsides, as discussed in Midtbøen

(2014), Liebkind et al. (2016), and Pager (2007); for instance, they may invalidate future experiments. Zschirnt (2019) provides a thorough overview of how the discussion and practices surrounding correspondence testing have evolved in the literature. In our experiment, we debriefed companies once the data collection period was completed. In early March 2019, we sent e-mails with attached letters that explained the setup, purpose, and key findings of the experiment to employers that had received applications from our fictitious candidates. The vast majority of employers did not react to the debriefing. Among the 11 responses we received via e-mail, some expressed dissent and discontent with the fact they had been confronted with fictitious applications, while others had critical comments or questions concerning the methodology, which we in turn answered in a subsequent e-mail. One reaction was positive and pointed out the importance of investigating discrimination.

# 5 Data and Descriptive Statistics

Our evaluation sample consists of 2928 observations and contains information about applications and (in anonymized form) employers. Application characteristics consist of apprenticeship tiers in terms of required qualifications, types in terms of gender orientation (female-dominated, gender neutral, male-dominated), applicant gender, parental occupation, the agglomeration in which the apprenticeship was located, and whether or not the fictitious applicant had moved from a different city (and thus had a certificate from a school located elsewhere). We also recorded the dates when an apprenticeship was posted (or, if unavailable, the date when it was found by the research team) and when an application was sent out.

Employer characteristics include categories for the (in many cases estimated) number of employees, the sector (i.e. public, trade and wholesale, manufacturing and goods, or services), the scale of the employer's operations (local, national, or international), the gender of the contact person in the company, whether or not there was an explicit anti-discrimination policy on the company's website, and the geographic distance (in kilometers) of the employer to the central station of the applicant's residential city. In addition to the characteristics, the data contain a binary outcome variable measuring employers' response to our applications and is one in case of an invitation to an interview, assessment center, or trial apprenticeship, and zero otherwise. The anonymized data set without the variable 'geographic distance' is publicly available at https://doi.org/10.7910/DVN/PIUJW4.

Table 1: Descriptive statistics by applicant gender

| | total sample | female | male | t-test | |
|---|---|---|---|---|---|
| | mean | mean | mean | diff | p-val |
| employees: 1 to 20 | 0.48 | 0.48 | 0.47 | 0.00 | 0.88 |
| employees: 21 to 50 | 0.24 | 0.24 | 0.24 | -0.01 | 0.63 |
| employees: 51 to 100 | 0.11 | 0.11 | 0.12 | -0.00 | 0.74 |
| employees: 101 to 250 | 0.09 | 0.09 | 0.08 | 0.01 | 0.52 |
| employes: 251 to 500 | 0.03 | 0.03 | 0.03 | -0.00 | 0.87 |
| employees: 501 to 1000 | 0.02 | 0.02 | 0.02 | -0.00 | 0.97 |
| employees: more than 1000 | 0.04 | 0.04 | 0.04 | 0.00 | 0.67 |
| sector: public | 0.05 | 0.05 | 0.06 | -0.00 | 0.69 |
| sector: trade and wholesale | 0.22 | 0.22 | 0.23 | -0.01 | 0.48 |
| sector: manufacturing and goods | 0.13 | 0.12 | 0.13 | -0.01 | 0.64 |
| sector: services | 0.60 | 0.61 | 0.59 | 0.02 | 0.27 |
| distance to city center | 16.37 | 16.22 | 16.55 | -0.33 | 0.57 |
| tier 1 job | 0.35 | 0.34 | 0.36 | -0.02 | 0.32 |
| tier 2 job | 0.36 | 0.38 | 0.35 | 0.03 | 0.15 |
| tier 3 job | 0.28 | 0.28 | 0.29 | -0.01 | 0.63 |
| type: gender-neutral | 0.33 | 0.32 | 0.33 | -0.01 | 0.56 |
| type: female-dominated | 0.25 | 0.27 | 0.22 | 0.05 | 0.00 |
| type: male-dominated | 0.43 | 0.41 | 0.45 | -0.04 | 0.03 |
| city: Bern | 0.21 | 0.21 | 0.21 | -0.00 | 0.91 |
| city: Zurich | 0.30 | 0.29 | 0.31 | -0.02 | 0.30 |
| city: Basel | 0.11 | 0.13 | 0.09 | 0.03 | 0.00 |
| city: Lausanne | 0.38 | 0.37 | 0.39 | -0.02 | 0.39 |
| activity: regional | 0.80 | 0.81 | 0.79 | 0.02 | 0.27 |
| activity: national | 0.12 | 0.11 | 0.13 | -0.02 | 0.16 |
| activity: international | 0.08 | 0.08 | 0.08 | 0.00 | 0.95 |
| antidiscrimination policy | 0.21 | 0.22 | 0.20 | 0.02 | 0.23 |
| contact: female | 0.31 | 0.32 | 0.30 | 0.02 | 0.29 |
| contact: male | 0.33 | 0.32 | 0.34 | -0.02 | 0.36 |
| contact: unknown | 0.36 | 0.36 | 0.36 | -0.00 | 0.90 |
| day job was published or found | 29.08 | 29.00 | 29.17 | -0.18 | 0.74 |
| day of application | 51.00 | 50.80 | 51.22 | -0.42 | 0.50 |
| father professor | 0.13 | 0.12 | 0.14 | -0.03 | 0.04 |
| father intermediate | 0.75 | 0.76 | 0.74 | 0.02 | 0.15 |
| father unskilled worker | 0.12 | 0.12 | 0.12 | 0.00 | 0.82 |
| mother teacher | 0.50 | 0.51 | 0.48 | 0.03 | 0.07 |
| applicant has moved | 0.49 | 0.50 | 0.48 | 0.02 | 0.29 |
| number of observations | 2928 | 1529 | 1399 | | |

Note: Means of characteristics in the total, female, and male samples, as well as mean differences ('diff') between females and males and p-values of two sample t-tests ('p-val')

Table 1 provides the means of all characteristics but gender in the total sample, as well as separately by gender, which is the key intervention variable of our experiment. It also contains mean differences across gender ('diff') and p-values ('p-val') of two sample t-tests. The characteristics' means are generally well balanced across gender as only few mean differences are statistically significant at the 5% level. We also test mean balance of all characteristics jointly based on the machine learning approach of Ludwig et al. (2017), which is outlined in Appendix B and provides no indication

of imbalances, with a p-value of 98.4%.

Table 2: Descriptive statistics by parental occupation

| | m_te_f_un | m_te_f_in | | m_te_f_pr | | m_ho_f_un | | m_ho_f_in | | m_ho_f_pr | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | mean | diff | p-val | diff | p-val | diff | p-val | diff | p-val | diff | p-val |
| employees: 1 to 20 | 0.56 | -0.09 | 0.03 | -0.17 | 0.00 | -0.10 | 0.07 | -0.08 | 0.06 | -0.13 | 0.02 |
| employees: 21 to 50 | 0.22 | 0.03 | 0.46 | 0.01 | 0.89 | 0.02 | 0.61 | 0.01 | 0.74 | 0.03 | 0.47 |
| employees: 51 to 100 | 0.09 | 0.02 | 0.30 | 0.07 | 0.04 | 0.05 | 0.16 | 0.03 | 0.20 | -0.01 | 0.74 |
| employees: 101 to 250 | 0.06 | 0.03 | 0.13 | 0.05 | 0.08 | 0.00 | 0.98 | 0.03 | 0.13 | 0.08 | 0.01 |
| employes: 251 to 500 | 0.04 | -0.02 | 0.16 | 0.00 | 0.91 | 0.00 | 0.90 | -0.02 | 0.28 | -0.03 | 0.13 |
| employees: 501 to 1000 | 0.01 | 0.01 | 0.14 | 0.03 | 0.06 | 0.01 | 0.23 | 0.01 | 0.27 | 0.02 | 0.13 |
| employees: more than 1000 | 0.02 | 0.02 | 0.12 | 0.00 | 0.83 | 0.01 | 0.73 | 0.02 | 0.21 | 0.03 | 0.13 |
| sector: public | 0.02 | 0.04 | 0.00 | 0.03 | 0.10 | 0.07 | 0.00 | 0.03 | 0.01 | 0.04 | 0.03 |
| sector: trade and wholesale | 0.21 | 0.01 | 0.78 | -0.01 | 0.83 | 0.02 | 0.65 | 0.03 | 0.44 | -0.03 | 0.54 |
| sector: manufacturing and goods | 0.16 | -0.03 | 0.29 | -0.06 | 0.12 | -0.05 | 0.19 | -0.03 | 0.28 | -0.02 | 0.65 |
| sector: services | 0.61 | -0.01 | 0.74 | 0.03 | 0.52 | -0.04 | 0.44 | -0.02 | 0.56 | 0.00 | 0.99 |
| distance to city center | 18.96 | -2.72 | 0.04 | -3.29 | 0.05 | -2.28 | 0.18 | -3.03 | 0.02 | -1.22 | 0.46 |
| tier 1 job | 0.36 | -0.02 | 0.61 | 0.05 | 0.38 | -0.01 | 0.82 | -0.01 | 0.76 | 0.02 | 0.64 |
| tier 2 job | 0.37 | -0.01 | 0.88 | -0.03 | 0.60 | 0.00 | 0.98 | -0.01 | 0.77 | -0.04 | 0.38 |
| tier 3 job | 0.26 | 0.03 | 0.48 | -0.02 | 0.68 | 0.01 | 0.83 | 0.02 | 0.52 | 0.02 | 0.67 |
| type: gender-neutral | 0.30 | 0.02 | 0.63 | 0.05 | 0.31 | 0.01 | 0.77 | 0.04 | 0.29 | 0.03 | 0.49 |
| type: female-dominated | 0.25 | -0.01 | 0.84 | -0.00 | 0.97 | 0.00 | 0.96 | -0.01 | 0.83 | -0.01 | 0.86 |
| type: male-dominated | 0.45 | -0.01 | 0.80 | -0.05 | 0.35 | -0.02 | 0.76 | -0.03 | 0.43 | -0.03 | 0.62 |
| city: Bern | 0.21 | 0.00 | 0.90 | 0.00 | 0.97 | -0.00 | 0.99 | -0.01 | 0.88 | 0.04 | 0.43 |
| city: Zurich | 0.31 | -0.02 | 0.66 | 0.01 | 0.92 | -0.02 | 0.71 | -0.01 | 0.73 | -0.01 | 0.79 |
| city: Basel | 0.10 | 0.00 | 0.99 | 0.02 | 0.55 | 0.03 | 0.42 | 0.01 | 0.84 | 0.00 | 0.94 |
| city: Lausanne | 0.37 | 0.01 | 0.76 | -0.03 | 0.60 | -0.01 | 0.86 | 0.01 | 0.75 | -0.02 | 0.64 |
| activity: regional | 0.83 | -0.03 | 0.36 | -0.04 | 0.36 | -0.03 | 0.50 | -0.04 | 0.26 | -0.05 | 0.25 |
| activity: national | 0.11 | 0.00 | 0.88 | 0.03 | 0.38 | 0.01 | 0.85 | 0.01 | 0.62 | 0.01 | 0.74 |
| activity: international | 0.06 | 0.03 | 0.20 | 0.01 | 0.78 | 0.02 | 0.42 | 0.02 | 0.25 | 0.04 | 0.19 |
| antidiscrimination policy | 0.17 | 0.04 | 0.18 | 0.06 | 0.16 | 0.01 | 0.88 | 0.04 | 0.22 | 0.07 | 0.09 |
| contact: female | 0.26 | 0.05 | 0.16 | 0.05 | 0.27 | 0.04 | 0.46 | 0.05 | 0.19 | 0.05 | 0.29 |
| contact: male | 0.34 | -0.01 | 0.76 | -0.02 | 0.70 | 0.02 | 0.74 | -0.02 | 0.65 | -0.00 | 0.95 |
| contact: unknown | 0.39 | -0.04 | 0.32 | -0.03 | 0.51 | -0.05 | 0.31 | -0.03 | 0.45 | -0.05 | 0.36 |
| day job was published or found | 28.44 | 0.66 | 0.60 | 0.82 | 0.62 | 0.18 | 0.91 | 1.04 | 0.41 | -0.79 | 0.61 |
| day of application | 49.45 | 1.98 | 0.17 | -0.48 | 0.80 | 0.80 | 0.66 | 2.38 | 0.10 | -1.66 | 0.37 |
| applicant: female | 0.55 | 0.00 | 0.98 | -0.06 | 0.25 | -0.03 | 0.53 | -0.03 | 0.42 | -0.08 | 0.11 |
| applicant has moved | 0.48 | 0.01 | 0.76 | -0.01 | 0.90 | 0.02 | 0.72 | 0.02 | 0.66 | -0.02 | 0.68 |
| number of observations | 163 | 1119 | | 176 | | 197 | | 1076 | | 197 | |

Note: 'm_te_f_un' provides the means of characteristics in the reference group (mother teacher, father unskilled worker), the other columns provide the mean differences ('diff') compared to the baseline group and the p-values ('p-val'), respectively. 'm_te_f_in': mother teacher, father intermediate; 'm_te_f_pr': mother teacher, father professor; 'm_ho_f_un': mother homemaker, father unskilled worker; 'm_ho_f_in': mother homemaker, father intermediate; 'm_ho_f_pr': mother homemaker, father professor.

Table 2 reports descriptives by parental occupation (rather than gender) as our second intervention variable of interest. In the first column, it displays the means of all characteristics but parental occupation for the group of applications with the mother being a teacher and the father being an unskilled worker ('mean'). Furthermore, it shows mean differences ('diff') between this reference group and other combinations of parental occupation, namely: mother is a teacher and father has an intermediate occupation (technical or commercial), mother is teacher and father is a university professor, mother is a homemaker and father is a low skilled worker, mother is a homemaker and father has an intermediate occupation (technical or commercial), and mother is homemaker and father is a university professor. P-values for the respective two sample t-tests are also reported ('p-val'). Again, the majority of mean differences is not statistically significant at the 5% level. We also apply the joint testing procedure of Ludwig et al. (2017) for the pairwise testing of mother is a

teacher vs. mother is a homemaker, father has an intermediate occupation vs. father has a different occupation, and father is a professor vs. father is not a professor. The respective p-values are 5.2%, 91.6%, and 96.7%. By and large, characteristics thus appear satisfactorily balanced across our intervention variables of interest, namely applicant gender and parental occupation. For the single variable of mother's occupation, however, balance is almost rejected at the 5% level of significance, but this p-value does not account for the fact that we run the Ludwig et al. (2017) test for multiple hypotheses. In any case, our empirical results presented in Section 6 are very similar when conditioning or not conditioning on application and employer characteristics to control for observed imbalances.

# 6 Results

We begin our analysis by running a fully saturated linear regression of the dependent variable 'employer's response' on all interactions of gender as well as maternal and paternal occupation. The exhaustive list of these interaction possibilities, which are our right-hand side variables, is as follows: mother teacher and father unskilled worker, mother teacher and father intermediate, mother teacher and father professor, mother homemaker and father unskilled worker, mother homemaker and father intermediate, mother homemaker and father professor – each interacted with applicant gender.

The results are presented in Table 3, where standard errors are computed by cluster bootstrapping the coefficients, with clustering on the employer level. The reference category is 'female applicants with mothers working as teachers and unskilled workers as fathers'. The average employer response (i.e. the share of invitations) for the reference category is reported ('est') and amounts to roughly 19%. For the other 11 categories defined by combinations of gender and parental occupation, we report the respective difference to the reference category ('est'), along with bootstrap standard errors ('boot se') and conventional p-values ('raw p-val') based on a t-test. However, these p-values do not take into account multiple hypothesis testing, i.e. the fact that we simultaneously test 11 differences. This is problematic because the likelihood of spuriously rejecting one or even several null hypotheses generally increases in the number of hypotheses tested. We therefore adjust the p-values of each difference for multiple testing ('adj p-val') using the stepdown approach of Romano and Wolf (2005) and Romano and Wolf (2016). The latter exploits the coefficient

estimates in the bootstrap samples in order to compute test statistics that are related to the maximum statistical significance among all coefficients, which in turn permits adjusting the p-values of individual coefficients.

Table 3: Effects of gender and parental occupation

| | est | boot se | raw p-val | adj p-val |
|---|---|---|---|---|
| female: mother teacher, father unskilled worker (mean) | 0.191 | 0.042 | 0.000 | |
| female: mother teacher, father intermediate | 0.131 | 0.047 | 0.005 | 0.076 |
| female: mother teacher, father professor | 0.221 | 0.070 | 0.002 | 0.004 |
| female: mother home, father unskilled worker | 0.096 | 0.062 | 0.118 | 0.216 |
| female: mother home, father intermediate | 0.088 | 0.044 | 0.045 | 0.216 |
| female: mother home, father professor | 0.205 | 0.064 | 0.001 | 0.004 |
| male: mother teacher, father unskilled worker | 0.066 | 0.066 | 0.318 | 0.280 |
| male: mother teacher, father intermediate | 0.093 | 0.046 | 0.043 | 0.216 |
| male: mother teacher, father professor | 0.062 | 0.062 | 0.320 | 0.280 |
| male: mother home, father unskilled worker | 0.090 | 0.063 | 0.151 | 0.216 |
| male: mother home, father intermediate | 0.074 | 0.045 | 0.103 | 0.280 |
| male: mother home, father professor | 0.073 | 0.060 | 0.226 | 0.280 |
| number of observations | 2928 | | | |

Note: estimates of (differences in) callback rates for the total sample, without control variables. 'est' provides the callback rate for the group 'female: mother teacher, father unskilled worker', as well as the differences in callback rates of all other groups relative to 'female: mother teacher, father unskilled worker'. 'boot se' reports bootstrap standard errors clustered at the employer level. 'raw p-val' gives the p-values not accounting for multiple hypothesis testing. 'adj p-val' provides adjusted p-values accounting for multiple hypothesis testing

When accounting for multiple testing, most differences relative to the reference category are statistically insignificant at conventional levels. One exception is having a professor as father, which boosts callback rates for females by more than 20 percentage points, independently of mother's occupation. The effect of either category with female applicants and professors as fathers is statistically significant at the 1% level. Furthermore, having a mother who is a teacher and a father with an intermediate occupation also increases callback rates for females relative to the reference group and is significant at the 10% level when accounting for multiple testing. In contrast, callback rates of male applications are rather stable and not significantly different across parental occupation.

Table 4: Treatment effects of gender and parental occupation with controls

| | est | boot se | raw pval | adj pval |
|---|---|---|---|---|
| female: mother teacher, father unskilled worker (intercept) | 0.323 | 0.087 | 0.000 | |
| female: mother teacher, father intermediate | 0.131 | 0.045 | 0.004 | 0.142 |
| female: mother teacher, father professor | 0.211 | 0.064 | 0.001 | 0.007 |
| female: mother home, father unskilled worker | 0.090 | 0.058 | 0.122 | 0.406 |
| female: mother home, father intermediate | 0.084 | 0.043 | 0.050 | 0.455 |
| female: mother home, father professor | 0.189 | 0.061 | 0.002 | 0.013 |
| male: mother teacher, father unskilled worker | 0.082 | 0.065 | 0.209 | 0.471 |
| male: mother teacher, father intermediate | 0.079 | 0.045 | 0.080 | 0.473 |
| male: mother teacher, father professor | 0.052 | 0.059 | 0.382 | 0.763 |
| male: mother home, father unskilled worker | 0.092 | 0.061 | 0.131 | 0.404 |
| male: mother home, father intermediate | 0.069 | 0.044 | 0.115 | 0.571 |
| male: mother home, father professor | 0.050 | 0.058 | 0.388 | 0.763 |
| number of observations | 2928 | | | |

Note: estimates of (differences in) callback rates for the total sample, with control variables. 'est' provides the callback rate for the group 'female: mother teacher, father unskilled worker', as well as the differences in callback rates of all other groups relative to 'female: mother teacher, father unskilled worker'. 'boot se' reports bootstrap standard errors clustered at the employer level. 'raw p-val' gives the p-values not accounting for multiple hypothesis testing. 'adj p-val' provides adjusted p-values accounting for multiple hypothesis testing.

As a robustness check, we include the applicant and employer characteristics reported in Tables 1 and 2 as control variables in our linear regression to account for observed imbalances.[10] This does not importantly change our findings, see Table 4. The effect of having a professor as father among female applications remains large (roughly 20 percentage points) and statistically significant at the 5% level. For any other combination of applicant gender and parental occupation, differences to the reference group are not statistically significant at the 10% level.

With the exception of the interaction between a female application and having a professor as father, we find no robust statistical evidence for a systematically differential treatment based on gender and parental occupation. We note that these other professions are empirically more relevant compared to the real-life rare case of a professor. Nonetheless, the estimates also suggest that parental occupation might have a signaling effect for female applications, which appears to be absent among males.

To present the key findings in a more parsimonious (and possibly more accessible) way, we split our sample into two subsamples based on paternal occupation. The first one excludes observations with university professor as parental occupation, while the

[10] See Table 13 in Appendix C for the coefficients of the control variables. Note that the dummy for whether the applicant moved from a different city is dropped as control due to multicollinearity.

second one exclusively contains such cases. In either subsample, we examine whether callback rates differ across applicant gender, both with and without linearly including control variables. Table 5 provides the results for the first subsample (devoid of observations with the father being a professor) in the top panel and for the second subsample in the bottom panel. Furthermore, the left panel provides the results without control variables, while the results on the right are based on conditioning on the application and employer characteristics listed in Tables 1 and 2.

Table 5: Gender differences in callbacks

| | est | boot se | raw pval | adj pval | est | boot se | raw pval | adj pval |
|---|---|---|---|---|---|---|---|---|
| father is not professor | no controls | | | | with controls | | | |
| male (mean / intercept) | 0.274 | | | | 0.397 | | | |
| female (diff) | 0.020 | 0.019 | 0.301 | 0.348 | 0.024 | 0.017 | 0.157 | 0.268 |
| number of observations | 2555 | | | | 2555 | | | |
| father is professor | no controls | | | | with controls | | | |
| male (mean / intercept) | 0.259 | | | | 0.373 | | | |
| female (diff) | 0.125 | 0.053 | 0.018 | 0.013 | 0.125 | 0.050 | 0.013 | 0.006 |
| number of observations | 373 | | | | 373 | | | |

Note: estimates of (differences in) callback rates across gender when father is reported or not reported to be a professor, without and with control variables. 'est' provides the callback rate or intercept for males and the difference in call back rates between females and males. 'boot se' reports bootstrap standard errors clustered at the employer level. 'raw p-val' gives the p-values not accounting for multiple hypothesis testing. 'adj p-val' provides adjusted p-values accounting for multiple hypothesis testing of differences by gender, professor, and the gender-professor-interaction.

Looking at the estimates ('est') reported in the first column of the top panel, the callback rate for male applicants amounts to 27%. The differential callback rate for females is 2 percentage points and not statistically different from zero based on cluster bootstrapping. This is the case both when considering conventional p-values ('raw pval') or adjusted p-values ('adj pval') that take into account multiple hypothesis testing, now accounting for three hypotheses to be tested (because of four possible gender-paternal occupation combinations). Including control variables (right panel) does not change these conclusions. Thus, our results are in line with employers not distinguishing, on average, between male and female applicants for the empirically most relevant case that paternal occupation is not a professor.[11]

[11] The absence of a significant gender effect on callback rates in the first subsample (excluding professors) is robust to differences in the variance of unobserved determinants of productivity across genders, see the discussion in Heckman (1998) and Heckman and Siegelman (1993). When applying the methodology of Neumark (2012) to decompose the total gender effect into its level and variance components, we find that the level effect, i.e. the component associated with (taste-based or statistical) discrimination, is very close to zero and statistically insignificant. The variance component is not statistically significant either. Results are provided in Appendix D.

The lower panel of Table 5 paints a rather different picture. Having a university professor as father results in a quantitatively important boost to female callback rates relative to males. This effect of more than 12 percentage points is robust to the inclusion of controls and highly statistically significant when accounting for multiple hypothesis testing. Even though being the daughter or son of a professor bears comparably little empirical relevance, this finding nevertheless points to distinct signaling effects for females and males at least in this specific case. Our results therefore provide some support for the enforcement of blind applications that do not reveal personal attributes like parental occupation in order prevent differential treatment due to signaling.

The results in Table 5 show that girls and boys do equally well in getting a callback, from a statistical point of view, if we exclude the case of a father with the parental background of a university professor. Nonetheless, this equality in the average callback rates across gender could mask a reality whereby each gender would do disproportionately well in occupations with a matching pattern in terms of gender dominance. This would correspond to the findings typified earlier characterizing the experimental results for adult persons. To check for this, we examine whether callback rates by gender remain statistically identical across the different occupation types in our sample: male- or female-dominated, or gender-neutral. Results are presented in Table 6. As in the previous table, we present results separately for the subsample devoid of applicants whose father was a university professor (top panel) and for the subsample exclusively composed of those cases (bottom panel).

Table 6 shows that the result of gender neutrality for average callback rates remains even when we consider the gender-type of occupations targeted. Indeed, for the top panel of the table, the differential callback rate for girls (compared to boys) is at most 3.4 pp and never statistically significant at conventional levels. These results do not extend to the subsample of applicants whose father was a university professor. There (bottom panel), once again, parental profession benefits girls in a very large and statistically significant way relative to boys in female-dominated occupations. This effect becomes marginally statistically insignificant for neutral occupations and vanishes all together in male-dominated occupations.

Table 6: Gender differences in callbacks by professor status and occupational gender types

| | est | boot se | raw pval | adj pval | est | boot se | raw pval | adj pval | est | boot se | raw pval | adj pval |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| father is not professor | female-dominated | | | | neutral | | | | male-dominated | | | |
| male (mean / intercept) | 0.191 | | | | 0.283 | | | 0.307 | | | | |
| female (diff) | 0.034 | 0.033 | 0.295 | 0.321 | 0.030 | 0.031 | 0.336 | 0.382 | 0.016 | 0.030 | 0.606 | 0.487 |
| number of observations | 626 | | | | 836 | | | | 1093 | | | |
| father is professor | female-dominated | | | | neutral | | | | male-dominated | | | |
| male (mean / intercept) | 0.089 | | | | 0.261 | | | 0.349 | | | | |
| female (diff) | 0.260 | 0.093 | 0.005 | 0.005 | 0.116 | 0.089 | 0.194 | 0.115 | 0.049 | 0.082 | 0.546 | 0.487 |
| number of observations | 92 | | | | 128 | | | | 153 | | | |

Note: estimates of (differences in) callback rates across gender when father is reported or not reported to be a professor by type, without control variables. 'est' provides the callback rate or intercept for males and the difference in call back rates between females and males. 'boot se' reports bootstrap standard errors clustered at the employer level. 'raw p-val' gives the p-values not accounting for multiple hypothesis testing. 'adj p-val' provides adjusted p-values accounting for multiple hypothesis testing of differences by gender, professor, and the gender-professor-interaction.

In Section 4, we discussed that to the best of our knowledge five employers detected that our applications were not related to existing students. Four detections were related to applications sent out between August 28th and September 7th, only one detection to applications in October. As a robustness check, we therefore run our main analysis for the month of September only, to investigate whether a potential communication among employers about the detection of fictitious applications affected our main findings. Even though we cannot rule out that some employers exchanged information on this issue and adapted their response behavior accordingly, our results suggest that this was not a widespread phenomenon. As can be seen by comparing Table 3 above and Table 12 in Appendix C, the results are qualitatively in line with those of the complete sample. This is visible both in the broad similarity of point estimates of company responses to our different applicant types as well as in the fact that estimates of the female-professor-interaction effect remain also quantitatively not too different from those in the main sample, albeit now less precisely estimated.

In a next step, we investigate the heterogeneity of our results across specific characteristics, starting with language regions. To this end, we run the main analysis as provided in Table 3 separately for the German (Basel, Bern, and Zurich) and French (Lausanne) speaking regions to explore relative effect sizes, see Table 8 in Appendix C. Having a university professor as father has a positive impact on the callback rate of female applicants in either language group, but this effect is on average larger in the German speaking sample. However, it cannot be rejected at conventional levels of significance that the respective estimates in the French and German speaking samples are actually the same, in particular when accounting for further multiple hypothesis testing issues introduced by splitting by language region. Any other difference in callback rates relative to the reference group is insignificant in either language group.

We consider three further heterogeneity checks based on conducting the main analysis separately by tiers (related to levels of qualifications), apprenticeship types in terms of gender orientation, or or company size (number of employees), see Tables 9, 10, and 11 in Appendix C. It appears that the female-professor interaction effect found in the main sample is predominantly driven by the lower (first and second) tiers, female-dominated apprenticeships, and smaller firms with up to 50 employees. However, we abstain from making strong claims about differences across subgroups, due to issues of multiple hypothesis testing.

The patterns of effect heterogeneity are by and large confirmed when investigating callbacks across applicant gender in subsamples with and without professor as paternal occupation similar to Table 5, however, separately by language regions, tiers, types, or company size. As can be seen from Tables 14, 15, and 16 in Appendix C, and Table 6 above, no statistically significantly different callback rates across females and males occur in the subsamples excluding professorship. In the subsample with professorship, the callback rate of females is more than 17 percentage points higher than that of males in the German speaking regions, while the difference is much closer to zero and statistically insignificant in the French speaking region. Furthermore, the female premium is 15 percentage points among tier one and two apprenticeships, but virtually nonexistent in the third tier. The gender difference is more pronounced among smaller companies with up to 50 employees. Finally, among female-dominated types, the respective effect amounts to 26 percentage points, but shrinks in magnitude and significance when going to gender neutral and male-dominated occupations.

We conclude our results section by pointing out that the striking and gendered difference in callback rates for candidates whose father is a university professor does not reflect a reaction to a hypothetical situation whereby girls with such a parental background applied seldomly to apprenticeship positions compared to boys. Indeed, as the picture in Appendix E shows, a university professor (presumably someone with a Doctoral degree) is a rare occurrence for *both* girls and boys. Using data from the European Social Survey for individuals who followed an apprenticeship and are over the age of 25 (thus presumably having completed their education), comprising the 2010, 2012, 2014, and 2016 waves, we were able to get information on the professions of the apprentices' fathers. As shown in Appendix E, the share of fathers with a doctoral degree is 0.80% for girls and 0.58% for boys. Parental doctoral education, if anything, is more common for girls than boys.

# 7 Conclusion

We investigated the effect of gender interacted with parental occupation on callback rates for applications to apprenticeship positions by means of a correspondence test. Sending out approximately 3000 fictitious applications in four regions of Switzerland, our intervention variables did not affect callbacks in a statistically significant way in most cases. We therefore found no robust evidence of employers applying

differential treatment to applicants w.r.t. to gender or parental occupation in the Swiss apprenticeship market. The one exception was when the applicant stated having a university professor as father, which boosted callbacks for females in a statistically significant way, even when accounting for multiple hypothesis testing, but not for males. Albeit paternal professorship is an empirically rare case, this finding points to the possibility of signaling effects of parental occupation among female applications. This suggests that applications should ideally be blind and not reveal socio-economic information in order to maximize fairness.

As outlined in the introduction, gender occupational segregation is often the object of policy focus as it is perceived to be a potential source of gender inequality in labor market outcomes. Our results represent rather positive news for the Swiss apprenticeship market. Companies do not appear to contribute to an early onset of gender occupational segregation – at least not to a level that we can statistically detect – as they mostly appear to carry out gender-blind recruiting. Therefore, gender occupational segregation at the apprenticeship level seems to have its roots on supply-side effects. Policies aimed at fostering gender equality across occupations should therefore focus on removing gender related educational or cultural barriers influencing occupational choices at young ages.

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# A List of Occupations

Table 7: List of Occupations

| id | Occupations in German | Occupations in French | Tendency |
|---|---|---|---|
| 1 | Bäcker/in-Konditor/in-Confiseur/in EFZ | Boulanger/ère-pâtisier/ière-confiseur/euse CFC | N |
| 2 | Coiffeur/-euse EFZ Hairdresser | Coiffeur/euse CFC | F |
| 3 | Detailhandelsassistent/in EBA Retail assistant | Assistant/e du commerce de détail AFP | N |
| 4 | Fachmann/-fachfrau Betriebsunterhalt EFZ | Agent/e d'exploitation CFC | M |
| 5 | Gärtner/in EFZ | Horticulteur/trice CFC | M |
| 6 | Koch/Köchin EFZ | Cuisinier/ière CFC | N |
| 7 | Logistiker/in EFZ | Logisticien/ne CFC | M |
| 8 | Restaurationsfachmann/-frau EFZ | Spécialiste en restauration CFC | N |
| 9 | Sanitärinstallateur/in EFZ | Installateur/trice sanitaire CFC | M |
| 10 | Schreiner/in EFZ | Charpentier/ière CFC | M |
| 11 | Montage-Elektriker/in EFZ | Electricien/ne de montage CFC | M |
| 12 | Automobil-Fachmann/-frau EFZ Automotive professionals | Mécanicien/ne en maintenance d'automobiles CFC | M |
| 13 | Maurer/in EFZ | Maçon/ne CFC | M |
| 14 | Polymechaniker/in EFZ, G-Profil | Polymechanicien/ne Profil G CFC | M |
| 15 | Dentalassistent/in EFZ | Assistant/e dentaire CFC | F |
| 16 | Fachmann/-fachfrau Betreuung EFZ | Assistant/e socio-éducatif/ve CFC | F |
| 17 | Kaufmann/-frau EFZ, B-Profil | Employé/e de commerce CFC, formation de base | N |
| 18 | Medizinische/r Praxisassistent/in EFZ | Assistant/e médical/e CFC | F |
| 19 | Pharma-Assistent/in EFZ | Assistant/e en pharmacie CFC | F |
| 20 | Detailhandelsfachmann/-frau EFZ, Beratung Retail professional | Gestionnaire du commerce de détail CFC, Conseil à la clientèle | N |
| 21 | Fachmann/-fachfrau Gesundheit EFZ | Assistant/e en soins et santé communautaire CFC | F |
| 22 | Automobil-Mechatroniker/in EFZ | Mécatronicien/ne d'automobiles CFC | M |
| 23 | Elektroinstallateur/in EFZ | Installateur/trice-électricien/ne CFC | M |
| 24 | Zeichner/in EFZ | Dessinateur/trice CFC | M |
| 25 | Metallbauer/in EFZ | Constructeur/trice métallique CFC | M |
| 26 | Kaufmann/-frau EFZ, E-Profil | Employé/e de commerce CFC, formation élargie | N |
| 27 | Informatiker/in in Applikationsentwicklung EFZ | Informaticien/ne en développement d'applications CFC | M |
| 28 | Informatiker/in in Betriebsinformatik EFZ | Informaticien/ne en informatique d'entreprise CFC | M |
| 29 | Informatiker/in in Systemtechnik EFZ | Informaticien/ne en technique des systèmes CFC | M |
| 30 | Polymechaniker/in EFZ, E-Profil | Polymécanicien/ne Profil E CFC | M |

Note: Gender Tendency: N = Neutral, M = Male, F = Female. Occupational tiers: Tier 1: id: 1 – 12; Tier 2: ids 13 – 22; Tier 3: ids 23 – 30.

# B Machine Learning-Based Balance Test

For jointly testing mean balance of all characteristics across the intervention variables gender or parental occupation as discussed in Section 5, we the apply machine learning-based test suggested by Ludwig et al. (2017). It is based on the intuition that the problem of obtaining too many significant results when testing multiple hypotheses (e.g. mean differences in multiple characteristics across gender), or false positives, is similar to the concern of overfitting in machine learning.

Applying the machine learning logic, we split our sample into training and testing data. In the training data, we run a lasso logit regression of the respective intervention variable on the characteristics using the 'rlogit' command with its default values in the 'hdm' package by Chernozhukov et al. (2015) for the statistical software 'R'. We then use the obtained coefficients for predicting the intervention in the test data and compare the prediction to the actual intervention variable to compute the mean squared error (MSE). We use 5-fold cross-validation, such that the roles of training and test data are swapped, and take the average of the 5 MSEs obtained. In a next step, we randomly relabel (or permute) the actual intervention and re-estimate the MSE using the same procedure. Repeating the permutation 999 times, we compute the p-value for the joint significance of the characteristics as the share of permutation based MSEs that are lower than the MSE with the correct coding of the intervention. The permutation test's intuition is that, if the characteristics are balanced across the intervention, relabeling does not systematically affect (i.e. increase) the MSE. If, on the other hand, characteristics are predictive for the intervention, the correct coding of the latter should likely entail a smaller MSE than the permuted versions.

# C Additional Tables

Table 8: Treatment effects of gender and parental occupation by language regions

| | est | boot se | raw pval | adj pval |
|---|---|---|---|---|
| German language region | | | | |
| female: mother teacher, father unskilled worker (mean) | 0.232 | 0.056 | 0.000 | |
| female: mother teacher, father intermediate | 0.112 | 0.062 | 0.069 | 0.241 |
| female: mother teacher, father professor | 0.222 | 0.088 | 0.011 | 0.025 |
| female: mother home, father unskilled worker | 0.127 | 0.084 | 0.129 | 0.206 |
| female: mother home, father intermediate | 0.096 | 0.058 | 0.098 | 0.323 |
| female: mother home, father professor | 0.259 | 0.086 | 0.003 | 0.008 |
| male: mother teacher, father unskilled worker | 0.072 | 0.089 | 0.416 | 0.461 |
| male: mother teacher, father intermediate | 0.118 | 0.062 | 0.059 | 0.215 |
| male: mother teacher, father professor | 0.068 | 0.082 | 0.407 | 0.461 |
| male: mother home, father unskilled worker | 0.030 | 0.078 | 0.699 | 0.484 |
| male: mother home, father intermediate | 0.064 | 0.058 | 0.271 | 0.461 |
| male: mother home, father professor | 0.035 | 0.078 | 0.651 | 0.484 |
| number of observations | 1815 | | | |
| French language region | | | | |
| female: mother teacher, father unskilled worker (mean) | 0.121 | 0.059 | 0.038 | |
| female: mother teacher, father intermediate | 0.161 | 0.066 | 0.014 | 0.170 |
| female: mother teacher, father professor | 0.212 | 0.107 | 0.047 | 0.075 |
| female: mother home, father unskilled worker | 0.041 | 0.083 | 0.624 | 0.496 |
| female: mother home, father intermediate | 0.081 | 0.064 | 0.206 | 0.419 |
| female: mother home, father professor | 0.114 | 0.093 | 0.222 | 0.309 |
| male: mother teacher, father unskilled worker | 0.057 | 0.094 | 0.541 | 0.496 |
| male: mother teacher, father intermediate | 0.069 | 0.065 | 0.284 | 0.453 |
| male: mother teacher, father professor | 0.040 | 0.089 | 0.652 | 0.496 |
| male: mother home, father unskilled worker | 0.193 | 0.098 | 0.049 | 0.097 |
| male: mother home, father intermediate | 0.094 | 0.064 | 0.142 | 0.349 |
| male: mother home, father professor | 0.136 | 0.096 | 0.159 | 0.253 |
| number of observations | 1113 | | | |

Note: estimates of (differences in) callback rates per language region, without control variables. 'est' provides the callback rate for the group 'female: mother teacher, father unskilled worker', as well as the differences in callback rates of all other groups relative to 'female: mother teacher, father unskilled worker'. 'boot se' reports bootstrap standard errors clustered at the employer level. 'raw p-val' gives the p-values not accounting for multiple hypothesis testing. 'adj p-val' provides adjusted p-values accounting for multiple hypothesis testing.

Table 9: Treatment effects of gender and parental occupation by tiers

| | est | boot se | raw pval | adj pval |
|---|---|---|---|---|
| Tiers 1 and 2 | | | | |
| female: mother teacher, father unskilled worker (mean) | 0.131 | 0.042 | 0.002 | |
| female: mother teacher, father intermediate | 0.152 | 0.046 | 0.001 | 0.059 |
| female: mother teacher, father professor | 0.278 | 0.073 | 0.000 | 0.001 |
| female: mother home, father unskilled worker | 0.108 | 0.068 | 0.111 | 0.131 |
| female: mother home, father intermediate | 0.108 | 0.045 | 0.017 | 0.131 |
| female: mother home, father professor | 0.275 | 0.073 | 0.000 | 0.001 |
| male: mother teacher, father unskilled worker | 0.089 | 0.069 | 0.198 | 0.147 |
| male: mother teacher, father intermediate | 0.116 | 0.047 | 0.014 | 0.111 |
| male: mother teacher, father professor | 0.123 | 0.066 | 0.063 | 0.111 |
| male: mother home, father unskilled worker | 0.133 | 0.066 | 0.043 | 0.106 |
| male: mother home, father intermediate | 0.086 | 0.045 | 0.055 | 0.147 |
| male: mother home, father professor | 0.090 | 0.062 | 0.151 | 0.147 |
| number of observations | 2097 | | | |
| Tier 3 | | | | |
| female: mother teacher, father unskilled worker (mean) | 0.321 | 0.086 | 0.000 | |
| female: mother teacher, father intermediate | 0.102 | 0.095 | 0.284 | 0.626 |
| female: mother teacher, father professor | 0.100 | 0.151 | 0.510 | 0.641 |
| female: mother home, father unskilled worker | 0.079 | 0.125 | 0.531 | 0.676 |
| female: mother home, father intermediate | 0.062 | 0.090 | 0.492 | 0.676 |
| female: mother home, father professor | 0.049 | 0.120 | 0.683 | 0.676 |
| male: mother teacher, father unskilled worker | 0.079 | 0.154 | 0.610 | 0.676 |
| male: mother teacher, father intermediate | 0.046 | 0.095 | 0.626 | 0.676 |
| male: mother teacher, father professor | -0.071 | 0.123 | 0.563 | 0.713 |
| male: mother home, father unskilled worker | 0.012 | 0.129 | 0.927 | 0.676 |
| male: mother home, father intermediate | 0.057 | 0.095 | 0.550 | 0.676 |
| male: mother home, father professor | 0.058 | 0.128 | 0.651 | 0.676 |
| number of observations | 831 | | | |

Note: estimates of (differences in) callback rates for tier 1 and 2 vs. tier 3, without control variables. 'est' provides the callback rate for the group 'female: mother teacher, father unskilled worker', as well as the differences in callback rates of all other groups relative to 'female: mother teacher, father unskilled worker'. 'boot se' reports bootstrap standard errors clustered at the employer level. 'raw p-val' gives the p-values not accounting for multiple hypothesis testing. 'adj p-val' provides adjusted p-values accounting for multiple hypothesis testing.

Table 10: Treatment effects of gender and parental occupation by types

| | est | boot se | raw pval | adj pval |
|---|---|---|---|---|
| Female-dominated apprenticeship types | | | | |
| female: mother teacher, father unskilled worker (mean) | 0.120 | 0.064 | 0.063 | |
| female: mother teacher, father intermediate | 0.137 | 0.072 | 0.057 | 0.167 |
| female: mother teacher, father professor | 0.315 | 0.121 | 0.009 | 0.022 |
| female: mother home, father unskilled worker | 0.065 | 0.101 | 0.520 | 0.469 |
| female: mother home, father intermediate | 0.093 | 0.075 | 0.217 | 0.363 |
| female: mother home, father professor | 0.213 | 0.107 | 0.047 | 0.122 |
| male: mother teacher, father unskilled worker | 0.192 | 0.136 | 0.156 | 0.144 |
| male: mother teacher, father intermediate | 0.027 | 0.073 | 0.710 | 0.574 |
| male: mother teacher, father professor | -0.072 | 0.080 | 0.364 | 0.808 |
| male: mother home, father unskilled worker | 0.184 | 0.115 | 0.110 | 0.144 |
| male: mother home, father intermediate | 0.070 | 0.070 | 0.317 | 0.460 |
| male: mother home, father professor | 0.005 | 0.092 | 0.957 | 0.631 |
| number of observations | 718 | | | |
| Gender neutral apprenticeship types | | | | |
| female: mother teacher, father unskilled worker (mean) | 0.182 | 0.082 | 0.026 | |
| female: mother teacher, father intermediate | 0.179 | 0.090 | 0.046 | 0.200 |
| female: mother teacher, father professor | 0.232 | 0.124 | 0.061 | 0.120 |
| female: mother home, father unskilled worker | 0.161 | 0.114 | 0.159 | 0.262 |
| female: mother home, father intermediate | 0.093 | 0.086 | 0.277 | 0.451 |
| female: mother home, father professor | 0.218 | 0.118 | 0.064 | 0.128 |
| male: mother teacher, father unskilled worker | 0.040 | 0.115 | 0.726 | 0.469 |
| male: mother teacher, father intermediate | 0.131 | 0.089 | 0.141 | 0.325 |
| male: mother teacher, father professor | 0.061 | 0.112 | 0.589 | 0.469 |
| male: mother home, father unskilled worker | 0.077 | 0.117 | 0.509 | 0.469 |
| male: mother home, father intermediate | 0.086 | 0.089 | 0.331 | 0.451 |
| male: mother home, father professor | 0.096 | 0.111 | 0.389 | 0.451 |
| number of observations | 964 | | | |
| Male-dominated apprenticeship types | | | | |
| female: mother teacher, father unskilled worker (mean) | 0.238 | 0.067 | 0.000 | |
| female: mother teacher, father intermediate | 0.098 | 0.075 | 0.189 | 0.433 |
| female: mother teacher, father professor | 0.156 | 0.110 | 0.156 | 0.259 |
| female: mother home, father unskilled worker | 0.070 | 0.104 | 0.502 | 0.506 |
| female: mother home, father intermediate | 0.088 | 0.069 | 0.201 | 0.476 |
| female: mother home, father professor | 0.194 | 0.098 | 0.048 | 0.156 |
| male: mother teacher, father unskilled worker | 0.020 | 0.100 | 0.842 | 0.506 |
| male: mother teacher, father intermediate | 0.084 | 0.075 | 0.259 | 0.476 |
| male: mother teacher, father professor | 0.140 | 0.102 | 0.170 | 0.273 |
| male: mother home, father unskilled worker | 0.045 | 0.098 | 0.648 | 0.506 |
| male: mother home, father intermediate | 0.064 | 0.073 | 0.379 | 0.506 |
| male: mother home, father professor | 0.088 | 0.095 | 0.355 | 0.476 |
| number of observations | 1246 | | | |

Note: estimates of (differences in) callback rates for tier 1 and 2 vs. tier 3, without control variables. 'est' provides the callback rate for the group 'female: mother teacher, father unskilled worker', as well as the differences in callback rates of all other groups relative to 'female: mother teacher, father unskilled worker'. 'boot se' reports bootstrap standard errors clustered at the employer level. 'raw p-val' gives the p-values not accounting for multiple hypothesis testing. 'adj p-val' provides adjusted p-values accounting for multiple hypothesis testing.

Table 11: Treatment effects of gender and parental occupation by size

| | est | boot se | raw pval | adj pval |
|---|---|---|---|---|
| Up to 50 employees (estimated) | | | | |
| female: mother teacher, father unskilled worker (mean) | 0.167 | 0.047 | 0.000 | |
| female: mother teacher, father intermediate | 0.144 | 0.053 | 0.007 | 0.087 |
| female: mother teacher, father professor | 0.267 | 0.083 | 0.001 | 0.001 |
| female: mother home, father unskilled worker | 0.048 | 0.068 | 0.484 | 0.414 |
| female: mother home, father intermediate | 0.085 | 0.050 | 0.088 | 0.319 |
| female: mother home, father professor | 0.167 | 0.073 | 0.022 | 0.057 |
| male: mother teacher, father unskilled worker | 0.059 | 0.071 | 0.407 | 0.414 |
| male: mother teacher, father intermediate | 0.092 | 0.052 | 0.079 | 0.274 |
| male: mother teacher, father professor | 0.009 | 0.068 | 0.897 | 0.441 |
| male: mother home, father unskilled worker | 0.119 | 0.072 | 0.099 | 0.161 |
| male: mother home, father intermediate | 0.067 | 0.050 | 0.183 | 0.375 |
| male: mother home, father professor | 0.080 | 0.072 | 0.264 | 0.333 |
| number of observations | 2092 | | | |
| More than 50 employees (estimated) | | | | |
| | est | boot se | raw pval | adj pval |
| female: mother teacher, father unskilled worker (mean) | 0.261 | 0.095 | 0.006 | |
| female: mother teacher, father intermediate | 0.093 | 0.101 | 0.357 | 0.429 |
| female: mother teacher, father professor | 0.114 | 0.128 | 0.374 | 0.412 |
| female: mother home, father unskilled worker | 0.191 | 0.133 | 0.151 | 0.296 |
| female: mother home, father intermediate | 0.085 | 0.095 | 0.376 | 0.442 |
| female: mother home, father professor | 0.275 | 0.132 | 0.038 | 0.119 |
| male: mother teacher, father unskilled worker | 0.156 | 0.174 | 0.370 | 0.387 |
| male: mother teacher, father intermediate | 0.084 | 0.102 | 0.414 | 0.442 |
| male: mother teacher, father professor | 0.121 | 0.127 | 0.338 | 0.412 |
| male: mother home, father unskilled worker | 0.008 | 0.130 | 0.949 | 0.523 |
| male: mother home, father intermediate | 0.089 | 0.103 | 0.386 | 0.441 |
| male: mother home, father professor | 0.042 | 0.128 | 0.742 | 0.523 |
| number of observations | 836 | | | |

Note: estimates of (differences in) callback rates for employers with up to 50 employees vs. more than 50 employees, without control variables. 'est' provides the callback rate for the group 'female: mother teacher, father unskilled worker', as well as the differences in callback rates of all other groups relative to 'female: mother teacher, father unskilled worker'. 'boot se' reports bootstrap standard errors clustered at the employer level. 'raw p-val' gives the p-values not accounting for multiple hypothesis testing. 'adj p-val' provides adjusted p-values accounting for multiple hypothesis testing.

Table 12: Treatment effects of gender and parental occupation in September 2018

| | est | boot se | raw pval | adj pval |
|---|---|---|---|---|
| female: mother teacher, father unskilled worker (mean) | 0.184 | 0.063 | 0.004 | |
| female: mother teacher, father intermediate | 0.118 | 0.069 | 0.088 | 0.272 |
| female: mother teacher, father professor | 0.248 | 0.102 | 0.014 | 0.035 |
| female: mother home, father unskilled worker | 0.030 | 0.089 | 0.736 | 0.549 |
| female: mother home, father intermediate | 0.076 | 0.066 | 0.248 | 0.426 |
| female: mother home, father professor | 0.159 | 0.099 | 0.111 | 0.200 |
| male: mother teacher, father unskilled worker | -0.036 | 0.094 | 0.702 | 0.621 |
| male: mother teacher, father intermediate | 0.132 | 0.071 | 0.063 | 0.226 |
| male: mother teacher, father professor | 0.087 | 0.090 | 0.337 | 0.426 |
| male: mother home, father unskilled worker | 0.142 | 0.096 | 0.140 | 0.217 |
| male: mother home, father intermediate | 0.058 | 0.069 | 0.404 | 0.474 |
| male: mother home, father professor | 0.066 | 0.092 | 0.474 | 0.474 |
| number of observations | 1248 | | | |

Note: estimates of (differences in) callback rates for September 2018, without control variables. 'est' provides the callback rate for the group 'female: mother teacher, father unskilled worker', as well as the differences in callback rates of all other groups relative to 'female: mother teacher, father unskilled worker'. 'boot se' reports bootstrap standard errors clustered at the employer level. 'raw p-val' gives the p-values not accounting for multiple hypothesis testing. 'adj p-val' provides adjusted p-values accounting for multiple hypothesis testing.

Table 13: Regression with control variables

| | estimate | clustered se | t-value | p-value |
|---|---|---|---|---|
| female: mother teacher, father unskilled worker (intercept) | 0.323 | 0.089 | 3.617 | 0.000 |
| female: mother teacher, father intermediate | 0.131 | 0.044 | 2.962 | 0.003 |
| female: mother teacher, father professor | 0.211 | 0.065 | 3.232 | 0.001 |
| female: mother home, father unskilled worker | 0.090 | 0.058 | 1.544 | 0.123 |
| female: mother home, father intermediate | 0.084 | 0.042 | 1.996 | 0.046 |
| female: mother home, father professor | 0.189 | 0.061 | 3.092 | 0.002 |
| male: mother teacher, father unskilled worker | 0.082 | 0.063 | 1.293 | 0.196 |
| male: mother teacher, father intermediate | 0.079 | 0.044 | 1.769 | 0.077 |
| male: mother teacher, father professor | 0.052 | 0.059 | 0.887 | 0.375 |
| male: mother home, father unskilled worker | 0.092 | 0.061 | 1.511 | 0.131 |
| male: mother home, father intermediate | 0.069 | 0.043 | 1.588 | 0.112 |
| male: mother home, father professor | 0.050 | 0.058 | 0.866 | 0.387 |
| employees: 1 to 20 | -0.051 | 0.053 | -0.951 | 0.342 |
| employees: 21 to 50 | -0.013 | 0.054 | -0.239 | 0.811 |
| employees: 51 to 100 | 0.005 | 0.056 | 0.096 | 0.924 |
| employees: 101 to 250 | 0.034 | 0.060 | 0.567 | 0.571 |
| employees: 251 to 500 | -0.053 | 0.083 | -0.639 | 0.523 |
| sector: trade and wholesale | 0.040 | 0.031 | 1.314 | 0.189 |
| sector: manufacturing and goods | 0.066 | 0.034 | 1.953 | 0.051 |
| distance to city center | -0.003 | 0.001 | -4.345 | 0.000 |
| tier 1 job | -0.091 | 0.028 | -3.204 | 0.001 |
| tier 2 job | -0.184 | 0.031 | -5.964 | 0.000 |
| type: gender-neutral | -0.026 | 0.029 | -0.900 | 0.368 |
| type: female-dominated | -0.020 | 0.033 | -0.625 | 0.532 |
| city: Bern | 0.201 | 0.034 | 5.868 | 0.000 |
| city: Zurich | 0.057 | 0.040 | 1.447 | 0.148 |
| city: Basel | -0.003 | 0.036 | -0.087 | 0.931 |
| activity: international | 0.012 | 0.046 | 0.256 | 0.798 |
| antidiscrimination policy | -0.011 | 0.029 | -0.388 | 0.698 |
| contact: female | 0.050 | 0.031 | 1.629 | 0.103 |
| contact: male | 0.061 | 0.030 | 2.020 | 0.043 |
| day job was published or found | 0.000 | 0.001 | 0.518 | 0.605 |
| day of application | -0.001 | 0.001 | -1.403 | 0.161 |

Note: Linear regression with cluster-robust standard errors, not accounting for multiple testing.

Table 14: Gender differences in callbacks by professor status and language regions

| | est | boot se | raw pval | adj pval | est | boot se | raw pval | adj pval |
|---|---|---|---|---|---|---|---|---|
| father is not professor | German speaking region | | | | French speaking region | | | |
| male (mean / intercept) | 0.316 | | | | 0.210 | | | |
| female (diff) | 0.016 | 0.025 | 0.517 | 0.496 | 0.020 | 0.027 | 0.460 | 0.478 |
| number of observations | 1572 | | | | 983 | | | |
| father is professor | German speaking region | | | | French speaking region | | | |
| male with prof | 0.282 | | | | 0.212 | | | |
| female with prof | 0.175 | 0.067 | 0.010 | 0.005 | 0.050 | 0.082 | 0.546 | 0.478 |
| number of observations | 243 | | | | 130 | | | |

Note: estimates of (differences in) callback rates across gender when father is reported or not reported to be a professor by language region, without control variables. 'est' provides the callback rate or intercept for males and the difference in call back rates between females and males. 'boot se' reports bootstrap standard errors clustered at the employer level. 'raw p-val' gives the p-values not accounting for multiple hypothesis testing. 'adj p-val' provides adjusted p-values accounting for multiple hypothesis testing of differences by gender, professor, and the gender-professor-interaction.

Table 15: Gender differences in callbacks by professor status and tiers

| | est | boot se | raw pval | adj pval | est | boot se | raw pval | adj pval |
|---|---|---|---|---|---|---|---|---|
| father is not professor | tiers 1 and 2 | | | | tier 3 | | | |
| male (mean / intercept) | 0.234 | | | | 0.371 | | | |
| female (diff) | 0.019 | 0.020 | 0.349 | 0.416 | 0.026 | 0.037 | 0.479 | 0.645 |
| number of observations | 1823 | | | | 732 | | | |
| father is professor | tiers 1 and 2 | | | | tier 3 | | | |
| male (mean / intercept) | 0.236 | | | | 0.321 | | | |
| female (diff) | 0.153 | 0.060 | 0.010 | 0.003 | 0.044 | 0.099 | 0.656 | 0.645 |
| number of observations | 274 | | | | 99 | | | |

Note: estimates of (differences in) callback rates across gender when father is reported or not reported to be a professor by tier, without control variables. 'est' provides the callback rate or intercept for males and the difference in call back rates between females and males. 'boot se' reports bootstrap standard errors clustered at the employer level. 'raw p-val' gives the p-values not accounting for multiple hypothesis testing. 'adj p-val' provides adjusted p-values accounting for multiple hypothesis testing of differences by gender, professor, and the gender-professor-interaction.

Table 16: Gender differences in callbacks by professor status and size

| | est | boot se | raw pval | adj pval | est | boot se | raw pval | adj pval |
|---|---|---|---|---|---|---|---|---|
| father is not professor | up to 50 employees | | | | more than 50 employees | | | |
| male (mean / intercept) | 0.247 | | | | 0.343 | | | |
| female (diff) | 0.023 | 0.021 | 0.282 | 0.336 | 0.009 | 0.037 | 0.803 | 0.607 |
| number of observations | 1846 | | | | 709 | | | |
| father is professor | up to 50 employees | | | | more than 50 employees | | | |
| male (mean / intercept) | 0.215 | | | | 0.343 | | | |
| female (diff) | 0.141 | 0.062 | 0.023 | 0.012 | 0.098 | 0.095 | 0.306 | 0.229 |
| number of observations | 246 | | | | 127 | | | |

Note: estimates of (differences in) callback rates across gender when father is reported or not reported to be a professor by number of employees, without control variables. 'est' provides the callback rate or intercept for males and the difference in call back rates between females and males. 'boot se' reports bootstrap standard errors clustered at the employer level. 'raw p-val' gives the p-values not accounting for multiple hypothesis testing. 'adj p-val' provides adjusted p-values accounting for multiple hypothesis testing of differences by gender, professor, and the gender-professor-interaction.

# D Neumark Correction for Unobservable Determinants of Productivity

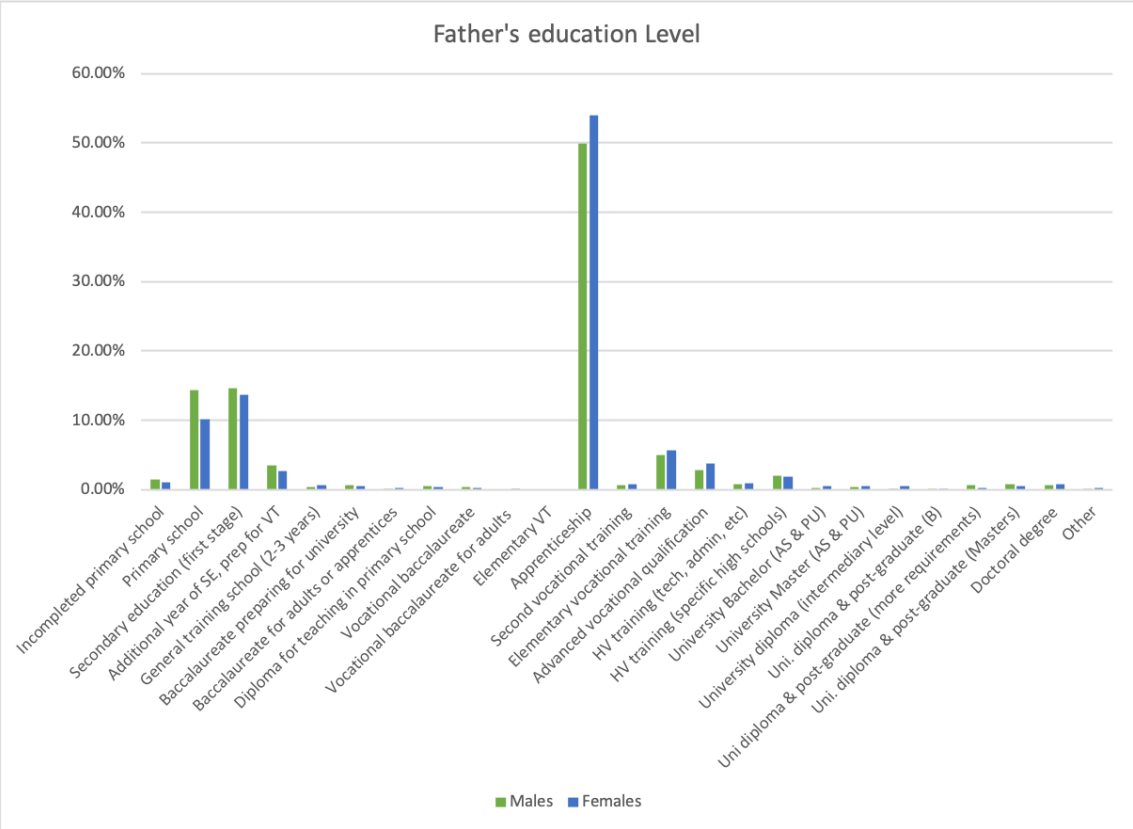
Table 17: Neumark (2012) Method: Heteroskedastic Probit Estimates for Callback wrt Gender

| **Variables** | **Father is not professor** | **Father is professor** |
|---|---|---|
| Estimates from basic Probit (marginal effects) | 0.027<br>(0.018) | 0.152***<br>(0.050) |
| Heteroskedasitc Probit Model (marginal effects) Females (unbiased estimates) | 0.030<br>(0.018) | 0.148***<br>(0.059) |
| Marginal effect of female through level | -0.003<br>(0.035) | 0.166<br>(0.109) |
| Marginal effect of female through variance | 0.033<br>(0.033) | -0.019<br>(0.130) |
| Standard deviation of unobservables: Female/Male | 1.178 | 0.901 |
| Wald test statistic: null hypothesis that ratio of standard deviations =1 (p-value) | 0.356 | 0.878 |
| Wald test statistic: null hypothesis that ratio of coefficients (of Female/Male)=1 (p-value) | 0.994 | 0.978 |
| Number of observations | 2555 | 373 |

p*** 0.01, p** 0.05, p* 0.10

*Notes:* The variable callback measures whether an applicant was invited for an interview, to visit an assessment center or to a trial period. Standard errors are clustered at the company level. Controls are: dummy variables for company size (number of employees), dummy variables for sector of operation, distance from company to city center, dummy variables for apprenticeship tier, type of gender dominated sector, city dummies, dummy for whether the company has an international range of operations, dummy for whether an antidiscriminatory policy is explicitly stated int eh company's website, and dummy variables for gender of contact person at company.

# E Parental Professions of Apprenticeship Applicants




Data are from the from the European Social Survey (ESS) for individuals over the age of 25, waves 2010, 2012, 2014 and 2016.