So Far Away?

Hiring Discrimination against Female Commuters

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Abstract

We investigate gender-based hiring discrimination related to commuting, using data from a large-scale correspondence test in Germany, Switzerland, and Austria. Our analysis reveals a systematic negative effect of commuting distance on interview invitation rates for female job applicants. A 10 km increase in driving distance reduces interview invitation rates for women by 1.8 percentage points, a result not observed for male applicants. The female distance gradient persists regardless of marital status or the presence of children, suggesting that discrimination against female commuters exists independently of female household responsibilities. Our findings highlight the importance of demand side effects in women's commuting patterns.

Keywords: Gender Discrimination, Commuting, Labor Market, Field Experiment, Germany, Switzerland, Austria

JEL codes: C93, J16, J61, J71, R41

1. Introduction

Women tend to commute shorter distances to work than men, a pattern that has remained consistent over several decades. The trend was first documented in studies focused on the United States (e.g., White, 1977; White, 1986) and has since been corroborated by numerous studies across various regions and time periods.[1] Over time, this "stylized fact" has become a well-established characteristic of commuting behavior, with research consistently indicating that women generally travel less distance for work compared to their male counterparts.

The literature has predominantly offered supply-side explanations for this phenomenon, arguing that women simply *prefer* short commutes (e.g., Le Barbanchon, Rathelot, and Roulet (2021), Mueller-Gastell and Pedulla (2023), Eriksson and Lagerström (2012)). The reason for this, it has frequently been argued, lies in the unequal burden of domestic tasks typically carried out by women in heterosexual families which restrict the time available for commuting (see e.g. Hanson and Johnston (1985), Johnston-Anumonwo (1992)). Demand-side explanations could be related to employer discrimination (Baert (2015), Van Borm and Baert (2022), Brandén, Bygren, and Gähler (2018)) against female distant commuters, possibly due to perceived lower commitment or higher turnover risk, particularly in connection with the presence of children.

Demand-side factors have received less attention largely due to the difficulty in isolating those effects in non-experimental settings. Our paper addresses this gap by using data from a large-scale correspondence test conducted in German-speaking countries (Germany, Switzerland and Austria) that allows us to explicitly focus on gender-based hiring discrimination related to commuting. By submitting fake applications from

[1] McLafferty (1997) and Preston and McLafferty (2016) for the New York metropolitan region, Petrongolo and Ronchi (2020) for the UK, Chidambaram and Scheiner (2020) for Germany, Le Barbanchon, Rathelot, and Roulet (2021) for France are representative papers of a vast literature on gender differences in commuting time. Interestingly, Giménez-Nadal, Molina, and Velilla (2022) detect a commuting gender gap in Anglo-Saxon and Continental economies but not in Nordic and Mediterranean countries, a finding that is robust to controlling for gender differences in the socio-demographic and labor market characteristics of workers.

equally qualified candidates with varying family situations to real job advertisements, we test whether employers are less likely to invite candidates for interviews if their residential address indicates a longer commuting distance. The varying distance from our candidates' addresses to those of their potential employers allows us to causally test whether companies invite more distant candidates for job interviews less frequently. In line with observed daily commuting times, we focus on commuting distances of up to 50 km.[2]

Our findings show that, while commuting distance does not reduce the interview invitation rate for male applicants, it does so for female applicants. Specifically, a 10 km increase in driving distance reduces callback rates for women by 1.8 percentage points which amounts to a 9% decline relative to the average interview invitation rate for women in our sample. Our results challenge the assumption that the gender commuting gap is driven solely by supply-side factors, indicating that demand-side discrimination is a quantitatively important part of that gap. Furthermore, we find unfavorable treatment for *all* women who live far away, irrespective of their family status. The fact that it is not the presence of children that drives the disadvantage of women with long commutes, suggests that it is *not* the assumed household responsibilities of women that are at the root of our results.

2. Literature Review

Various reasons may be responsible for different employment patterns depending on where one lives. Some are independent of gender. The literature on spatial discrimination looks at differential treatment based on the location of an individual's residence. Spatial discrimination includes postcode discrimination (which involves bias against individuals who are based in particular residential areas),[3] and, relatedly but more immediately relevant for our setting, discrimination based on commuting distance. The

[2] In Germany, roughly 95% of the working population commute up to 50 km or up to 60 minutes to get to work in 2019 (Federal Statistical Office of Germany, 2020).

[3] See e.g. Bunel, L'Horty, and Petit (2016) and L'Horty, Bunel, and Petit (2019) for a correspondence test in relation to male job applicants in the Paris area where they found strong evidence of postcode discrimination.

latter may arise because longer commutes reduce worker productivity. For example, using the German Socio-Economic Panel (GSOEP), Van Ommeren and Gutiérrez-i Puigarnau (2011) found that distance to work raises employee absenteeism, for men and women equally. In his theoretical model, also Zenou (2002) assumed that workers who live farther away employ lower effort at work as a result of their tiredness from commuting. In equilibrium, firms endogenously determine a red line defining the distance from the firm beyond which they no longer hire workers. The mechanism at play here is gender neutral.[4]

One possible reason for shorter commutes of women, related to spatial reasons but not to discrimination, is that female-dominated jobs (e.g., service jobs) may be distributed more evenly than male-dominated jobs (e.g., production). This has been confirmed, for example, in a study on the metropolitan area of Baltimore by Hanson and Johnston (1985) who found that because women also disproportionately resided in the city center compared to men, they had shorter commutes. More recently, also Liu and Su (2024) related the gender gap in commuting to the geographical distribution of jobs and showed that gender commuting gaps are considerably smaller among workers living in city centers than in the periphery.

The most prominent reason proposed for different commuting times of men and women, however, is the unequal division of labor within heterosexual households, which often puts women in a time crunch. As a result, so the argument, women seek work closer to home. This supply-side factor affecting commuting times is known as the "household responsibility hypothesis" (see e.g. Hanson and Johnston (1985), Johnston-Anumonwo (1992))[5] and has attracted significant interest recently. For example, Bütikofer,

[4]The model originally served to explain differential access to jobs between black inner-city residents and white suburban workers, the latter residing closer to jobs locations. According to the "spatial mismatch hypothesis", low-skilled minorities residing in US inner cities experience poor labour market outcomes because they are disconnected from suburban job opportunities. See Gobillon, Selod, and Zenou (2007) for a review.

[5]A related hypothesis from the urban geography literature is the "spatial entrapment theory," emphasizing the effects of the spatial structure of labor markets. As Rapino and Cooke (2011) note, traditional gender roles assign child minding and housework to women, inhibiting their labor market status by constraining their space–time budgets. This limits women's time to travel for jobs compared to males, which reduces the number and quality of jobs from which women have to choose, potentially

Karadakic, and Willén (2023) and Borghorst, Mulalic, and van Ommeren (2024) conducted event studies with Norwegian and Danish register data, respectively, and showed that commuting distances start to differ between men and women right after childbirth. The latter also found that women with long commutes are much more likely to switch jobs upon having a child, an effect not present for men. For Germany, using a fixed-effects model based on the German Socioeconomic Panel (GSOEP), Skora, Rüger, and Stawarz (2020) identified a 33% reduction in commuting distance associated with the transition to motherhood, with no corresponding effect for the transition to fatherhood. Mothers who reduced their commuting time also experienced a larger wage reduction than those who did not, partly because of losses in firm-specific human capital and partly because they took jobs less suited to their skills and in smaller firms, as the authors argue.[6] Also for Germany, but using administrative social security records, Bergemann, Brunow, and Stockton (2024) found that *single* women's marginal willingness to pay for reducing commuting distance is similar to men's; however, it more than doubles after the birth of a first child and significantly contributes to the motherhood wage gap.

For France, Le Barbanchon, Rathelot, and Roulet (2021) exploited the fact that in order to register as unemployed, job seekers must report their reservation wage and commuting threshold to the French Public Employment Service (PES). The study shows that the gender differences in acceptable commuting thresholds intensify after the birth of a first child and explain about 14% of the residualized gender wage gap.[7] Importantly, the authors explore a rich administrative data set which also includes hiring outcomes. Their results show that firms do not distinguish between women and men when applicants live further away, suggesting that most of the gender gap

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resulting in lower pay and worse employment outcomes. See e.g. Kwan (1999) and Hanson and Pratt (1995).

[6] Petrongolo and Ronchi (2020) pointed out already earlier that in the UK the gender wage gap and the gender commuting gap follow similar life-cycle patterns.

[7] As Liu and Su (2024) emphasize, gendered preferences for shorter commutes only result in gender wage gaps if there is a wage penalty for shortening commutes. They show that gender commuting and wage gaps are smaller for people living in city centers, especially for occupations with a high geographic concentration of well-paying jobs.

in commuting is driven by the supply side of the labor market.[8] Further evidence for a supply-side effect in line with the "household responsibility hypothesis" has been provided by Mueller-Gastell and Pedulla (2023) who examined job applications through the National Longitudinal Study of Job Search (NLSJS) for the US. They found that *partnered* women (unlike women who had never married) are less likely than comparable men to apply for a job that would require a move.[9]

Gender norms appear to play a crucial role in how gender commuting gaps relate to the family status of workers. For example, employing an epidemiological approach, Marcén and Morales (2021) found that parents originating in more gender equal countries display a lower commuting gender gap.[10] Additionally, while gender norms matter with regard to household responsibilities in heterosexual partnerships, they do not in same-sex partnerships. Gender commuting gaps should therefore be smaller for partnered gays and lesbians than for partnered heterosexuals, as has been confirmed by Oreffice and Sansone (2023).

Taking stock, the labor supply side of the literature has very much focused on the household responsibilities hypothesis in conjunction with children. Preferences of mothers contribute to the gender commuting gap, possibly as their threshold for the maximal acceptable commute declines after a first birth. While the literature suggests that labor supply aspects quantitatively matter for the gender commuting gap, it is important to examine whether labor *demand* also plays a role.

We are aware of only a few experimental studies that test how employers react to commuting distances of workers. In a correspondence test in Belgium, Baert (2015) found that applicants who lived far away were less likely to receive invitations for inter-

[8]Other evidence for the "household responsibility hypothesis" comes from Giménez-Nadal and Molina (2016), who, using Dutch time-use survey data and employing propensity score matching techniques to address endogeneity in the choice of time devoted to household tasks, found that the effect of home production on commuting time is more than twice as intense for women as for men, whereas hours devoted to childcare only impact female commuting time. Relatedly, Chidambaram and Scheiner (2020) report, on the basis of German time-use data, that an increase in time spent on unpaid work by the male partner in dual-earner couples decreases the gender commuting gap.

[9]Eriksson and Lagerström (2012) demonstrated, using a Swedish online database, that women search less often for jobs farther from home, but were unable to distinguish by family status.

[10]See also Farré, Jofre-Monseny, and Torrecillas (2023) for the impact of culture on the effects of commuting distance on the labor force participation of married women.

views, but there was no gender difference. In a vignette study for the US, Van Borm and Baert (2022) showed that hiring chances for applicants with longer commutes (exceeding 50 miles) were significantly lower – also irrespective of gender. Brandén, Bygren, and Gähler (2018), in a correspondence test in Sweden that focused on applicants who lived at least 50 km away from the employer, found that callback rates declined with distance and, further, that they declined more for female than male applicants. This was attributed to the 'trailing spouse phenomenon', where long commutes (> 50 km) necessitate a relocation and one partner presumably has to follow the other's job opportunities.

In this paper, and in contrast with Brandén, Bygren, and Gähler (2018), we contribute to the literature by examining whether employers discriminate by gender in relation to actual daily commuting distances of up to 50 km.

3. Experimental Design

To explore the demand-side factors contributing to why women commute shorter distances, we use data from a correspondence study[11] conducted in Germany, Austria, and Switzerland by Becker, Fernandes, and Weichselbaumer (2019).[12] This experiment, conducted between April 2013 and May 2015, aimed to uncover potential labor market discrimination against women based on specific family profiles, such as marital status and the presence of children. To achieve this, over 8,000 fictitious, well-tailored applications with identical human capital but different family profiles were sent to real firms.

The experiment focused on two female-dominated occupations: accountants and secretaries. These professions were selected because their job tasks are largely the same across companies and industries, with numerous similar job postings available from various employers in different cities. Additionally, the required qualifications are relatively standardized across firms, enabling the use of a single set of application

[11] See Baert (2018) for an overview of correspondence studies trying to test for hiring discrimination.

[12] The correspondence study received ethics approval in the early 2010s before pre-registered field experiments were commonplace. Hence, we cannot provide a link to a pre-analysis plan.

documents for all employers. Furthermore, these jobs allow for email applications as well as the construction of realistic résumés. However, it is important to note that accountants and secretaries are not representative of the entire economy, and therefore, the findings may not generalize to other occupations.

In the German-speaking countries where the study was conducted, it is common for job candidates to include personal details in their résumés, such as marital status and the number of children. Leveraging this institutional setting, the study categorized applicants into five ”family types”: (1) single, no kids (default); (2) married, no kids; (3) married, 2 young kids (ages 3 and 5); (4) married, 2 older kids (ages 7 and 9); and (5) no information provided.[13] These family types implied varying probabilities of childbirth in the near future as well as differing household responsibilities.

All applicants had similar birth dates, around the end of May 1982, placing them between the ages of 31 and 33 at the time of the experiment. The correspondence testing experiment was implemented across several cities in Germany (Berlin, Cologne, Frankfurt, Hamburg, Munich, Stuttgart), Switzerland (Basel, Bern, Zurich), and Austria (Vienna). We carefully prepared two sets of experimental materials—including cover letters, résumés, school reports, and reference letters.[14] These occupation-specific templates, which determined the visual style of the application as well as personal details like birthplace and school attended, were based on real life applications and indicated identical levels of human capital.

Two centrally located applicant addresses were chosen in each city, with one male and one female applicant sharing the same surname assigned to each address. Two applications were sent to each firm. These always used different city addresses as well as templates and differed in at least one demographic characteristic, gender and/or family status. Otherwise, family profiles and gender were randomized. For instance, if

[13]Appendix Figure A1 shows how the family type was indicated in our experiment. Another distinctive feature of the local customs in German-spreaking countries is the inclusion of photographs in the résumé (see Weichselbaumer (2020)). We adhered to this custom and included photos (some provided by Weichselbaumer (2017), which we controlled for in our analysis.

[14]A fraction of applications were ”high quality” and also included IT and English language certificates.

two females applied to the same job at Company A, they would have identical human capital but differ with regard to their family type. For each application, women were selected about two-thirds of the time and males one third. This over-sampling of females was based on the expectation that fertility-related effects would be more relevant to female applicants, which was confirmed by the results. Companies could contact the fictitious applicants by email, telephone, or mail. When our candidates received interview invitations, we promptly declined, citing the acceptance of another offer, to minimize any inconvenience or costs to the employer.[15]

4. Data

This paper focuses on how companies respond to varying commuting distances across different types of applicants. Although in our experiment the applicants' addresses were fixed in each city, the firms could be located anywhere within the city, or in the suburbs, leading to considerable variation in commuting distances. In Germany, roughly 95% of the working population travel under 50 km to get to work (Federal Statistical Office of Germany, 2020). Therefore, we focus on distances under 50 km, when commuting is possible without a move. We will show that our results are not sensitive to this particular threshold.

Our dataset is somewhat smaller than that used by Becker, Fernandes, and Weichselbaumer (2019). Many companies did not include addresses in their job advertisements. Sometimes, the headquarter address of a large company was given instead of the location of the workplace. By dropping these cases, we lose 8.8% of the observations, as detailed in Table 1.[16] Additionally, when restricting distances to be under the 50 km threshold, we lose a total of 19.1% of the original 8,669 observations, leaving us with N=7,004.[17] Importantly, there is sufficient variation in commuting distance to identify

[15]While critics of correspondence studies often highlight the burden these 'fake applications' place on employers, we mitigated this by swiftly declining interview requests. It is crucial to note that the German Federal Antidiscrimination Agency (2010) explicitly affirmed the legality of correspondence testing as a legitimate method for uncovering discrimination.

[16]In line with Becker, Fernandes, and Weichselbaumer (2019), we present our sample for full- and part-time jobs separately. Jobs that are advertised as 80% or less are classified as "part-time".

[17]Appendix A includes additional information about the experimental design and data distributions.

potential discrimination based on commuting distance across different family profiles.

Table 1: Summary of observations, before and after data cleaning

	Female		Male		Total
	Full-Time	Part-Time	Full-Time	Part-Time	
(1) Original sample	4245	1332	2445	647	8669
(2) Observations with company addresses	3873	1210	2228	591	7902
(3) Observations with driving distance $\leq 50km$	3416	1101	1961	526	7004
Loss (2) relative to (1)	8.8%	9.2%	8.9%	8.7%	8.8%
Loss (3) relative to (1)	19.4%	17.2%	19.7%	18.7%	19.1%

Notes: The table shows the sample size at each stage of data cleaning (starting with the original sample used by Becker, Fernandes, and Weichselbaumer (2019)), with observations categorized by gender and employment type (full-time, part-time). The initial sample was reduced by excluding observations lacking valid company addresses, followed by a further reduction to observations within a 50 km driving distance from the applicant. The final two rows indicate the percentage of observations lost at each stage.

4.1 Measures of commuting distance

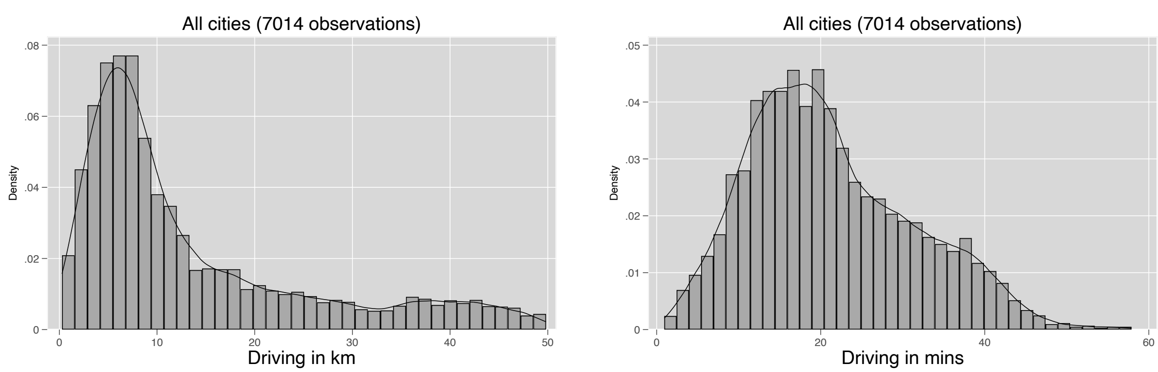
Commuting distance was calculated on the basis of the candidates' home addresses and the company locations given in the firms' job ads. For each applicant, we calculated the commuting distance and commuting duration between home address and firm address using Google Maps for a typical 8 a.m. Monday morning commute. Google Maps calculates the 8 a.m. commute by estimating real-time traffic conditions using a combination of historical traffic data, live traffic conditions, and predictive algorithms. The optimal route is determined based on typical road conditions, including traffic congestion, accidents, and road closures, to provide the most efficient travel time. The proposed route and commuting times may vary slightly from day to day due to fluctuating traffic patterns; however, the retrieved values offer a reliable approximation of typical driving distances and durations at 8 a.m.

In our main results, we focus on driving distance primarily because most people in Germany drive to work (Federal Statistical Office of Germany, 2020). However, Google Maps provides commuting times and distances in minutes and kilometers for different modes of transport—driving, cycling, public transport, and walking. In addition, we calculated the geodesic distance, which is the shortest path between two points on a curved surface. These measures we use for robustness tests.

Figure 1 presents the distribution of commuting distances and durations for the 8 a.m. commute across all cities in the study. Panel (a) displays the histogram of driving distance, measured in kilometers, while panel (b) shows the histogram of driving duration, measured in minutes. Both distributions are skewed, with most job advertisements located within 10 to 20 kilometers of the applicant addresses. However, some firms are located much further away, with distances reaching up to 50 kilometers (or more, if we do not restrict our data). This distribution suggests that, while most advertised jobs are relatively close to the applicant addresses, there is a notable spread, with some firms situated in the broader metropolitan area and beyond. The shape of the distributions suggests that commuting distances and durations are not normally distributed but rather exhibit a skew akin to log-normal distributions.

Figure 1: Histograms of Distance and Duration Driving: 8 a.m. commute

(a) Distance Driving **(b)** Duration Driving

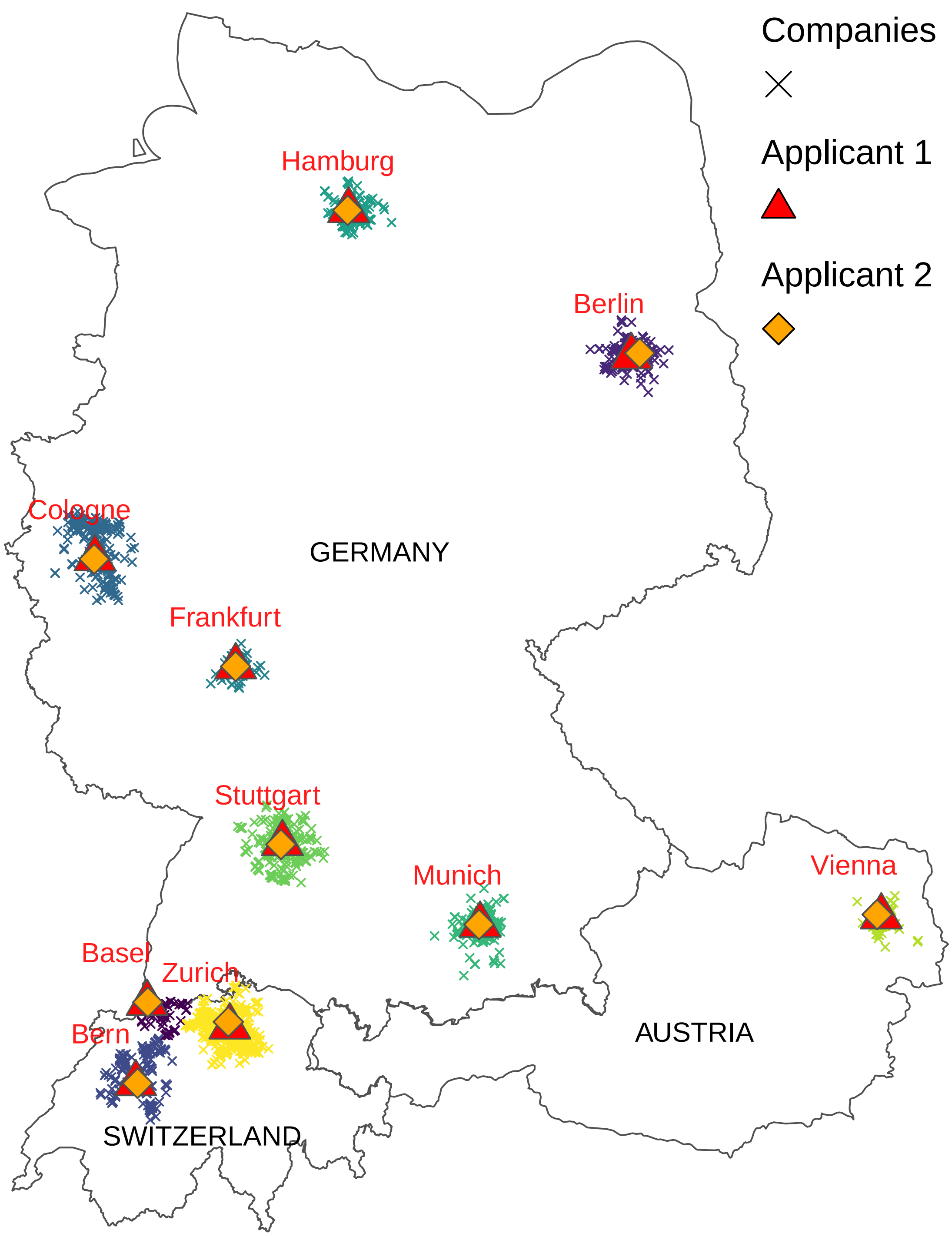


Notes: This table presents histograms of commuting distance and duration for an 8 a.m. Monday trip. The commuting distance was calculated based on candidates' home addresses and firm locations listed in job advertisements, using Google Maps. Panel (a) displays the histogram of commuting distances in kilometers. The distribution exhibits a rightward skew, with distances of 2-12 km having the highest densities. Panel (b) shows the histogram of commuting durations in minutes. This distribution also has a rightward skew, with distances of 9-25 min having the highest densities.

In Appendix A, we provide more information by city and mode of transportation.[18]

[18]For example, Appendix Figures A2, A3, and A4 display histograms of commuting duration and distance for cycling, walking, and public transport. Figure A5 presents histograms for commuting distance by city.

Figure 2: Applicants and firms across countries and cities, driving distance ≤50km



Notes: This map shows the applicant and company addresses for the different cities investigated, up to 50 km. The experiment was carried out in Basel, Bern and Zurich in Switzerland; Berlin, Cologne, Frankfurt, Hamburg, Munich, and Stuttgart in Germany; and Vienna in Austria. In each city, we had two distinct applicant addresses – one shown with a red triangle, the other with a yellow diamond. Crosses (in different colors for different cities) show the firm addresses. Figures A6 and A7 provide the respective information for commuting distances up to 75km and 100km. To zoom-in, Figure A8 shows firm and applicant addresses for each city separately.

Figure 2 depicts the applicant and company addresses for the different cities investigated (for commuting driving distances up to 50 km). The red triangle and the yellow diamond represent the two applicant addresses per city (these are typically too close to be visually distinguishable), the colored crosses show the firm addresses. The resulting commuting distances are the focus of this study.

4.2 Interview invitation rates

Our outcome variable of interest is the interview invitation probability. Table 2 provides first insights into the invitation rates of our applicants for driving distances $\leq$50 km). Like Becker, Fernandes, and Weichselbaumer (2019), we find that invitation rates are substantially lower for men (11%) than for women (21%) in the female-dominated occupations that we examined. This aligns with the experimental literature, which shows that men often face discrimination in female-dominated fields, while women are frequently discriminated against in male-dominated jobs (Adamovic and Leibbrandt, 2023; Galos and Coppock, 2023; Yavorsky, 2019; Weichselbaumer, 2004).

The differential treatment by gender is particularly striking in Austria, where female applicants have a callback rate of 19% compared to only 6% for men, but also Switzerland and Germany show considerable gaps. The data also show a notable difference between occupations, with accountants being in higher demand (with invitation rates for women of 25% and men of 15%) than secretaries (women: 17%, men: 7%).

When examining different family types, as in Becker, Fernandes, and Weichselbaumer (2019), we observe no significant differences in invitation rates for female applicants, suggesting that family status or assumed caregiving responsibilities do not strongly influence employers' decisions in this context. Also men are unaffected by their family type, as was expected given men's role as the main breadwinner in German-speaking countries.[19]

[19] Appendix Tables A1 and A2 show summary tables disaggregated for part- and full-time workers. Like Becker, Fernandes, and Weichselbaumer (2019), we find differences by family type only for women in part-time jobs, with married women with two old children receiving the most invitations to interviews and married women with no children (who are most likely to be planning for a child) receiving the

Table 2: Interview invitation rates – summary, both part- and full-time jobs

	Female		Male	
	Callback Rate (in %)	Obs.	Callback Rate (in %)	Obs.
All types, countries, occupations	20.68	4517	10.78	2487
Germany	22.49	2579	12.46	1565
Switzerland	17.93	1461	8.81	647
Austria	19.29	477	5.82	275
Accountant	25.23	2128	15.08	1227
Secretary	16.62	2389	6.59	1260
Single No Kids	20.26	1002	11.5	426
Married No Kids	19.44	993	9.0	411
Married 2 Young Kids	20.35	791	11.84	608
Married 2 Old Kids	22.95	732	12.06	630
No Info on Family Status	20.92	999	8.25	412

Notes: Callback rates represent the percentage of applicants who were invited for an interview in a correspondence testing field experiment conducted between March 2013 and June 2015. Each firm received two applications with identical human capital (work experience and education) and randomized gender and family attributes. Each application package included a cover letter, résumé, reference letter, and educational certificates. Résumé elements such as candidate photo, name, and application template (determining visual style of the application as well as personal details like birthplace and school attended) were randomized. While this table reports part- and full-time jobs combined, Tables A1 and A2 report the callback rates for part- and full-time jobs separately.

4.3 Control Variables

In the following, we estimate the likelihood of an applicant being invited for an interview depending on how far they live from the company. Our estimates are based on a broad set of controls with the main variable of interest being 'driving distance in km'.

Other control variables include dummy variables for the different family types, as well as for cities (Basel, Zurich, Berlin, Cologne, Frankfurt, Hamburg, Stuttgart, Mu-

fewest.

nich, and Vienna, with Bern being the reference city). The latter are crucial to capture regional heterogeneity in labor market conditions, economic environment, and other city-specific factors that could differentially impact the probability of receiving a job invitation. Time dummies control for the quarter and year an application was sent.

We also control for application characteristics such as occupation (accountant versus secretary), applicant gender, the template and photo used in a specific application, the quality of the application (we considered an application to be high quality, when it included IT and English language certificates), and the quality of the fit between our applicant's profile and a particular vacancy.[20]

Firm-level controls include the geographic scope of the firm's operations, distinguishing between locally, nationally, and internationally active firms, as well as firm size, ranging from small enterprises with 1-20 employees to large organizations with more than 1,000 employees. We also controlled for the industry sector, with specific variables accounting for public, trade, manufacturing and service sectors. Additionally, we included a variable indicating whether a firm explicitly referred to its anti-discrimination policy in the job ad, ensuring that our results are not biased by potentially different hiring behaviors of firms publicly committed to anti-discrimination practices.

5. Results

As pointed out before, the existing literature largely attributes the observed gender commuting gap to supply-side factors and argues that women do not *want* to commute long distances. With our experimental data we are able to examine whether the gender commuting gap is also influenced by demand-side factors.

[20] Three dummy variables reflected how well the set of fixed skills possessed by our applicants matched the requirements of each specific job ad that we answered. "Good fit" is a dummy variable coded as one when all the job requirements were met by our candidates; if our candidates' qualifications did not fully meet the advertisement specifications, they were coded as having an "average fit" (when only minor requirements were not met), or as a "bad fit" (when one crucial or two or more minor requirements were not satisfied).

Table 3: Probability of interview invitation by gender

Panel A: Female Applicants

	(1)	(2)	(3)	(4)
Driving distance in km	-0.0029***	-0.0020***	-0.0020***	-0.0018***
	(0.0005)	(0.0005)	(0.0005)	(0.0006)
Married, no kids	-0.0073	-0.0055	-0.0073	-0.0095
	(0.0176)	(0.0176)	(0.0174)	(0.0174)
Married, 2 young kids	-0.0024	-0.0001	-0.0055	-0.0072
	(0.0194)	(0.0193)	(0.0192)	(0.0192)
Married, 2 old kids	0.0270	0.0271	0.0286	0.0267
	(0.0204)	(0.0203)	(0.0202)	(0.0202)
No info on family status	0.0068	0.0047	0.0065	0.0052
	(0.0182)	(0.0182)	(0.0182)	(0.0182)
Mean of dependent variable	0.207	0.207	0.207	0.207
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Observations	4502	4502	4502	4502
R-squared	0.008	0.020	0.040	0.042

Panel B: Male Applicants

	(1)	(2)	(3)	(4)
Driving distance in km	-0.0003	0.0000	-0.0001	0.0003
	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Married, no kids	-0.0251	-0.0251	-0.0220	-0.0234
	(0.0219)	(0.0217)	(0.0214)	(0.0216)
Married, 2 young kids	0.0035	0.0017	0.0051	0.0048
	(0.0208)	(0.0208)	(0.0205)	(0.0205)
Married, 2 old kids	0.0066	0.0074	0.0115	0.0103
	(0.0206)	(0.0205)	(0.0203)	(0.0203)
No info on family status	-0.0327	-0.0342	-0.0282	-0.0308
	(0.0213)	(0.0211)	(0.0208)	(0.0208)
Mean of dependent variable	0.108	0.108	0.108	0.108
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Observations	2480	2480	2480	2480
R-squared	0.003	0.014	0.037	0.044

Notes: Standard errors (clustered at the company level) in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Hamburg, Frankfurt, Munich, Stuttgart, Vienna, with Bern being the reference city), time (quarter and year sent), application characteristics (template, picture, occupation, application quality), and firm characteristics (size, local/national/international, sector, anti-discrimination policy). Appendix Tables B1 and B2 show the results for part-time and full-time applicants separately, indicating even higher penalties for women who live far away and apply for part-time jobs. Male interview invitation rates remain unaffected by commuting distance, regardless of whether the job is full-time or part-time.

Table 3 presents the results of a linear probability model with which we estimate the probability that an applicant receives an interview invitation as a function of driving distance and family type, including additional control variables from column 2 onwards. Panel A shows the results for women. Column 1 of Panel A reports results without controls, showing a coefficient of -0.0029 for females, which is statistically significant at the 1% level. This coefficient represents the distance gradient per km and implies that for every 10 kilometers a woman lives further away from the workplace, her chance of being invited to a job interview decreases by 2.9 percentage points. Given that the mean invitation rate for females in our sample is 20.7%, this effect is equivalent to a 14% reduction in invitation rates (2.9 relative to 20.7). Columns (2) through (4) add different sets of controls. The negative relationship between commuting distance and interview invitations remains statistically significant at the 1% level in all specifications. Controlling for city reduces the magnitude of the effect, but with full controls it still amounts to -0.0018, which represents a 8.7% reduction in invitation rates.[21] Panel B shows the results for male applicants, for whom no statistically significant effect of commuting distance is observed.

Like Becker, Fernandes, and Weichselbaumer (2019) we do not find that the family type of an applicant affects the response of employers, not for men – but not for women either.[22] In subsequent tables we will therefore refrain from reporting the coefficients for the different family types.

While most of our analysis focuses on distance traveled by car, for robustness we next examine the effects of commuting distance by different modes of transport. Table 4 reports the results for our distance measures concerning walking, cycling, taking public transportation, driving, and straight-line (geodesic) distance and uses the same specification as column 4 of Table 3 (which includes applicant, family type, city, and

[21]Appendix Table B3 presents the results when we combine both female and male applicants and include a gender $\times$ distance interaction term. Results are comparable to those in Table 3. For simplicity and ease of interpretation, we will analyze females and males in separate tables throughout the rest of the paper.

[22]Specifically, Becker, Fernandes, and Weichselbaumer (2019) does not find effects of family type for full-time jobs, but for part-time vacancies. Because of the different focus of this paper, full-time and part-time applications are usually analyzed together.

firm-level controls).

Table 4: Probability of interview invitation, all transport types

Panel A: Female Applicants

	(1)	(2)	(3)	(4)	(5)
Walking distance in km	-0.0021***				
	(0.0006)				
Bicycling distance in km		-0.0019***			
		(0.0005)			
Public transport distance in km			-0.0013***		
			(0.0005)		
Driving distance in km				-0.0018***	
				(0.0006)	
Straight line distance in km					-0.0024***
					(0.0007)
Mean of dependent variable	0.207	0.207	0.207	0.207	0.207
Applicant, city, time and firm controls	Yes	Yes	Yes	Yes	Yes
Family types	Yes	Yes	Yes	Yes	Yes
Observations	4492	4492	4492	4492	4492
R-squared	0.043	0.043	0.042	0.043	0.042

Panel B: Male Applicants

	(1)	(2)	(3)	(4)	(5)
Walking distance in km	0.0002				
	(0.0007)				
Bicycling distance in km		0.0002			
		(0.0006)			
Public transport distance in km			0.0002		
			(0.0005)		
Driving distance in km				0.0003	
				(0.0006)	
Straight line distance in km					0.0002
					(0.0008)
Mean of dependent variable	0.108	0.108	0.108	0.108	0.108
Applicant, city, time and firm controls	Yes	Yes	Yes	Yes	Yes
Family types	Yes	Yes	Yes	Yes	Yes
Observations	2476	2476	2476	2476	2476
R-squared	0.044	0.044	0.044	0.044	0.044

Notes: Standard errors (clustered at the company level) in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Hamburg, Frankfurt, Munich, Stuttgart, Vienna, with Bern being the reference city), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types.

As Table 4 shows, our results are not sensitive to the choice of means of transport. Panel A reports the results for women. Irrespective of the mode of transport, we find significant disadvantages for women who live far away. The commuting distance by public transport has the smallest estimated distance coefficient. This is likely due to the fact that public transport connections are, on average, longer than walking, cycling, or driving distances, as trains, trams, or buses do not necessarily take the shortest route between place of residence and place of work. Panel B illustrates the results for men and confirms that there are no systematic effects for men when applying for jobs that are far away – regardless of the distance measure applied.

So far we have only examined observations, where the applicants lived a maximum of 50 km away from the workplace. As has been pointed out before, the choice of our distance cutoff of 50 km is guided by statistical reports from Germany, indicating that for approximately 95% of workers their commute is less than 50 km (Federal Statistical Office of Germany, 2020). In the next step, we explore the sensitivity of our results to the cut-off we have chosen. Specifically, we apply the following alternative driving distance cut-offs: 25 km, 50 km (our benchmark), 75 km, and 100 km, using the specification from column 4 of Table 3 .

Table 5: Probability of interview invitation, alternative driving distance specifications

Panel A: Female Applicants

	$\leq$ 25 km	$\leq$ 50 km	$\leq$ 75 km	$\leq$ 100 km
Driving distance in km	-0.0033**	-0.0018***	-0.0022***	-0.0021***
	(0.0014)	(0.0006)	(0.0004)	(0.0003)
Mean of dependent variable	0.221	0.207	0.199	0.198
Applicant, city, time and firm controls	Yes	Yes	Yes	Yes
Family types	Yes	Yes	Yes	Yes
Observations	3706	4505	4795	4835
R-squared	0.044	0.042	0.045	0.046

Panel B: Male Applicants

	$\leq$ 25 km	$\leq$ 50 km	$\leq$ 75 km	$\leq$ 100 km
Driving distance in km	-0.0002	0.0003	0.0000	-0.0002
	(0.0013)	(0.0006)	(0.0004)	(0.0004)
Mean of dependent variable	0.109	0.108	0.106	0.105
Applicant, city, time and firm controls	Yes	Yes	Yes	Yes
Family types	Yes	Yes	Yes	Yes
Observations	2074	2483	2653	2677
R-squared	0.045	0.043	0.041	0.041

Notes: Standard errors (clustered at the company level) in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Hamburg, Frankfurt, Munich, Stuttgart, Vienna, with Bern being the reference city), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types.

Table 5 presents the results for these different commuting distance cut-offs. The findings remain remarkably consistent, regardless of the specific cut-off point applied. Our benchmark results are reported in column 2, where commuting distances (by car) are limited to less than 50 km. For women (Panel A), as previously shown, this cut-off yields a -0.0018 lower probability of receiving an interview invitation per driving kilometer. Compared to the estimates in the other columns, this benchmark specification produces the smallest value, making it the most conservative estimate. Panel B of Table 5, further confirms our earlier findings with regard to men as we do not observe any impact of driving distance on male applicants.

Table 6: Checking linearity of our results, female applicants

	(1)	(2)	(3)	(4)
5-10 km driving distance	-0.0296*	-0.0249	-0.0280	-0.0271
	(0.0177)	(0.0183)	(0.0181)	(0.0182)
10-20 km driving distance	-0.0438**	-0.0422**	-0.0455**	-0.0432**
	(0.0208)	(0.0210)	(0.0207)	(0.0210)
20-30 km driving distance	-0.0872***	-0.0757***	-0.0775***	-0.0735***
	(0.0248)	(0.0249)	(0.0248)	(0.0254)
30-40 km driving distance	-0.1064***	-0.0656**	-0.0655**	-0.0632**
	(0.0262)	(0.0268)	(0.0263)	(0.0270)
40-50 km driving distance	-0.1234***	-0.0807***	-0.0798***	-0.0763***
	(0.0258)	(0.0261)	(0.0260)	(0.0265)
Mean of dependent variable	0.207	0.207	0.207	0.207
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Family types	Yes	Yes	Yes	Yes
Observations	4502	4502	4502	4502
R-squared	0.008	0.020	0.040	0.042

Notes: The commuting distance bin 0−5 km is the reference category. Standard errors (clustered at the company level) in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Hamburg, Frankfurt, Munich, Stuttgart, Vienna, with Bern being the reference city), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types. Table B4 in the Appendix reports the results for males. Table B5 does an alternative check for linearity by including a quadratic term for distance.

As we have now established that commuting distances are irrelevant for men's chances of receiving interview invitations, in the following we explore women's penalties for living further away in more detail.

So far, we have implicitly assumed that the effect of commuting distance on callback rates is linear in distance. To check whether this assumption holds, we create a set of indicator variables for distance bins of $0-5$ km, $5-10$ km, $10-20$ km, $20-30$ km, $30-40$ km, and $40-50$ km (reference group: $0-5$ km). The results are shown in Table 6. Without controls (column 1), the effects are approximately linear; however, in the fullest specification (column 4), the effects are linear up to 30 km after which the relationship reaches a kind of plateau. While this pattern suggests a concave shape, it is important to note that in our sample more than 90% of all commutes are less than 30 km as can be seen in Figure 1, which means that the linear specification is a fair approximation in our sample. We further check our linearity assumption by adding a quadratic in distance to our empirical model. As is shown in Table B5, the quadratic term is not significant, further supporting our use of linear specifications throughout the paper.

Further robustness checks

Before we explore what drives the penalty for female commuters in more detail, we conduct further robustness tests. These are presented in Appendix B. Table B6 examines the gender commuting gap across different industry sectors. Interestingly, the penalty for women who live far away is highest in the public sector (reducing the invitation probability by 6.2 percentage points for every 10 km commuting distance), followed by the service sector (-1.9 percentage points for every 10 km). Additionally, in Table B7 we do a jackknife exercise where in every column we exclude one single sector from the full sample to see if any sector is particularly influential in driving our results. The results for female applicants (Panel A) show that the negative effect of commuting distance on interview invitation rates remains statistically significant across all jackknife specifications. This indicates that the commuting penalty observed for female applicants is robust also with regard to industry as is the absence of such an effect for male applicants (Panel B).

Similarly, we do a jackknife exercise for different cities. Again, our main results do not seem to be driven by any particular city, as shown in Table B8.

In summary, we have demonstrated that across a wide range of specifications and samples, the negative effect of commuting distance on interview invitation rates is consistently observed only for women but not for men.

5.1 What drives the penalty for female commuters?

To better understand what drives the penalty for female commuters, in the following we examine the effect of firm size, part-time work and family type. In Table 7 we first study the gender commuting gap across firms of different sizes for females. For example, Kaas and Manger (2012) showed that hiring discrimination is larger in small firms. One reason for this may be that larger firms have a human resources department with qualified staff who are also trained not to discriminate. In our case, it may also be that employers in small and medium-sized firms are particularly concerned about potential disruptions due to long distance commuters, as they often have only one or two secretaries or accountants, with no possibility of substituting if one is unable to make it to work or decides to leave the job.

Table 7: Probability of interview invitation for females, by firm size (employees)

	1-20	21-100	101-500	500+
Driving distance in km	-0.0037***	-0.0025***	-0.0003	-0.0005
	(0.0013)	(0.0009)	(0.0010)	(0.0014)
Mean of dependent variable	0.209	0.217	0.192	0.206
Applicant, city, time and firm controls	Yes	Yes	Yes	Yes
Family types	Yes	Yes	Yes	Yes
Observations	938	1559	1222	786
R-squared	0.086	0.040	0.073	0.080

Notes: Standard errors (clustered at the company level) in the brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Frankfurt, Hamburg, Stuttgart, Munich, and Vienna, with Bern being the reference city), time (quarter and year sent), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types. Appendix Table B9 shows the results for males by firm size.

With a specification identical to column 4 of Table 3, we split firms into groups that have 1-20, 21-100, 101-500, and over 500 employees. Table 7 shows that the penalties faced by female commuters are primarily observed in small and medium-sized firms with up to 100 employees. The effect is especially pronounced in small firms with up to 20 employees, where the probability of receiving an invitation decreases by 3.7 percentage points for every 10 km commuting distance. In contrast, for larger firms with more than 100 employees, the commuting penalty for women disappears. This fits our expectation that larger firms discriminate less against female commuters.

Table 8: Probability of interview invitation, part-time × distance, female applicants

	(1)	(2)	(3)	(4)
Driving distance in km	-0.0024***	-0.0013**	-0.0013**	-0.0011*
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Driving in km × Part-time	-0.0021*	-0.0023**	-0.0025**	-0.0026**
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Part-time	0.0235	0.0361	0.0305	0.0326
	(0.0244)	(0.0245)	(0.0242)	(0.0243)
Mean of dependent variable	0.207	0.207	0.207	0.207
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Family types	Yes	Yes	Yes	Yes
Observations	4502	4502	4502	4502
R-squared	0.009	0.020	0.041	0.044

Notes: Standard errors (clustered at the company level) in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Hamburg, Frankfurt, Munich, Stuttgart, Vienna, with Bern being the reference city), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types. Table B10 shows the results for males. Again, we do not observe any distance gradient for males.

Previous scholars (e.g., Madden (1981), McQuaid and Chen (2012)) have emphasized that also hours worked may play a role in the gender commuting gap. Part-time work (particularly prevalent among women in the German-speaking countries) shifts the balance between earnings and commuting costs and therefore may make long commutes less acceptable to workers. As a result, employers may fear that a part-time job that requires long commutes will ultimately be unattractive. In the next step, we therefore differentiate whether our candidates apply to full- or part-time jobs by including an interaction term "distance × part-time" in our linear probability model. Table 8 shows the results for female job applicants. We find that, indeed, for part-time jobs, women who live further away are particularly disadvantaged, as the interaction term between driving distance and part-time is negative, statistically significant and also economically large. However, the main effect for commuting distance also remains significant, indicating the disadvantages faced by full-time employers.

While in reality much more women than men hold part-time jobs, in our experimental setting, men and women applied to part-time vacancies with equal probabilities. Table B10 in the Appendix shows that men are less likely to be invited to interviews for part-time compared to full-time positions, potentially because male part-time employment violates the gender norm of the male breadwinner. However, commuting distance does not not matter for men's likelihood of being invited, even when applying for part-time positions.

Table 9: Distance with family type interaction terms, female applicants

	(1)	(2)	(3)	(4)
Driving distance in km	-0.0036***	-0.0026***	-0.0023**	-0.0022**
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Driving distance in km × married, no kids	0.0012	0.0013	0.0010	0.0010
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Driving distance in km × married, 2 young kids	0.0002	0.0003	-0.0001	-0.0001
	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Driving distance in km × married, 2 old kids	0.0023	0.0020	0.0019	0.0019
	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Driving distance in km × no info	-0.0000	-0.0001	-0.0007	-0.0007
	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Mean of dependent variable	0.207	0.207	0.207	0.207
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Family types	Yes	Yes	Yes	Yes
Observations	4502	4502	4502	4502
R-squared	0.009	0.020	0.040	0.043

Notes: Standard errors (clustered at the company level) in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Hamburg, Frankfurt, Munich, Stuttgart, Vienna, with Bern being the reference city), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types. Table B11 in the Appendix presents the same analysis for male applicants, where no significant effects are observed for driving distance or any interaction with family type.

As noted above, much of the literature on supply-side factors affecting commuting times has relied on the ”household responsibility hypothesis” (Hanson and Johnston (1985), Johnston-Anumonwo (1992)), which argues that women in heterosexual households experience a time crunch that necessitates short commutes, particularly if they have children (e.g., Bütikofer, Karadakic, and Willén (2023), Borghorst, Mulalic, and van Ommeren (2024), Le Barbanchon, Rathelot, and Roulet (2021)). Employers may account for these multiple time pressures faced by women, especially mothers: The longer the commute, the more challenging it becomes to combine family-related tasks and responsibilities with work. This strain can lead to higher rates of absenteeism, reduced job satisfaction, and early turnover.

As a result employers might engage in statistical discrimination (Arrow (1973), Phelps (1972)) against mothers – and potentially married women without children – by using family-related information from the résumé to base their expectations on. Possibly the commuting penalty we have identified is linked to the family demographics of female applicants, particularly the presence of children.

To test for this, we interact distance with our different family profiles – inclusive of number of children and marital status. Table 9 presents the results. Interestingly, our findings indicate that the negative commuting distance gradient is uniform across family types, with none of the interaction terms between distance and family types proving significant. This means that single women, as well as women who do not provide information about their family situation, are equally penalized for living further away as mothers. These findings indicate that childcare responsibilities alone cannot explain our results.

6. Discussion

This study contributes to the growing body of literature examining gender disparities in labor market outcomes that are related to commuting distance. Our findings indicate that demand-side factors play a crucial role in explaining the gender gap in commuting distances and provide clear evidence of discrimination against women on this basis.

Such gender-based discrimination in relation to commuting distance implies differential access to the labor market and employment opportunities.

As demonstrated throughout this paper, the likelihood of women being invited to a job interview decreases the farther they live from the workplace. This effect is substantial in magnitude and robust to multiple tests. Moreover, this effect is not observed for men. Within heterosexual families, gendered norms assign women the role of the primary homemaker and men the role of the primary breadwinner. Employers may therefore be concerned that household responsibilities (Hanson and Johnston (1985), Johnston-Anumonwo (1992)) may make it difficult for women with a family to engage in long commutes and statistically discriminate against them. However, according to our findings, commuting penalties are not associated with particular family configurations. Instead, our results show a generalized negative effect of commuting distance on *all* women, regardless of their marital status and the presence of children.

While the theory of statistical discrimination usually assumes that employers hold expectations that are correct on the average, the persistence of the observed negative effect across all groups of women lends support to the idea of inaccurate statistical discrimination, as discussed by Bohren, Haggag, and Pope (2024). This form of discrimination reflects a reliance on erroneous stereotypes rather than an accurate assessment of each candidate's situation. In our case it appears that employers are making generalized assumptions about women's commitment or availability based on their commuting distance, without considering individual circumstances or actual responsibilities.

To further explore the underlying causes of these discriminatory practices, in the following, we examine data from the German Socio-Economic Panel (GSOEP).[23] This dataset provides valuable insights into gender differences in unpaid household labor as well as commuting behaviors, which may inform employers' perceptions. The GSOEP data reveal that women, on average, spend significantly more time on housework than men, regardless of their family structure. However, as shown in Table 10, these gen-

[23]While our data covers three different German-speaking countries, the largest number of observations come from Germany.

der differences in unpaid housework are minimal among singles but become more pronounced among married individuals with children. Furthermore, childcare creates an additional disparity in time use between married fathers and mothers (see Table 11). These data provide little justification for imposing identical penalties on all women with long commutes, regardless of their family situation.

Table 10: Mean Daily Hours Spent on Unpaid Housework (washing/cooking/cleaning)

	Female		Male	
	Housework	Obs.	Housework	Obs.
Single, no kids	1.19	185	1.00	219
Married, no kids	1.54	92	0.83	66
Married, 2 young kids (ages 1 to 5)	1.93	615	0.68	748
Married, 2 old kids (ages 7 to 11)	2.08	756	0.67	752

Note: This table uses the German Socio-Economic Panel (GSOEP) to infer potential empirical patterns and provide insights into why employers might hold the observed beliefs. The individual ages are restricted to 25 to 40 years old to substantiate the findings. The GSOEP data used in the analysis is from 2014 and 2015.

Table 11: Mean Daily Hours Spent on Child Care

	Female		Male	
	Child Care	Obs.	Child Care	Obs.
Married, 2 young kids (ages 1 to 5)	4.72	615	2.07	748
Married, 2 old kids (ages 7 to 11)	4.55	756	1.83	752

Note: This table uses the German Socio-Economic Panel (GSOEP) to infer potential empirical patterns and provide insights into why employers might hold the observed beliefs. The individual ages are restricted to 25 to 40 years old to substantiate the findings. The GSOEP data used in the analysis is from 2014 and 2015.

Regarding commuting distances, the GSOEP data show that women's commutes tend to be shorter than men's. This pattern is also observed among singles, although the differences are larger for married individuals with children, as shown in Table 12. Of course, we cannot determine whether these patterns result from supply-side effects or from discrimination against women who live far away. Employers may, nevertheless, generalize from such information that women prefer jobs that are closer to home, and consequently engage in potentially inaccurate statistical discrimination against *all* women with long commutes. An underlying stereotype could be, for example, that women are generally less mobile or averse to traveling.

Table 12: Mean Distance to Place of Work (km)

	Female		Male	
	Distance (km)	Obs.	Distance (km)	Obs.
Single, no kids	15.63	234	18.22	260
Married, no kids	17.76	110	16.46	111
Married, 2 young kids (ages 1 to 5)	15.20	608	19.53	719
Married, 2 old kids (ages 7 to 11)	13.88	708	19.03	677

Note: This table uses the German Socio-Economic Panel (GSOEP) to infer potential empirical patterns and provide insights into why employers might hold the observed beliefs. The individual ages are restricted to 25 to 40 years old to substantiate the findings. The GSOEP data used in the analysis is from 2014 and 2015.

The implications of these findings are significant. If employers continue to base hiring decisions on generalized beliefs about women's commuting preferences, they risk perpetuating gender disparities in the labor market. This could result in the under-utilization of female labor, particularly in regions or industries where jobs are located farther from residential areas. From an economic perspective, such inefficiencies in the labor market can lead to suboptimal outcomes, both for individuals and for the economy as a whole.

Generalizability of our results. While our results seem to match the generally observed gender commuting gap, we cannot rule out that our findings are specific to our experimental setting.[24] As discussed, we examine two female-dominated occupations, in which men receive fewer interview invitations than women. In other words, overall, it is men who seek jobs as secretaries or accountants, who are being discriminated against. The absence of a distance gradient for males is consistent with the idea that, given firms' general aversion to hiring males in female-dominated occupations, there is no scope for additional discrimination based on commuting distance. It is important to note, though, that given the large size of our sample, we *would* be able to detect a distant gradient for men despite the lower overall interview invitation rate for men

[24]We thank Andreas Leibbrandt for this suggestion.

compared to women. The absence of such a gradient is, therefore, not the result of a lack of statistical power.

Potential solutions: merits and problems. Our results are consistent with the stereotyping of women as immobile or as less committed to the labor market under adverse conditions, which leads to inequalities in access to jobs between those with longer and shorter commutes, alongside the absence of a distance gradient for men.[25] Our focus in this section is on potential solutions to the unequal treatment of women with longer commuting times, which generates a particular type of labor market inequality that should be of concern to policy makers.

In the literature, anonymous application procedures (AAP) have been proposed as one solution to discrimination in the recruitment process – particularly if it is based on gender or ethnicity. However, hiding an applicant's residence address would also withhold from employers the very information they need to discriminate on the basis of distance. Yet, studies on the effectiveness of AAP interventions have produced mixed findings. For example Krause, Rinne, and Zimmermann (2012), reviewing evidence from multiple countries, suggest that preset online application forms are the best way to reduce discrimination. Rather than giving applicants leeway to submit application materials of their choice, standardized online forms take away the opportunity to either benefit from positive discrimination or to suffer from negative discrimination. Yet, anonymity may also prevent employers from favoring minority applicants. Similarly, removing candidates' postal addresses may help women with longer expected commutes to make it to the interview stage, but it may also simply defer discrimination to a later stage when information about the residential address is available.

Unlike AAP interventions, a potentially more effective way to eliminating (inaccurate) statistical discrimination under conditions of uncertainty may be to encourage employers to gather *more*, rather than less, information about a qualified candidate

[25]It bears reminding though, that in our two female-dominated occupations, overall invitation rates for men are lower than those for women.

whose dedication is unclear. This approach would enable women living farther away to demonstrate their labor market commitment. Naturally, the likelihood of such a procedure is higher in contexts where there is a scarcity of clearly well-suited candidates.

Women may also face implicit discrimination (Bertrand, Chug, and Mullainathan (2005)), being unconsciously associated with reduced mobility, family obligations, and time constraints, regardless of their actual family situation. In that case, employers may make better decisions when dedicating more time for screening applications, thereby avoiding the pitfalls of unconscious bias.

Of course, we cannot rule out that hires with longer commutes are more likely to change to a job closer to home at the earliest opportunity. However, why this should be more of a risk for single women than single men remains unclear.

We believe that the most promising development would be a sharing of care responsibilities between men and women that would permanently shift employer beliefs about people's labor market commitment and their risks of absence due to carer roles – as well as their unconscious associations. For example, Farré et al. (2023) present evidence suggestive of the impact of the introduction of paternity leave in Spain on more gender equal attitudes and less stereotypical social norms of the children who were exposed to that policy change.

7. Conclusion

Employers exhibit discriminatory behavior towards women based on residential distance. Our analysis reveals that no discernible distance gradient is observed for men, indicating that this pattern of discrimination is unique to female applicants. Moreover, this pattern *does not vary by family type*, suggesting that employers' biases against women based on commuting distance are generalized rather than targeted towards specific groups, such as mothers or women with young children. Our results remain robust across various alternative specifications, including interactions, linearity checks, and comparisons between different job roles, such as full- versus part-time positions, different industries and cities. These robustness checks confirm the consistency of the observed discriminatory behavior against female commutes across different contexts and applicant characteristics.

Our findings are robust to the consideration of individual family profiles. Despite gender norms that disproportionately associate women with childcare, and expected as well as unexpected child chores making it much more difficult to engage in long commutes – we find no relationship between the commuting distance penalty we uncovered and the family situation. Instead, our results suggest that the negative impact of commuting distance on interview invitation rates broadly applies to all women, raising important questions about whether employers hold generalized beliefs that women, in general, are less willing or able to commute longer distances. This pattern may indicate a case of inaccurate belief-based statistical discrimination (Bohren, Haggag, and Pope (2024)), where employers erroneously generalize about women's commuting preferences based on stereotypes or misconceptions rather than actual evidence. It may also be the result of an unconscious bias where women are associated with a lack of mobility (Bertrand, Chug, and Mullainathan (2005)). The question remains: do employers inaccurately assume that all women prefer shorter commutes, leading to biased hiring practices?

The observed patterns suggest that the discriminatory behavior we identify is not explained by differences in household responsibilities alone. Instead, it appears that deeper-seated biases or misconceptions about women's commuting preferences and capabilities may be at play. This misalignment between actual preferences and perceived norms could contribute to the persistence of gender-based disparities in the labor market, particularly in contexts where commuting distance is a critical factor in employment decisions. The consistent negative effect on women's employment opportunities, regardless of family type, underscores the need for further investigation into the specific beliefs and assumptions driving this discriminatory behavior.

We have shown that demand-side factors contribute to the gender gap in commuting, with a focus on daily commuting distances. Contrary to some previous findings that emphasized supply-side explanations, such as women's preferences or constraints, our study suggests that employer discrimination also plays a crucial role in shaping the observed gender disparities in commuting patterns and related labor market outcomes.

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So Far Away?

Hiring Discrimination against Female Commuters

Appendix

Sascha O. Becker, Ana Fernandes, Nurlan Lalayev and Doris Weichselbaumer

December 19, 2024

A. Data Appendix

In this section, we provide some additional details on the correspondence experiment conducted in Germany, Switzerland, and Austria from 2013 to 2015 and its data.

Figure A1: Example candidate

Lebenslauf

Personalien

Stephanie Fischer
Im Tale 39
20251 Hamburg
0160 998 911 65
stephanie.fischer13@gmail.com

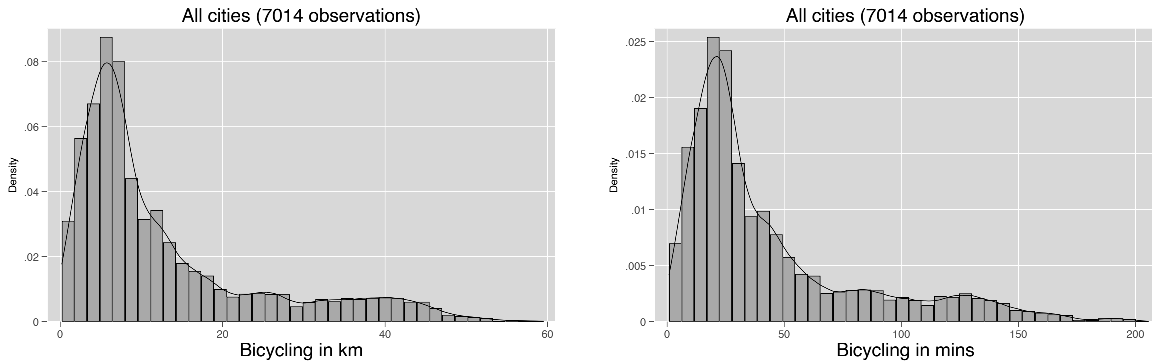
Geburtsdatum 13.05.1982
Geburtsort Paderborn
Familienstand verheiratet, 2 Kinder: Tim (5) und Julia (3)

Notes: This figure shows the header of an example résumé for an applicant based in Hamburg. It provides details about the candidate's name, age, address, contact details, and family status (in this case: married with two young children). Throughout the experiment, elements of the résumé such as the candidate's photo, name, and application template (which determined the visual aspects of the application as well as personal details like birthplace and school attended) were randomized. The date of birth was fixed around May or June 1982, so the applicants were 31 years old at the start of the experiment in 2013, and 33 years old when the experiment ended in 2015.

The commuting distances in each city were determined by the two applicant addresses (located in the city center) and the workplace addresses. Google Maps was used to calculate driving distances and durations from the applicants' residences to the companies. In addition to driving data, we also collected Google Maps cycling distances and durations (shown in Figure A2), walking distances and durations (shown in Figure A3), and public transport distances and durations (shown in Figure A4).

Figure A2: Histograms of Distance and Duration Cycling

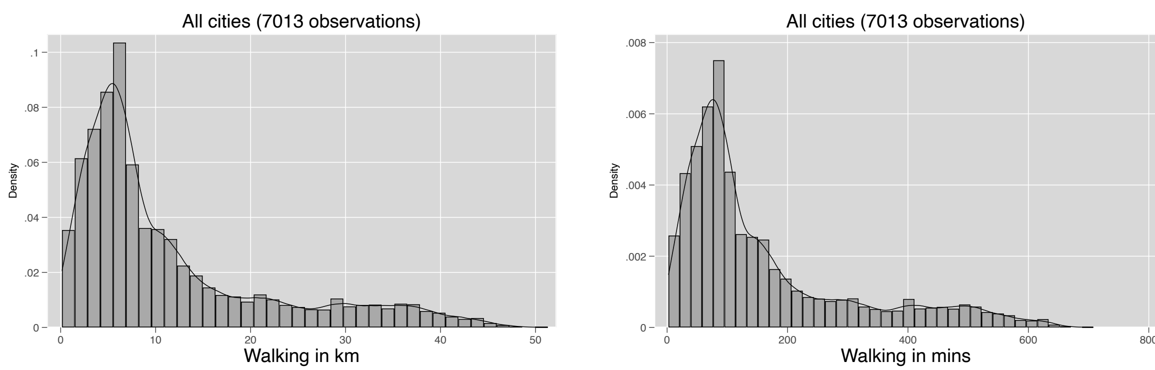
(a) Distance Cycling **(b)** Duration Cycling



Notes: This figure presents histograms of cycling distance and duration for an 8 a.m. Monday trip. The cycling distance was calculated based on candidates' home addresses and firm locations listed in job advertisements, using Google Maps. Panel (a) displays the histogram of cycling distances in kilometers. Panel (b) shows the histogram of cycling durations in minutes.

Figure A3: Histograms of Distance and Duration Walking

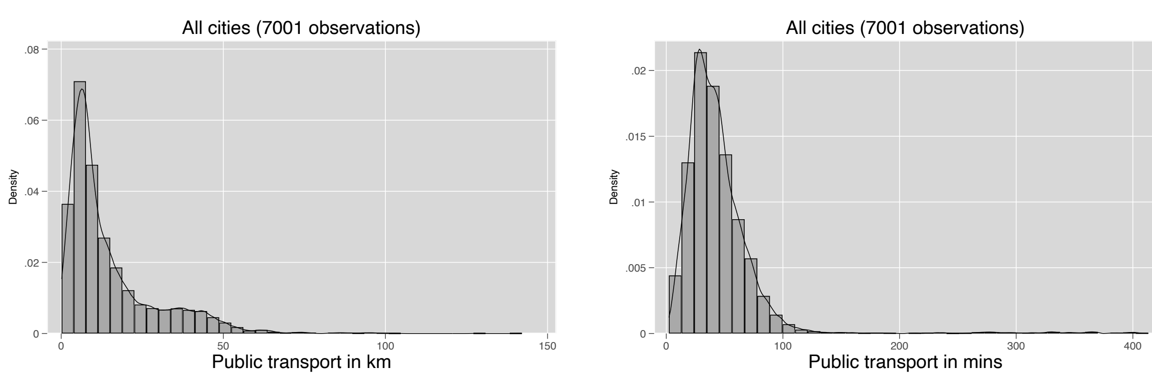
(a) Distance Walking **(b)** Duration Walking



Notes: This figure presents histograms of walking distance and duration for an 8 a.m. Monday trip. The walking distance was calculated based on candidates' home addresses and firm locations listed in job advertisements, using Google Maps. Panel (a) displays the histogram of walking distances in kilometers. Panel (b) shows the histogram of walking durations in minutes.

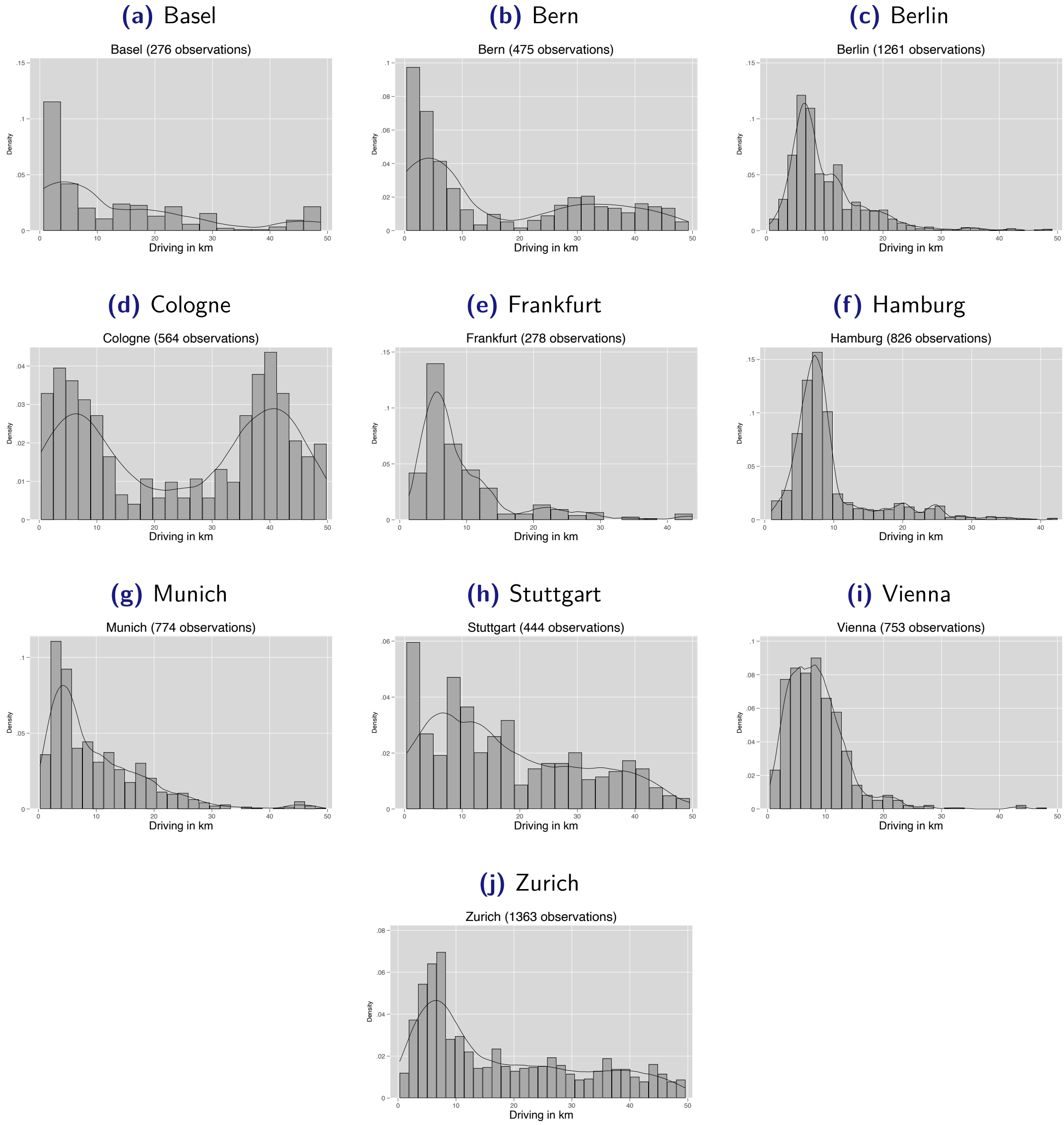
Figure A4: Histograms of Distance and Duration Public Transport

(a) Distance Public Transport **(b)** Duration Public Transport



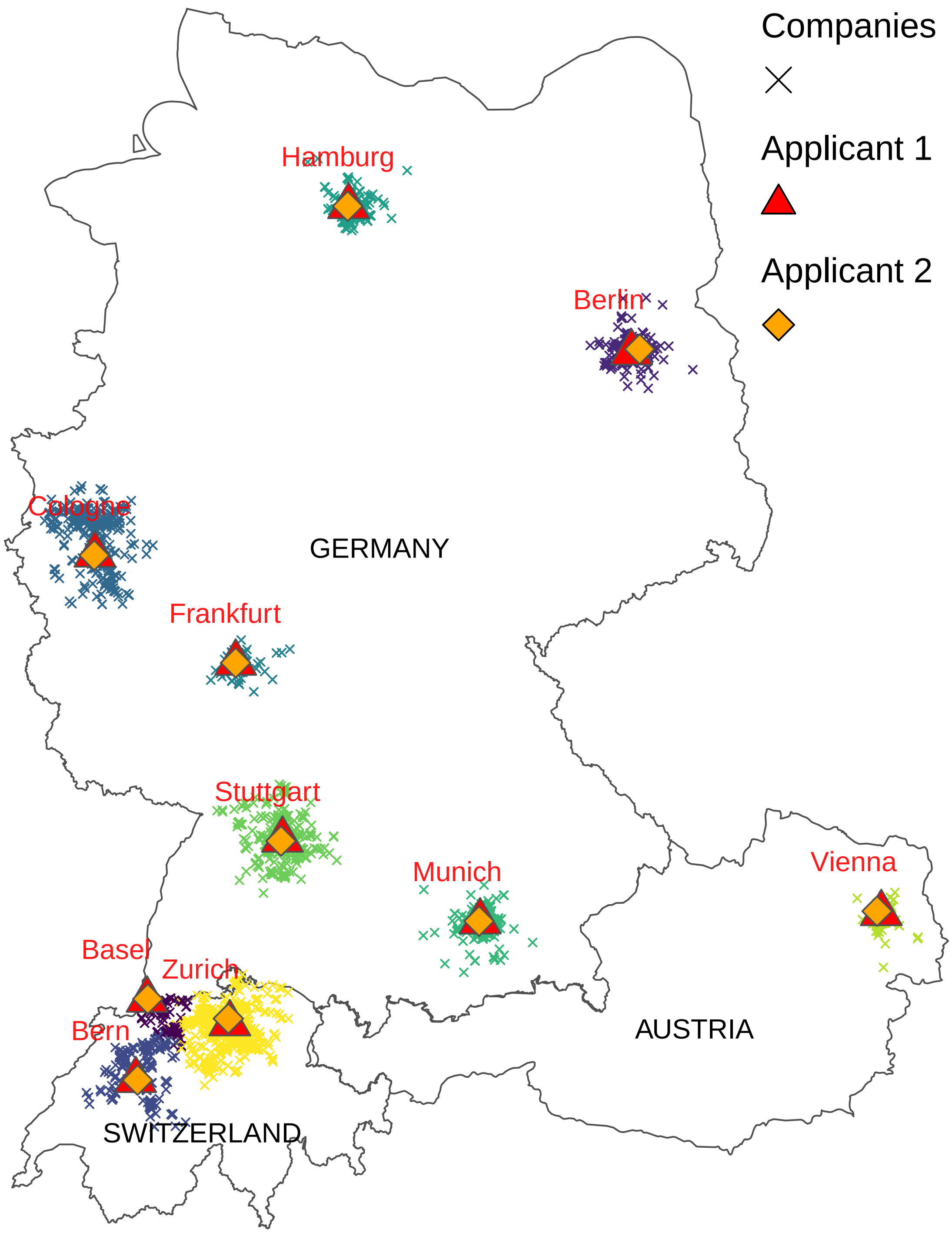
Notes: This figure presents histograms of public transport distance and duration for an 8 a.m. Monday trip. The public transport distance was calculated based on candidates' home addresses and firm locations listed in job advertisements, using Google Maps. Panel (a) displays the histogram of public transport distances in kilometers. Panel (b) shows the histogram of public transport durations in minutes.

Figure A5: Histograms of Commuting Distance: 8am commute, by cities



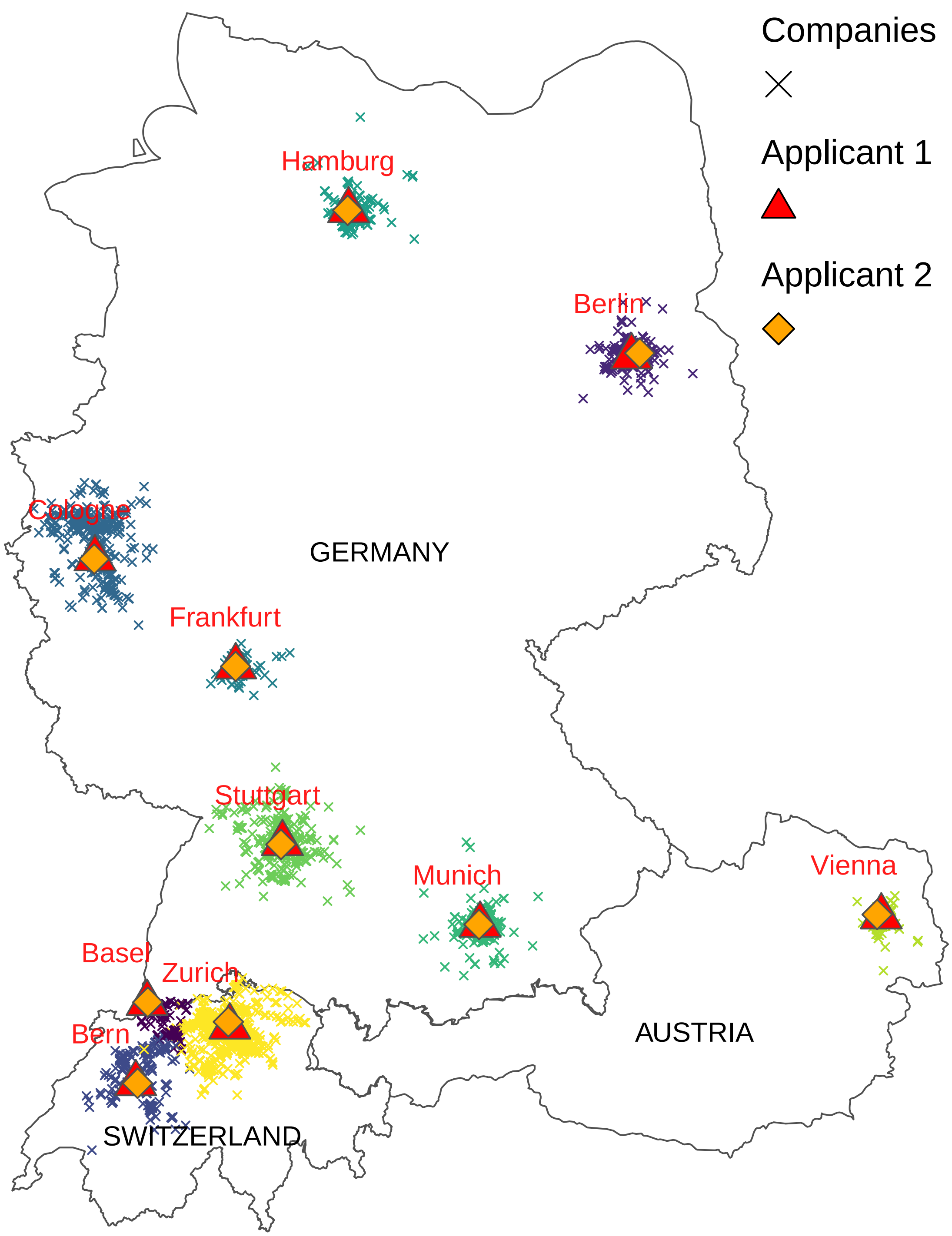
Notes: This figure presents histograms of driving distance for an 8 a.m. Monday trip across various cities. The driving distance was calculated based on candidates' home addresses and firm locations listed in job advertisements, using Google Maps. Panels (a) to (j) display the histograms of driving distances in kilometers for Basel, Bern, Berlin, Cologne, Frankfurt, Hamburg, Munich, Stuttgart, Vienna, and Zurich, respectively. Most cities exhibit a roughly log-normal distribution. However, Cologne has a bimodal distribution, likely due to its location within the Rhein-Ruhr metropolitan area, where firms from nearby cities like Düsseldorf (approximately 40 km away) advertise jobs to applicants in Cologne. Bern, Zurich and Stuttgart are associated with longer commuting distances, possibly due to good local public transportation networks.

Figure A6: Applicants and firms across countries and cities, driving distance ≤75km



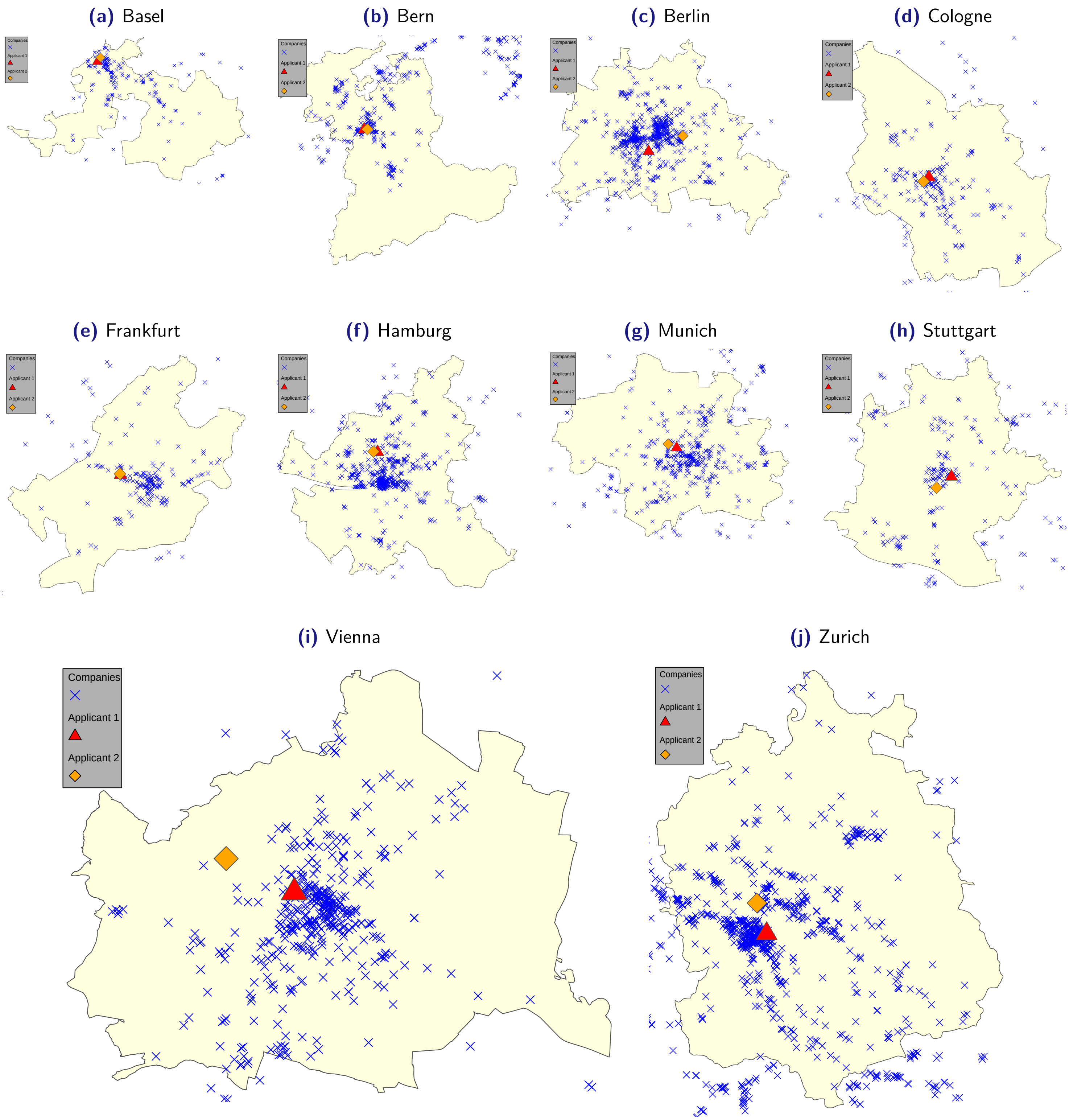
Notes: This map shows the applicant and company addresses for the different cities investigated, up to 75 km. We had our experiment carried out in Basel, Bern and Zurich in Switzerland; Berlin, Cologne, Frankfurt, Hamburg, Munich, and Stuttgart in Germany; and Vienna in Austria. In each city, we have two distinct applicant addresses – one is shown with a red triangle, the other with a yellow diamond. Crosses (in different colors for different cities) show the firm addresses. Table 2 and A7 report the information for commuting distances up to 50km and 100km respectively.

Figure A7: Applicants and firms across countries and cities, driving distance ≤100km



Notes: This map shows the applicant and company addresses for the different cities investigated, up to 100 km. We had our experiment carried out in Basel, Bern and Zurich in Switzerland; Berlin, Cologne, Frankfurt, Hamburg, Munich, and Stuttgart in Germany; and Vienna in Austria. In each city, we have two distinct applicant addresses – one is shown with a red triangle, the other with a yellow diamond. Crosses (in different colors for different cities) show the firm addresses. Table 2 and A6 report the information for commuting distance up to 50km and 75km respectively.

Figure A8: City maps with applicant and firm addresses, by cities



Notes: Applicant and company addresses are reported on this map for each city separately. In each city, we have two distinct applicant addresses. One applicant address is shown with a red triangle, the other with a yellow diamond shape for a given city. Blue crosses show the firm addresses. Shown are all firm addresses with commuting driving distances up to 50km. Panels (a) to (j) display the company and applicant addresses for Basel, Bern, Berlin, Cologne, Frankfurt, Hamburg, Munich, Stuttgart, Vienna, and Zurich, respectively. Tables 2, A6 and A7 report all of these figures on country-level maps of Germany, Switzerland and Austria for up to 50km, 75km and 100km respectively.

Table A1: Interview invitation rates by gender, part-time jobs

	Female		Male	
	Callback Rate (in %)	Obs.	Callback Rate (in %)	Obs.
All types, countries, occupations	20.16	1101	8.17	526
Germany	24.88	434	9.45	275
Switzerland	16.37	568	7.44	215
Austria	21.21	99	2.78	36
Accountant	27.39	533	9.74	308
Secretary	13.38	568	5.96	218
Single No Kids	18.85	244	7.61	92
Married No Kids	14.4	250	7.32	82
Married 2 Young Kids	22.9	214	9.77	133
Married 2 Old Kids	28.85	156	8.45	142
No Info on Family Status	19.41	237	6.49	77

Note: Callback rates represent the percentage of applicants who were invited for an interview in a correspondence testing field experiment conducted between March 2013 and June 2015. Each firm received two applications with identical human capital (work experience and education) and randomized gender and family attributes. Each application package included a cover letter, résumé, reference letter, and educational certificates. Résumé elements such as candidate photo, name, and application template (determining the visual style of the application as well as personal details like birthplace and school attended) were randomized. This table reports results for part-time jobs. Table A2 reports the interview invitation rates for full-time jobs.

Table A2: Interview invitation rates by gender, full-time jobs

	Female		Male	
	Callback Rate (in %)	Obs.	Callback Rate (in %)	Obs.
All types, countries, occupations	20.84	3416	11.47	1961
Germany	22.0	2145	13.1	1290
Switzerland	18.92	893	9.49	432
Austria	18.78	378	6.28	239
Accountant	24.51	1595	16.87	919
Secretary	17.63	1821	6.72	1042
Single No Kids	20.71	758	12.57	334
Married No Kids	21.13	743	9.42	329
Married 2 Young Kids	19.41	577	12.42	475
Married 2 Old Kids	21.35	576	13.11	488
No Info on Family Status	21.39	762	8.66	335

Note: Callback rates represent the percentage of applicants who were invited for an interview in a correspondence testing field experiment conducted between March 2013 and June 2015. Each firm received two applications with identical human capital (work experience and education) and randomized gender and family attributes. Each application package included a cover letter, résumé, reference letter, and educational certificates. Résumé elements such as candidate photo, name, and application template (determining the visual style of the application as well as personal details like birthplace and school attended) were randomized.

B. Additional regression results

Table B1: Probability of interview invitation, part-time

(a) Panel A: Female Applicants

	(1)	(2)	(3)	(4)
Driving distance in km	-0.0045***	-0.0029***	-0.0030***	-0.0034***
	(0.0009)	(0.0010)	(0.0010)	(0.0010)
Married, no kids	-0.0412	-0.0287	-0.0363	-0.0425
	(0.0330)	(0.0328)	(0.0325)	(0.0328)
Married, 2 young kids	0.0441	0.0600	0.0466	0.0388
	(0.0389)	(0.0386)	(0.0385)	(0.0385)
Married, 2 old kids	0.1082**	0.1102**	0.0932**	0.0891**
	(0.0442)	(0.0438)	(0.0436)	(0.0441)
No info on family status	0.0096	0.0094	-0.0029	-0.0122
	(0.0366)	(0.0357)	(0.0358)	(0.0360)
Mean of dependent variable	0.202	0.202	0.202	0.202
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Observations	1097	1097	1097	1097
R-squared	0.032	0.066	0.109	0.120

(b) Panel B: Male Applicants

	(1)	(2)	(3)	(4)
Driving distance in km	0.0000	0.0004	0.0001	0.0013
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Married, no kids	-0.0029	-0.0048	0.0002	-0.0208
	(0.0401)	(0.0407)	(0.0411)	(0.0443)
Married, 2 young kids	0.0217	0.0190	0.0187	0.0152
	(0.0361)	(0.0371)	(0.0369)	(0.0367)
Married, 2 old kids	0.0096	0.0050	0.0013	-0.0017
	(0.0371)	(0.0373)	(0.0370)	(0.0375)
No info on family status	-0.0111	-0.0190	-0.0270	-0.0259
	(0.0396)	(0.0394)	(0.0407)	(0.0423)
Mean of dependent variable	0.082	0.082	0.082	0.082
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Observations	524	524	524	524
R-squared	0.002	0.022	0.044	0.085

Notes: Standard errors (clustered at the company level) in the brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Frankfurt, Hamburg, Stuttgart, Munich, and Vienna, with Bern being the reference city), time (quarter and year sent), application characteristics (template, picture, occupation, application quality), and firm characteristics (size, local/national/international, sector, anti-discrimination policy). Like Becker, Fernandes, and Weichselbaumer (2019) we find that married women with older children have some advantage over other family types in part-time jobs.

Table B2: Probability of interview invitation, full-time

(a) Panel A: Female Applicants

	(1)	(2)	(3)	(4)
Driving distance in km	-0.0024***	-0.0017**	-0.0016**	-0.0013*
	(0.0006)	(0.0007)	(0.0006)	(0.0007)
Married, no kids	0.0049	0.0057	0.0040	0.0014
	(0.0208)	(0.0207)	(0.0205)	(0.0205)
Married, 2 young kids	-0.0178	-0.0165	-0.0203	-0.0220
	(0.0223)	(0.0222)	(0.0221)	(0.0220)
Married, 2 old kids	0.0052	0.0061	0.0115	0.0107
	(0.0230)	(0.0229)	(0.0228)	(0.0227)
No info on family status	0.0063	0.0051	0.0097	0.0092
	(0.0210)	(0.0210)	(0.0211)	(0.0210)
Mean of dependent variable	0.208	0.208	0.208	0.208
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Observations	3405	3405	3405	3405
R-squared	0.006	0.016	0.036	0.040

(b) Panel B: Male Applicants

	(1)	(2)	(3)	(4)
Driving distance in km	-0.0004	-0.0001	-0.0003	0.0000
	(0.0006)	(0.0007)	(0.0007)	(0.0007)
Married, no kids	-0.0314	-0.0310	-0.0262	-0.0269
	(0.0254)	(0.0252)	(0.0248)	(0.0250)
Married, 2 young kids	-0.0013	-0.0045	-0.0012	-0.0014
	(0.0246)	(0.0245)	(0.0242)	(0.0243)
Married, 2 old kids	0.0061	0.0073	0.0138	0.0132
	(0.0242)	(0.0241)	(0.0238)	(0.0238)
No info on family status	-0.0392	-0.0406*	-0.0325	-0.0342
	(0.0247)	(0.0246)	(0.0242)	(0.0241)
Mean of dependent variable	0.115	0.115	0.115	0.115
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Observations	1956	1956	1956	1956
R-squared	0.003	0.014	0.046	0.052

Notes: Standard errors (clustered at the company level) in the brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Frankfurt, Hamburg, Stuttgart, Munich, and Vienna, with Bern being the reference city), time (quarter and year sent), application characteristics (template, picture, occupation, application quality), and firm characteristics (size, local/national/international, sector, anti-discrimination policy).

Table B3: Probability of interview invitation, gender × distance, all applicants

	(1)	(2)	(3)	(4)
Driving distance in km	-0.0003	0.0004	0.0002	0.0004
	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Driving in km × Female	-0.0026***	-0.0025***	-0.0023***	-0.0023***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Female	0.1370***	0.1395***	0.1131***	0.1135***
	(0.0136)	(0.0135)	(0.0159)	(0.0158)
Mean of dependent variable	0.172	0.172	0.172	0.172
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Family types	Yes	Yes	Yes	Yes
Observations	6982	6982	6982	6982
R-squared	0.022	0.032	0.051	0.053

Notes: Standard errors (clustered at the company level) in the brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Frankfurt, Hamburg, Stuttgart, Munich, and Vienna, with Bern being the reference city), time (quarter and year sent), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types.

Table B4: Checking linearity of our results, male applicants

	(1)	(2)	(3)	(4)
5-10 km driving distance	-0.0024	-0.0028	-0.0093	-0.0098
	(0.0174)	(0.0180)	(0.0179)	(0.0180)
10-20 km driving distance	0.0075	0.0111	0.0041	0.0099
	(0.0199)	(0.0204)	(0.0202)	(0.0206)
20-30 km driving distance	-0.0433**	-0.0405*	-0.0521**	-0.0425*
	(0.0213)	(0.0213)	(0.0211)	(0.0217)
30-40 km driving distance	0.0191	0.0389	0.0377	0.0474
	(0.0312)	(0.0326)	(0.0326)	(0.0330)
40-50 km driving distance	-0.0189	-0.0044	-0.0110	0.0045
	(0.0279)	(0.0293)	(0.0287)	(0.0290)
Mean of dependent variable	0.108	0.108	0.108	0.108
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Family types	Yes	Yes	Yes	Yes
Observations	2480	2480	2480	2480
R-squared	0.002	0.014	0.038	0.044

Notes: The commuting distance bin $0 - 5km$ is the reference category. Standard errors (clustered at the company level) in the brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Frankfurt, Hamburg, Stuttgart, Munich, and Vienna, with Bern being the reference city), time (quarter and year sent), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types. The results show that most distance bins do not have a statistically significant impact on callback rates for male applicants, consistent with earlier findings that commuting distance does not significantly affect male applicants' likelihood of receiving a callback. The one exception is the 20-30 km driving distance bin, which shows a statistically significant negative coefficient. The lack of consistent significance across the different distance bins supports the conclusion that commuting distance does not have a linear or systematic impact on male applicants' callback rates.

Table B5: Probability of interview invitation, linearity check with distance[2]

(a) Panel A: Female Applicants

	(1)	(2)	(3)	(4)
Driving distance in km	-0.0040*	-0.0040*	-0.0047**	-0.0044**
	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Driving distance in km^2	0.0000	0.0000	0.0001	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Mean of dependent variable	0.207	0.207	0.207	0.207
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Family types	Yes	Yes	Yes	Yes
Observations	4515	4515	4515	4505
R-squared	0.009	0.021	0.040	0.042

(b) Panel B: Male Applicants

	(1)	(2)	(3)	(4)
Driving distance in km	-0.0009	-0.0009	-0.0012	-0.0016
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Driving distance in km^2	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Mean of dependent variable	0.108	0.108	0.108	0.108
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Family types	Yes	Yes	Yes	Yes
Observations	2487	2487	2487	2483
R-squared	0.003	0.016	0.037	0.040

Notes: Standard errors (clustered at the company level) in the brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Frankfurt, Hamburg, Stuttgart, Munich, and Vienna, with Bern being the reference city), time (quarter and year sent), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types.

Table B6: Probability of interview invitation, by **sector**

(a) Panel A: Female Applicants

	Service	Manufacturing	Trade	Public
Driving distance in km	-0.0019***	-0.0007	-0.0014	-0.0062***
	(0.0007)	(0.0012)	(0.0016)	(0.0022)
Mean of dependent variable	0.215	0.178	0.220	0.177
Applicant, city, time and firm controls	Yes	Yes	Yes	Yes
Family types	Yes	Yes	Yes	Yes
Observations	2835	841	603	226
R-squared	0.043	0.067	0.111	0.187

(b) Panel B: Male Applicants

	Service	Manufacturing	Trade	Public
Driving distance in km	-0.0009	0.0021	-0.0002	0.0036
	(0.0008)	(0.0013)	(0.0015)	(0.0023)
Mean of dependent variable	0.122	0.081	0.086	0.067
Applicant, city, time and firm controls	Yes	Yes	Yes	Yes
Family types	Yes	Yes	Yes	Yes
Observations	1625	452	301	105
R-squared	0.049	0.093	0.198	0.447

Notes: Standard errors (clustered at the company level) in the brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Frankfurt, Hamburg, Stuttgart, Munich, and Vienna, with Bern being the reference city), time (quarter and year sent), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types.

Table B7: Probability of interview invitation, by **sector jackknife**

(a) Panel A: Female Applicants

	No Service	No Manufacturing	No Trade	No Public
Driving distance in km	-0.0018**	-0.0020***	-0.0020***	-0.0017***
	(0.0009)	(0.0006)	(0.0006)	(0.0006)
Mean of dependent variable	0.193	0.213	0.205	0.208
Applicant, city, time and firm controls	Yes	Yes	Yes	Yes
Family types	Yes	Yes	Yes	Yes
Observations	1670	3664	3902	4279
R-squared	0.054	0.045	0.039	0.043

(b) Panel B: Male Applicants

	No Service	No Manufacturing	No Trade	No Public
Driving distance in km	0.0019**	-0.0004	0.0000	-0.0004
	(0.0009)	(0.0007)	(0.0007)	(0.0006)
Mean of dependent variable	0.081	0.113	0.111	0.109
Applicant, city, time and firm controls	Yes	Yes	Yes	Yes
Family types	Yes	Yes	Yes	Yes
Observations	858	2031	2182	2378
R-squared	0.073	0.048	0.036	0.042

Notes: Standard errors (clustered at the company level) in the brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Frankfurt, Hamburg, Stuttgart, Munich, and Vienna, with Bern being the reference city), time (quarter and year sent), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types.

Table B8: Probability of interview invitation, jackknife by **city**

Panel A: Female Applicants

	No Basel	No Zurich	No Berlin	No Frankfurt	No Stuttgart	No Cologne	No Hamburg	No Munich	No Vienna
Driving distance in km	-0.0016***	-0.0019***	-0.0019***	-0.0018***	-0.0019***	-0.0026***	-0.0021***	-0.0016***	-0.0016***
	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0006)
Mean of dependent variable	0.203	0.221	0.202	0.203	0.207	0.214	0.204	0.199	0.209
Applicant, city, time and firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family types	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4327	3547	3718	4331	4218	4159	4001	4028	4028
R-squared	0.040	0.038	0.049	0.039	0.043	0.041	0.047	0.043	0.046

Panel B: Male Applicants

	No Basel	No Zurich	No Berlin	No Frankfurt	No Stuttgart	No Cologne	No Hamburg	No Munich	No Vienna
Driving distance in km	0.0003	0.0001	0.0004	0.0004	0.0004	0.0006	0.0002	0.0003	0.0004
	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0006)
Mean of dependent variable	0.106	0.116	0.101	0.108	0.108	0.109	0.105	0.103	0.114
Applicant, city, time and firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family types	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2391	2090	2011	2381	2326	2265	2162	2186	2208
R-squared	0.043	0.044	0.055	0.044	0.043	0.044	0.043	0.043	0.043

Notes: Standard errors (clustered at the company level) in the brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Frankfurt, Hamburg, Stuttgart, Munich, and Vienna, with Bern being the reference city), time (quarter and year sent), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types.

Table B9: Probability of interview invitation for males, by firm size (employees)

	1-20	21-100	101-500	500+
Driving distance in km	0.0021	-0.0002	0.0002	0.0006
	(0.0015)	(0.0011)	(0.0010)	(0.0014)
Mean of dependent variable	0.093	0.123	0.094	0.117
Applicant, city, time and firm controls	Yes	Yes	Yes	Yes
Family types	Yes	Yes	Yes	Yes
Observations	483	843	694	463
R-squared	0.087	0.087	0.096	0.064

Notes: Standard errors (clustered at the company level) in the brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Frankfurt, Hamburg, Stuttgart, Munich, and Vienna, with Bern being the reference city), time (quarter and year sent), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types.

Table B10: Probability of interview invitation, part-time × distance, male applicants

	(1)	(2)	(3)	(4)
Driving distance in km	-0.0004	-0.0002	-0.0003	0.0001
	(0.0006)	(0.0007)	(0.0007)	(0.0007)
Driving in km × Part-time	0.0004	0.0006	0.0008	0.0008
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Part-time	-0.0391*	-0.0394*	-0.0518**	-0.0536**
	(0.0218)	(0.0217)	(0.0223)	(0.0225)
Mean of dependent variable	0.108	0.108	0.108	0.108
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Family types	Yes	Yes	Yes	Yes
Observations	2480	2480	2480	2480
R-squared	0.005	0.016	0.040	0.047

Notes: Standard errors (clustered at the company level) in the brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Frankfurt, Hamburg, Stuttgart, Munich, and Vienna, with Bern being the reference city), time (quarter and year sent), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types.

Table B11: Distance with family interaction terms, male applicants

	(1)	(2)	(3)	(4)
Driving distance in km	-0.0004	-0.0001	-0.0003	-0.0001
	(0.0015)	(0.0016)	(0.0016)	(0.0016)
Driving distance in km × married, no kids	0.0016	0.0016	0.0015	0.0017
	(0.0021)	(0.0021)	(0.0020)	(0.0020)
Driving distance in km × married, 2 young kids	0.0001	0.0001	0.0003	0.0006
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Driving distance in km × married, 2 old kids	-0.0005	-0.0003	-0.0002	0.0000
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Driving distance in km × no info	-0.0004	-0.0002	-0.0002	-0.0000
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Mean of dependent variable	0.108	0.108	0.108	0.108
City and time controls		Yes	Yes	Yes
Applicant controls			Yes	Yes
Firm controls				Yes
Family types	Yes	Yes	Yes	Yes
Observations	2480	2480	2480	2480
R-squared	0.003	0.014	0.038	0.044

Notes: Standard errors (clustered at the company level) in the brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include city (Basel, Zurich, Berlin, Cologne, Frankfurt, Hamburg, Stuttgart, Munich, and Vienna, with Bern being the reference city), time (quarter and year sent), application characteristics (template, picture, occupation, application quality), firm characteristics (size, local/national/international, sector, anti-discrimination policy), and family types.