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Gender-Specific Application Behaviour, Matching, and the Residual Gender Earnings Gap*

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Abstract

This paper examines how gender-specific application behaviour, firms' hiring practices, and flexibility demands relate to the gender earnings gap, using linked data from the German Job Vacancy Survey and administrative records. Women are less likely than men to apply to high-wage firms with high flexibility requirements, although their hiring chances are similar when they do. We show that compensating differentials for firms' flexibility demands help explain the residual gender earnings gap. Among women, mothers experience the largest earnings penalties relative to men in jobs with high flexibility requirements.

Keywords: Job Search, Application Behaviour, Gender Earnings Gap

JEL Classifications: E24, J16, J31

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1 Introduction

Despite several decades of gender convergence, substantial differences in earnings between men and women persist. Part of this gap can be explained by men and women working in different occupations and sectors (Blau and Kahn, 2017) or in firms with different wage premia (Card et al., 2016; Bruns, 2019). However, even within narrowly defined sectors and occupations, a substantial gender earnings gap remains. A recent strand of literature has analysed the role of gender-specific search behaviour in gender earnings gaps, combining search theory and newly available microeconomic datasets (see, among others, Cortés et al., 2023; Faberman et al., 2017; Fluchtmann et al., 2024). Furthermore, recent studies emphasise the importance of non-wage job characteristics or amenities for labour market outcomes (see, among others, Lamadon et al., 2022; Hall and Mueller, 2018; Taber and Vejlin, 2020; Sorkin, 2017, 2018).

Our paper analyses the interaction between the gender-specific application behaviour of workers, the gender-specific hiring behaviour of firms, employer-side flexibility requirements, and the gender earnings gap. To this end, we exploit detailed application and recruitment data from the German Job Vacancy Survey (JVS), which we link to administrative employment records, both of which are provided by the Institute for Employment Research (IAB). This unique dataset combination allows us to uncover and disentangle important aspects of the search and matching process. Unlike other datasets that only capture realised worker transitions, we observe both workers' application margin and firms' hiring margin, conditional on workers' applications. Along these two margins, the data allow us to capture important characteristics of the hiring firm (e.g., wage premium), the hired worker (e.g., whether a woman is a mother), and the recruitment process itself (e.g., the gender distribution in the applicant pool).¹ We show that men and women apply to very different firms² and different jobs. These differences can explain a significant portion of the residual gender earnings gap. Specifically, using a two-way fixed effects regression approach (Abowd et al., 1999; Card et al., 2013), we show that women in Germany are less likely than men to apply for jobs at firms with high wage premia, even when controlling for occupation, sector, and firm size. Using the same controls, we find, however, that once workers apply, the probability of being hired by these high-wage firms is similar for men and women. At the job level, the share of male applicants³ increases with various employer-side flexibility requirements (such as working irregular hours or at multiple locations). Adding these flexibility requirements or the share of male applicants to standard Mincer earnings regressions leads to a sizeable narrowing of the residual gender earnings gap. Women who match at jobs with a high share

¹To the best of our knowledge, we are the first to use data containing information on the pool of gender-specific applicants for a particular job in a particular firm.

²Although we refer to firms, the IAB data identify plants/establishments, i.e., individual production units. We use these terms interchangeably throughout the paper.

³We residualise the share of male applicants by controlling for occupation, sector, and firm size.

of male applicants earn substantially more than do women at comparable jobs with a more female-dominated applicant pool (netting out worker, firm, and job characteristics). Furthermore, we show that there is an important interaction between employer-side flexibility requirements and motherhood. Women with children face a particularly large wage discount in jobs with high employer-side flexibility requirements.

In the first step of the empirical analysis, we disentangle the hiring process into two distinct components: the application behaviour of workers and, conditional on these applications, the corresponding hiring behaviours of firms. We then examine how these components relate to wages. To this end, we sort different hiring firms according to their Abowd–Kramarz–Margolis (AKM, henceforth) firm wage effects (Abowd et al., 1999; Card et al., 2013). We find that the probability of women applying for a job decreases almost monotonically in the firm wage premium. After accounting for differences in sectors, occupations, and firm size, we find that women have an about 10 percentage point higher probability of applying in the lowest AKM firm wage effect decile and an about 6 percentage point lower probability of applying in the highest AKM firm wage effect decile. Next, we construct two different gender-specific measures to evaluate how firms select hires from the pool of applicants, which we refer to as selection measures. Importantly, after controlling for sector, occupation, and firm size, we find that the selection measures between men and women appear to be indistinguishable. This indicates that, conditional on application, firms do not systematically hire men over women or vice versa. We also explore whether hired women are systematically different from their male counterparts at certain parts of the firm wage premium distribution. When we proxy worker heterogeneity by using worker fixed effects from the AKM wage regression, we observe positive sorting for both men and women, consistent with the assortative matching literature. Across the entire distribution of firm wage premia, women consistently exhibit lower worker fixed effects than men. Notably, the worker fixed effect gap between men and women is larger at high-wage firms compared to low-wage firms. This speaks against the idea that high-wage firms only hire women at the same probability as men if women exhibit higher ability than men, as imperfectly proxied by the worker fixed effect.

In the second step, we show at the job level that the (residualised) share of male applicants increases with respect to various indicators of employer-side flexibility requirements (i.e., longer working hours, changes in working hours, working overtime, and mobility). We construct a composite index of flexibility requirements and observe that, similar to the patterns seen with different firm wage premia, women have a considerably lower probability of applying to jobs with high flexibility requirements, whereas gender-specific selection measures are similar. Furthermore, we show that wages within the same occupation, sector, and firm size category increase with the composite index of flexibility requirements.

In the third step of the empirical analysis, we analyse the role of employer-side flexibility

requirements and application behaviour for the gender pay gap. We estimate Mincer earnings regressions controlling for detailed worker, firm, and job characteristics. We add the flexibility requirements and the share of male applicants for a specific job and find that these measures have significant explanatory power beyond the standard observables. The residual gender earnings gap declines significantly in all our specifications (up to 53%). Additionally, we find that women who match with jobs that have a high share of male applicants earn on average 6.4 percentage points more than comparable women who match with jobs that have a medium share of male applicants. Conversely, women who match with jobs that have only a low share of male applicants earn on average 6.2 percentage points less than comparable women who match with jobs that have a medium share of male applicants.

In addition, we show that the residual gender earnings gap is significantly larger for mothers than for women without children and that there is a strong interaction with flexibility requirements. If mothers match with jobs that require high degrees of flexibility, then they face substantially larger discounts relative to both men and women without children.

In the Appendix, we show that there is a significant interaction among gender, motherhood, and commuting distance. We show that the commuting distance increases with the level of firm fixed effects, starting at a lower level for women and mothers and being less steep than for men.

Finally, we discuss the components that a theoretical model would require to be consistent with our main results. Our primary conclusion is that our empirical facts support an environment where firms offer jobs that differ in a margin beyond just wages, namely non-wage characteristics or (dis)amenities, specifically employer-side flexibility requirements. Additionally, workers would have to have different preferences for these (dis)amenities or gender-specific abilities to meet these employer-side flexibility requirements. In such an environment with two-sided heterogeneity (demand and supply of amenities), employers offer compensating differentials in terms of higher wages for workers who can meet the employer-side requirements.⁴ Women would then be disproportionately sorting into jobs with lower employer-side flexibility requirements (e.g., with less overtime or less business travel) potentially due to their, on average, greater share of childcare and other caregiving responsibilities compared to men. However, women who can satisfy the necessary flexibility may be sorting into higher-paying jobs with more employer-side flexibility demands and then have a similar likelihood of being selected. We also discuss the potential interaction with other amenities.

The remainder of this paper proceeds as follows. Section 2 briefly reviews our contribution to the related literature. Section 3 provides details on the datasets employed. Section 4 provides the empirical results. Section 5 presents the theoretical considerations. Section 6 concludes.

⁴This feature can be found in the works of several authors, including [Rosen \(1986\)](#), [Goldin and Katz \(2011\)](#), [Goldin \(2014\)](#), [Sorkin \(2018\)](#), and [Iacopo and Moser \(2024\)](#).

2 Relation to the Literature

[Card et al. \(2016\)](#) show, for Portugal, that firm wage premia are important for the gender wage gap. For Germany, [Bruns \(2019\)](#) shows that the sorting effect (gender segregation across firms) clearly dominates the bargaining effect (differences in wage premia within the same firm). This finding implies that the primary source of firm wage premium differentials between genders is the underrepresentation of women in high-wage firms.⁵ We complement this literature in several ways. First, we show that gender-specific behaviour in applying to high-wage firms (not firms' selection behaviour) is a key determinant of gender-specific sorting. Second, using the rich information on flexibility requirements (which is absent in typical administrative data), we show the importance of these requirements for application behaviour and gender pay differentials. Finally, according to our results, the sorting channel is key for understanding gender earnings differences. In addition, we show in [Appendix B.1](#) that the observed patterns are equally present for firms that have an organised bargaining regime (collective or firm-level bargaining).

Our findings complement a recent strand of literature that analyses gender wage gaps for specific industries or firms ([Azmat and Ferrer, 2017](#); [Bolotnyy and Emanuel, 2022](#); [Cook et al., 2021](#)). These authors find that once they control for detailed working behaviour (e.g., working longer hours or working night shifts), the gender wage gap decreases considerably. While these studies provide very detailed information on the gender-specific behaviour of workers within certain industries or firms, we have a dataset that represents an entire economy and contains information on application behaviour and flexibility requirements that are typically absent from standard datasets.

Our work is most closely related to another recent strand of literature that analyses gender issues, combining insights from search and matching theory with rich microeconomic data. Using U.S. survey data, [Faberman et al. \(2017\)](#) document the job search behaviours of men and women and the implications for the gender wage gap. Moreover, [Cortés et al. \(2023\)](#) show a substantial difference between men and women in terms of the timing of their job acceptance based on a sample of (former) undergraduate students. [Xiao \(2021\)](#) analyses the gender wage gap from a life cycle perspective and finds that both statistical discrimination based on fertility concerns and different labour force attachments play important roles in explaining the gender wage gap in Finland. While these studies are similar in spirit to our paper, the unique combination of the IAB JVS and its linkages to administrative employment and wage data allows us to shed light on the intertwining of the gender-specific application of workers and the selection behaviour of firms. Specifically, the data allow us to explore the role of job characteristics such as employer-side flexibility requirements while simultaneously

⁵For the sample period 2001-2008, [Bruns \(2019\)](#) shows that the bargaining effect, i.e., differentials in gender-specific wage premia within the firm, is negligible in comparison to the effect of gender segregation across firms with different wage premia.

controlling for important worker and firm characteristics. Due to the cross-sectional nature of our data, we have less to say about the lifecycle component. However, in Appendix B.2, we show that the residual gender earnings gap is particularly large for women who match in their 30s and 40s (when childcare considerations may be most important). In addition, we directly show that mothers face the largest earnings discount among all women in male-dominated jobs. This observation is in line with results by [Illing et al. \(2024\)](#) who show that having children sharply increases the gender gap in earnings losses after displacement. The work of [Fluchtmann et al. \(2024\)](#) is probably closest to our paper: the authors use Danish unemployment insurance recipient data to empirically show that gender differences in application behaviour can explain large parts of the traditional gender wage gap. Those data are very similar to our data. However, we have specific information about the gender distribution of the pool of applicants for each specific recruitment process, together with hiring information of firms and measures of employer-side flexibility requirements. All of this allows us to disentangle important factors of the search and matching process and explore their role for the gender earnings gap.

Our paper contributes to a recent stream of literature that highlights the importance of non-pay-attributes or job amenities (e.g., [Hall and Mueller \(2018\)](#), [Lamadon et al. \(2022\)](#), and [Sorkin \(2018\)](#)). Several papers analyse the role of compensating differentials. For the U.S., [Sorkin \(2018\)](#) shows that compensating differentials can explain approximately two-thirds of the variance in firm-level earnings. [Iacopo and Moser \(2024\)](#) show that compensating differentials can explain a large fraction of the gender wage gap in Brazil. For Denmark, [Taber and Vejlin \(2020\)](#) show that preferences for non-pecuniary aspects are very important for job choices. Our empirical findings are in line with these findings. Compared with men, women have a greater probability of applying for low-wage jobs and of being compensated in terms of low employer-side flexibility requirements. Similarly, [Budig and Hodges \(2010\)](#) show that mothers are more willing than women without children to trade their wages for family-friendly employment.

Based on experimental data, [Wiswall and Zafar \(2017\)](#) show that women have a greater willingness to pay for non-wage job features than men do. In the same vein, [Le Barbanchon et al. \(2020\)](#) analyse gender differences in terms of employees' willingness to commute and show that women in France commute much shorter distances than men do. Based on their search model, the above authors find that 14% of the residualised gender wage gap can be explained by this mechanism. Consistent with these results, we show that in Germany, longer commuting distances are associated with higher firm wage premia and that men, on average, commute longer distances than women do, especially mothers. On average, matches that require longer commuting times can be expected to be disliked by women (particularly those with care responsibilities). When we add commuting distances to our earnings regressions with the proxies for the required flexibility of a job, the gender earnings

gap is further narrowed.

Our paper is also highly relevant from an economic policy perspective. In particular, working from home arrangements during the COVID-19 pandemic provided a laboratory in which to test whether a greater degree of flexibility on the employee side is possible. [Barrero et al. \(2021\)](#) argue that these work-from-home arrangements boosted productivity. To the extent that these arrangements have changed the production process and become permanent, the results of our paper imply that this change will lead to a narrowing of the residual earnings gap, as certain jobs will become increasingly accessible and attractive to women.

3 Data

3.1 Data Sources

We use the IAB JVS ([Kubis et al., 2018](#)) as our primary source of data. The JVS is a representative survey of establishments in Germany from all sectors and includes all establishment size classes, covering up to 14,000 establishments per year. Each year, the survey collects information on the hiring process of German establishments.⁶

An important component of the JVS is an array of questions regarding the recruitment process for the most recent new hire (within the last 12 months).⁷ These questions help the JVS gather information on job characteristics such as formal job requirements, search channels, search duration, exact hiring date, and individual hire attributes, including gender, education, and age. As is crucial for our purposes, the JVS asks for details on the pool of applicants for the most recent hire. Specifically, employers report the number of female and male applicants for each of their reported recruitments. In addition, they report the contractual working hours and specific job-specific flexibility requirements, such as the need to work overtime, short-notice schedule changes, and work-related mobility. From the worker’s perspective, these requirements represent disamenities, as they demand significant flexibility from them.

We complement the JVS data with information from the German social security system. Specifically, we use the method developed by [Lochner \(2019\)](#) to identify establishments’ most recent hires in administrative records, the Integrated Employment Biographies (IEB, [IAB, 2019](#)). The identification is based on overlapping information such as the hiring date

⁶We use the information from the ‘main’ survey, which is conducted every fourth quarter. For a subset of establishments, there are follow-up questionnaires in the following three quarters.

⁷In the JVS, establishments are asked to report the most recent recruitment of one worker. The underlying assumption is that only one worker is recruited from this pool of applicants. This assumption is considered valid since multiple hires are uncommon. Administrative data show that only 3% of hires share the same firm identifier, five-digit occupational code, and calendar starting date as those recorded in the JVS (see [Carrillo-Tudela et al., 2023](#)).

and workers’ age, gender, and occupational code. Using a deterministic matching algorithm, approximately 70% of the most recent hires from the JVS can be found in the administrative records (see [Lochner, 2019](#), p.10). Table 2 in [Lochner \(2019\)](#) shows that the identified JVS hires are similar to new hires in terms of observable worker characteristics.⁸ The IEB encompasses labour market information for the majority of workers in Germany.⁹ Combining the survey data with administrative records allows us to observe workers’ entire employment and earnings history.

In our baseline specifications, we restrict the sample to full-time jobs, which we define as those jobs with more than 25 contractual working hours. In Appendix B.3, we additionally show that all our results are robust when abandoning this restriction and considering part-time jobs.

3.2 Administrative Data Linkages and Imputations

The social security data report the total sum of wages over workers’ employment. These sums are right censored at the contribution assessment ceiling (“Beitragsbemessungsgrenze”), given by the statutory pension fund. We follow [Dustmann et al. \(2009\)](#) and fit a series of Tobit regressions to impute the censored part of the wage distribution.¹⁰

For workers’ educational attainment, we construct a variable from information on both schooling and education in terms of the German vocational system. First, we correct for misreporting and inconsistencies using the procedure proposed by [Fitzenberger et al. \(2006\)](#). We then construct a categorical variable with five distinct values: 1) intermediate school exit certificate without vocational training, 2) intermediate school exit certificate with vocational training, 3) upper secondary school exit certificate without vocational training, 4) upper secondary school exit certificate with vocational training, and 5) college or university degree.

To identify the role of children, we use established proxies for motherhood ([Müller and Strauch, 2017](#)).¹¹ The proxy uses family-related breaks in the employment biographies of women to identify childbirth in the administrative data. For identification, the approach uses either employment notifications (maternity allowance payments by the statutory health insurance provider during paid maternal leave) or detailed process data from the Federal Employment Agency (e.g., withdrawal from the maternity allowance) regarding unemploy-

⁸The algorithm performs several plausibility checks with respect to deviations in the overlapping information. Note that hires with missing information for the key variables are not considered.

⁹The IEB covers approximately 80% of the German working population, excluding civil servants and self-employed individuals (see [IAB, 2019](#)).

¹⁰First, wages are deflated. Then, Tobit regressions are performed separately for East and West Germany and for men and women. All regressions control for age and education categories and all possible interactions. Since the administrative data lack detail on working hours, only the wages of full-time workers can be estimated. However, the share of part-time observations with censored wages is negligibly small.

¹¹The use of administrative data allows us to additionally use a proxy for marriage ([Bächmann et al., 2021](#)). We experimented with this proxy. However, motherhood appears to be a more meaningful variable in the context of our paper.

ment and benefits. Since this procedure is suitable for the administrative data, we can run it on our linked JVS-IEB sample and hence identify mothers among the identified JVS hires.

Additionally, we use the commuting distance of hired workers as a control in our wage regressions. To this end, we approximate the distance by the beeline distance between the center of the municipality of a worker’s main residence and that of his or her workplace.

3.3 Final Sample

For our analysis, we use the JVS from 2010-2016.¹² We then link the administrative data to the survey information. Ultimately, our estimation sample consists of 23,519 distinct new hires for which we have information on the recruitment process, such as the pool of applicants. Furthermore, we can link workers’ full employment history to the new hire data. Table 1 shows the descriptive statistics for our main variables separately for women and men.

Table 1: *Main variables by gender*

	Women		Men	
Individual characteristics	Mean	Std. dev	Mean	Std. dev
Age	35.93	10.76	36.54	10.91
Share with college or university degree*	17.86		14.19	
Experience (years)	8.06	7.47	9.57	8.34
Match characteristics	Mean	Std. dev	Mean	Std. dev
Working hours (contractual)	34.33	7.72	38.79	4.31
Share jobs requiring college degree**	2.83		3.11	
Firm size decile	5.47	2.93	5.43	2.89
Firm wage premium decile	5.32	2.89	5.58	2.84
Log daily earnings	4.11	0.47	4.34	0.44
Log daily earnings if full-time	4.19	0.43	4.36	0.43

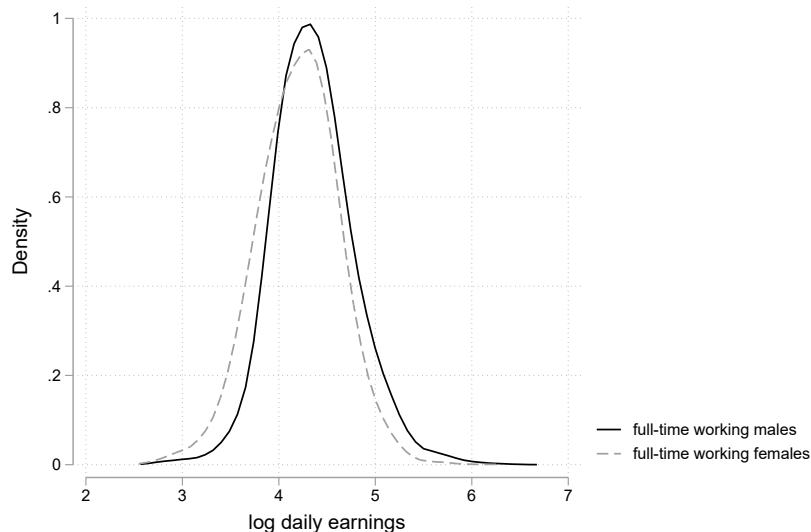
Note: * based on the education variable with five categories: 1) intermediate school exit certificate without vocational training, 2) intermediate school exit certificate with vocational training, 3) upper secondary school exit certificate without vocational training, 4) upper secondary school exit certificate with vocational training, and 5) college or university degree; ** based on four job requirements: 1) unskilled 2) vocational training, and 3) college or university degree. Source: IEB, JVS.

On average, at the time of hire, men are 0.6 years older than the women in our sample. Women are somewhat more educated. On average, men work approximately four hours longer than women do. Men and women are hired in jobs with similar formal education requirements and firm sizes. However, when we consider earnings outcomes, we observe large differences. The unconditional difference in daily hiring earnings averages 23 log points across

¹²For legal reasons, we can link only individual information from the administrative sources to the JVS from 2010 onward.

all jobs in our sample and 17 log points for full-time jobs. Figure 1 shows the distributions of the hiring earnings for women and men in full-time jobs.¹³

Figure 1: *Hiring earnings distribution by gender*



Note: Kernel density estimates for full-time workers using an Epanechnikov kernel with a bandwidth of 0.1. Source: IEB, JVS.

Table 2: *Share of male hires and applicants across occupations*

Occupation in (KldB2010 1-digit)	Total Hires	Male hires (%)	Male applicants (%)
1 Agriculture, forestry, farming, etc.	781	68.12	66.06
2 Production of raw materials, manufacturing etc.	5,154	84.52	82.2
3 Construction, architecture, techn. building services etc.	1,762	91.09	89.34
4 Natural sciences, geography, informatics etc.	956	77.3	75.55
5 Traffic, logistics, etc.	2,149	79.57	76.23
6 Commercial services, trading, sales, hotels, etc.	1,955	40.36	39.97
7 Business organization, accounting, law, etc.	6,052	30.54	34.56
8 Health care, the social sector, teaching, education etc.	3,978	17.77	19.26
9 Philology, humanities, soc. sciences, media, etc.	622	41.64	42.57
Total	23,409	53.59	53.78

Note: Column 2 shows the average share of men among newly hired workers in a given occupation. Column 3 shows the average share of men among applicants for newly filled positions in a given occupation. The shares of female and male applications always sum to one, hence the share of women can be calculated as one minus the share of males. Source: IEB, JVS.

In contrast to most other datasets, the IAB JVS contains information on the pool of applicants for a particular hire. Specifically, firms report the number of male and female applicants for their most recent hire. Hence, we can calculate the share of male/female applications. Table 2 shows the distribution of the share of male applications for different occupations. For example, women are more likely to apply for health care-related occupations than men are, whereas the opposite is the case in occupations related to construction

¹³Even when we restrict the analysis to full-time jobs, the earnings measure reflects both wage and hours variation. Additionally, we observe hiring earnings as those accepted by the workers and earned during their first employment spell in the administrative data.

and architecture. Table A1 in the Appendix shows similarly distinct application patterns across industry sectors. For example, the share of male applicants is much greater in manufacturing than in certain service sectors (e.g., education).¹⁴

4 Empirical Results

4.1 Motivating Framework

To find a job, workers must apply to a particular firm, and they must be selected/hired by the firm. Therefore, the gender-specific probability of being hired for a job (or within a certain labour market segment), $\mu_{p,j}$, is defined as the gender-specific application probability, $\alpha_{p,j}$, multiplied by the gender-specific selection measure, $\eta_{p,j}$ (the probability of being selected by this firm conditional on applying):¹⁵

$$\mu_{p,j} = \alpha_{p,j}\eta_{p,j}, \quad (1)$$

where j denotes the gender (men or women) and p denotes either a specific job profile or a specific segment of the labour market (e.g., firms with different wage premia). We are ultimately interested in whether the gender-specific probabilities of being hired for certain jobs are driven by workers' application or firms' selection behaviour (as defined in Equation 1).¹⁶

Beyond observable factors such as occupation or sector, gender-specific differences in the application and selection behaviour may be related to different combinations of wages and amenities. The latter are usually unobservable in standard datasets.¹⁷ Workers may have distinct preferences for these combinations and adjust their applications accordingly. Their preferences might also be influenced by differences in their ability to meet certain employer-side requirements. Additionally, in theory, workers may form expectations about the likelihood of being hired conditional on application, which further shapes gender-specific application patterns. Firms' selection behaviour may also reflect firm-specific preferences, such as a bias toward a particular gender.

¹⁴In line with the results obtained by [Gomes and Kuhn \(2019\)](#), female application rates are much higher in the public sector than in other economic sectors. The results are available upon request.

¹⁵Importantly, our data allow us to distinctly separate both margins. [Lochner et al. \(2021\)](#), [Chugh and Merkl \(2016\)](#), [Carrillo-Tudela et al. \(2023\)](#), and [Davis et al. \(2013\)](#) analyse the selection and recruiting intensity from a theoretical and empirical perspective.

¹⁶In addition, there may be dependencies on unobserved worker types, T , such that $\mu_{p,j,T} = \alpha_{p,j,T}\eta_{p,j,T}$. For example, if men and women differ in unobserved ability, this may be an additional driver for both the application and selection behaviour. We omit the type index from our baseline equation, as we do not have any proxies for the worker type for the pool of applicants. However, in Section 4.2.3, we will analyse whether type may be driving our results based on worker fixed effects of realised matches.

¹⁷Employers may either offer different amenities because of heterogeneous costs of amenity provision (e.g., [Rosen, 1986](#); [Goldin and Katz, 2011](#)) or because of heterogeneous production functions (e.g., linear vs. non-linear jobs in the spirit of [Goldin, 2014](#)). See Section 5 for a detailed discussion.

In the first part of our empirical analysis, we investigate gender differences in the hiring process. Specifically, we explore the gender-specific application behaviour of workers and the selection behaviour of firms with different wage premia. In the second part of our empirical analysis, we investigate how the gender-specific application and selection behaviour interact with employer-side flexibility requirements. In the third step, we analyse whether and how the application behaviour and employer-side flexibility requirements matter for the gender earnings gap and how they interact with motherhood.

4.2 Application, Selection, and Firm Wage Premia

4.2.1 Gender-Specific Application Patterns

We start by investigating the application behaviour of men and women. For this purpose, we utilise the applicant pool information from the IAB JVS, which provides the gender composition of applicants for various jobs, i.e., the number of male and female applicants, but does not include other applicant characteristics.

We analyse gender-specific application behaviour across firm fixed effects through two-way fixed effects regressions, following the methodology described in AKM and [Card et al. \(2013\)](#). Specifically, we run the following wage regression on the universe of German administrative data for 2010-2017: $y_{it} = \gamma_i + \psi_{J(i,t)} + x'_{it}\beta + r_{it}$, where y_{it} represents worker i 's log real daily wage in year t . We assume that y_{it} is an additive separable function of the time-invariant worker fixed effect, γ_i , the firm fixed effect of firm J , $\psi_{J(i,t)}$, an index of time-varying observable characteristics, $x'_{it}\beta$, and an error component, r_{it} .¹⁸ By including both men and women in the regression, we obtain gender-pooled firm effects, thus limiting gender wage gaps to differences across firms. Additional results from gender-specific firm fixed effects are provided in [Appendix B.4](#).

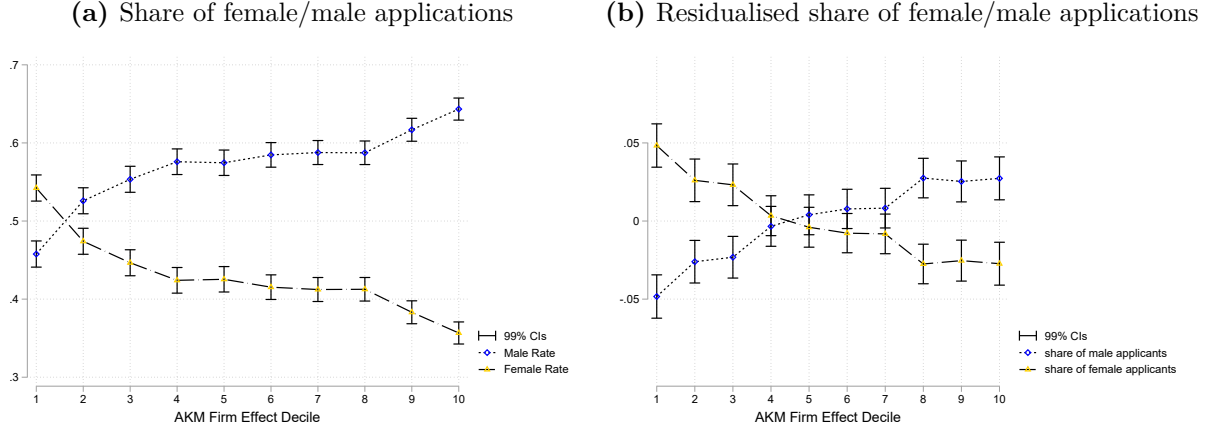
Panel (a) of [Figure 2](#) shows the share of male and female applicants for firms ranked by AKM firm fixed effect deciles from those with the largest average discount (left) to the largest premium (right), corresponding to $\alpha_{p,j}$ in [Equation \(1\)](#). In the highest decile, male applicants exceeds female applicants by over 25 percentage points, while in the lowest decile, female applicants exceed male applicants by about 9 percentage points.

A sizeable part of these patterns is attributable to women and men applying to different sectors and occupations, as is visible in [Tables 2](#) and [A1](#). To account for this, we control for occupation, industry, and firm size in Panel (b) of [Figure 2](#). One striking insight is that despite these detailed controls, a substantial gender gap in application behaviour remains. Specifically, men are approximately 6 percentage points more likely to apply to the highest-

¹⁸The function $J_{i,t}$ identifies the unique establishment employing worker i in year t . We include an unrestricted set of year dummies as well as quadratic and cubic terms in age fully interacted with educational attainment in x'_{it} . We normalise the age variable around 40 years. See [Bellmann et al. \(2020\)](#) and [Lochner et al. \(2020\)](#) for details.

paying firms, whereas women are approximately 10 percentage points more likely to apply to the lowest-paying firms.

Figure 2: *Application rates by gender and AKM firm effect deciles*



Note: Full-time jobs only. The variables are defined as the number of gender-specific applicants divided by the number of overall applicants at the firm level. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

In the Appendix, we demonstrate that the pattern of higher female application rates at low-paying firms and lower female application rates at high-paying firms is highly robust. The results are consistent under various wage formation regimes (see Appendix B.1), when the full-time restriction is removed (see Figure B4 in Appendix B.3), when estimating firm fixed effects separately for men and women (see Appendix B.4), and across different task complexity groups (see Appendix B.5).

In summary, we observe substantial differences in application behaviour between men and women. After analysing the gender-specific selection behaviour of firms in the next subsection, we will explore the potential reasons for the application differences and examine their implications for the gender earnings gap.

4.2.2 Gender-Specific Selection Patterns

At the second stage of the matching process, applicants need to be hired by firms, i.e., they need to be selected conditional on having applied. To analyse this stage, we define two selection measures at two different levels of aggregation.

Our first gender-specific selection measure is defined *at the job level*, utilising information on the most recent hire. We are ultimately interested in disentangling the gender-specific probabilities of being hired for certain jobs, which may either be driven by application or selection behaviour. Therefore, we define the gender-specific selection measure at the job-level as follows:

$$\eta_{p,j} = I(h_{p,j} = j) / \alpha_{p,j}, \quad (2)$$

where $I(h_{p,j})$ is an indicator variable equal to one if a man (woman) is hired and zero otherwise. $\alpha_{p,j}$ is the share of male (female) applicants.

To be more precise: If a woman (man) is hired, then the female (male) selection measure is one over the share of female (male) applicants and zero for the gender that is not hired. Let us assume that a firm has ten applicants, five women and five men. Furthermore, assume that a woman is hired. In this case, the selection measure for women would be 2. If a firm has 100 applicants, five women and 95 men and a man is hired, the selection measure for women would be 20.

This first selection measure has the advantage in its job-level definition, which enables us to observe variations across establishments within wage premium deciles. Another advantage is that it accounts for the exact gender composition of the application pool.¹⁹ Based on this, larger values correspond to a higher probability of being selected for the average man or woman. The job-level selection measure, though not immediately intuitive, follows the logic of Equation (1), where according to the job-specific definition a realised match is associated with a 100% hiring probability for one gender and 0% for the other gender.²⁰

To complement the job-level measure, we define an alternative selection measure *at the firm wage premium decile level* that compares how the hiring pool differs from the application pool at different firm fixed effects deciles. Specifically, we define the second selection measure as the ratio of the share of gender-specific hires within an AKM firm effect decile to the share of gender-specific applicants within the same decile. For men, this measure is

$$\eta_{p,men} = \frac{\sum_p Hires_{men}}{\sum_p (Hires_{men} + Hires_{women})} / \frac{\sum_p Applications_{men}}{\sum_p (Applications_{men} + Applications_{women})} \quad (3)$$

Intuitively, this measure indicates how the gender-specific hire share differs from the gender-specific application share in a given decile, revealing how firms select men and women given the gender composition of applicants. If firms are equally selective toward men and women in a given decile of the wage premium distribution, then this measure is equal to 1 for both men and women.²¹ In this case, they have the same probability of being selected from the pool of applicants (i.e., the selection measure has a slightly different interpretation than in the job-level variant).²²

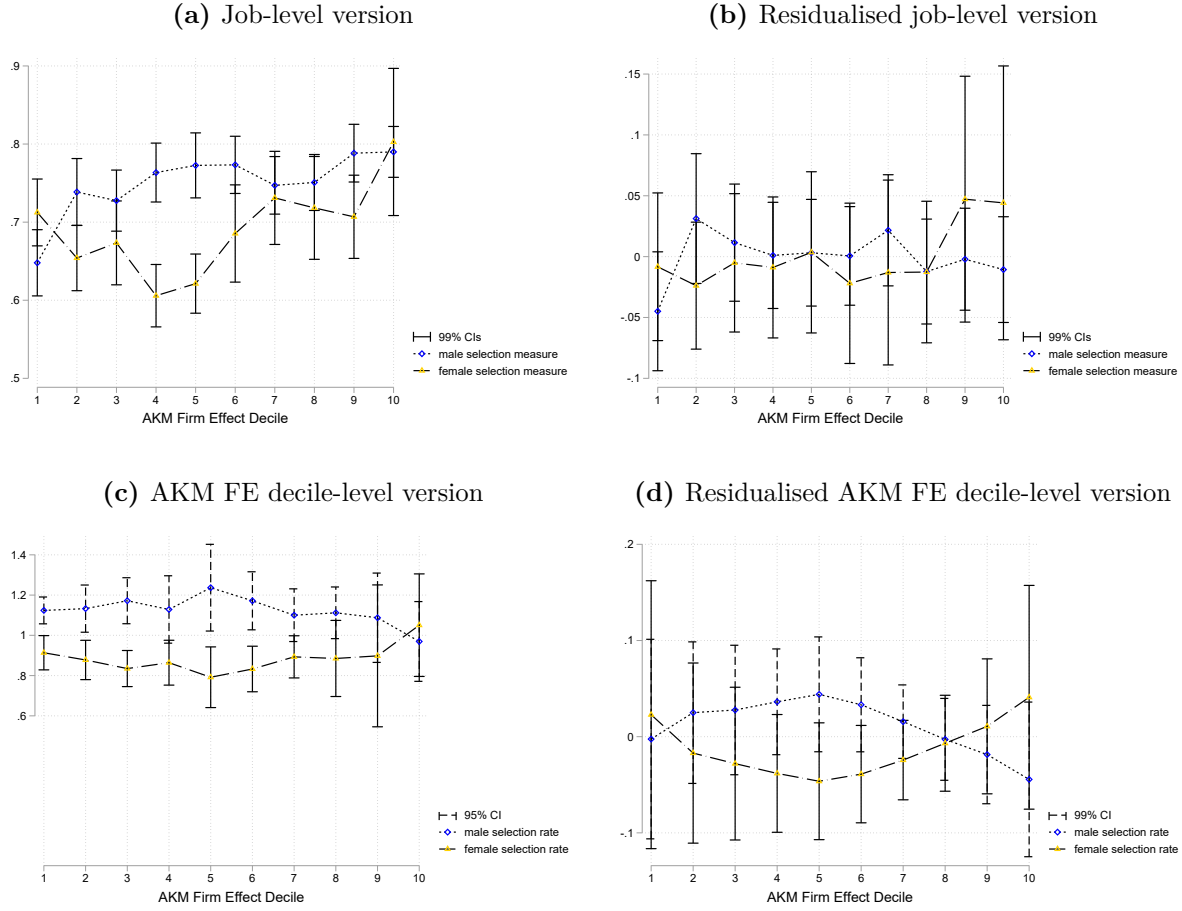
¹⁹We thank an anonymous referee for highlighting this point.

²⁰In a prior version of this paper, we defined the selection rate as the probability of one man or one woman (instead of men or women on average) to be either selected from the gender-specific pool of applicants (or the pool in general). This measure was in line with propositions by [Hochmuth et al. \(2021\)](#) and [Lochner et al. \(2021\)](#). Interestingly, with all of these measures, we find no differences in the residual gender-specific selection measures. See Appendix B.6 for details.

²¹This would not be the case for the limiting case of zero applicants from a specific gender, for which the measure is not defined. However, we do not encounter this limiting case at the decile level.

²²At the decile level, the probability of finding a job is also defined by Equation (1). Note that we have to define the gender-specific application rate in a slightly different manner for this purpose. The share of male applicants is the sum of gender-specific applicants divided by overall applicants in a decile (not the

Figure 3: Selection measures by gender and AKM firm effect deciles



Note: Full-time jobs only. The variables are defined as follows: a) and b) male selection rate= $1/\text{share of male appl. if a man is hired}$ and in this case, the female selection rate equals zero, and the female selection rate= $1/\text{share of female applicants if a woman is hired}$, and in this case, the male selection rate equals zero. c) and d), see Equation (3). Standard errors in c) and d) are bootstrapped (with replacement, 100 replications). Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

Figure 3 displays the two selection measures across the firm wage premium distribution. Panels (a) and (c) indicate that, without controls, the selection measures are somewhat higher for men in certain parts of the firm wage premium distribution. The selection measure is somewhat larger for men than women in the middle of the firm fixed effects distribution. Interestingly, the gender-specific point estimates are much closer to one another at the top deciles of the firm wage premium distribution and confidence bands overlap. However, after controlling for industry, firm size, and occupation (panels b and d), the differences in selection measures become both economically small and statistically insignificant.²³ This finding indicates that when women apply to firms with a high firm-wage premium, they have approximately the same probability of being selected as men, given the same occupation, sector, and firm size category.

In the Appendix, we demonstrate that the indistinguishable residualised selection measures for men and women across different AKM deciles are very robust. Our results also hold under different wage formation regimes (Appendix B.1), when the full-time restriction is relaxed (Figure B4 in Appendix B.3), when firm fixed effects are estimated separately for men and women (Appendix B.4), and within various task complexity groups (Appendix B.5). In addition, Appendix B.6 shows that our findings are consistent across five other selection measures.

In summary, comparing workers' application behaviour with firms' selection behaviour reveals notable differences. After controlling for observables, significant differences remain in gender-specific application rates, while no meaningful differences persist in selection measures. This finding suggests that the sorting of men and women into firms with different wage premia is driven primarily by gender-specific application behaviour.

4.2.3 Worker-Firm Sorting

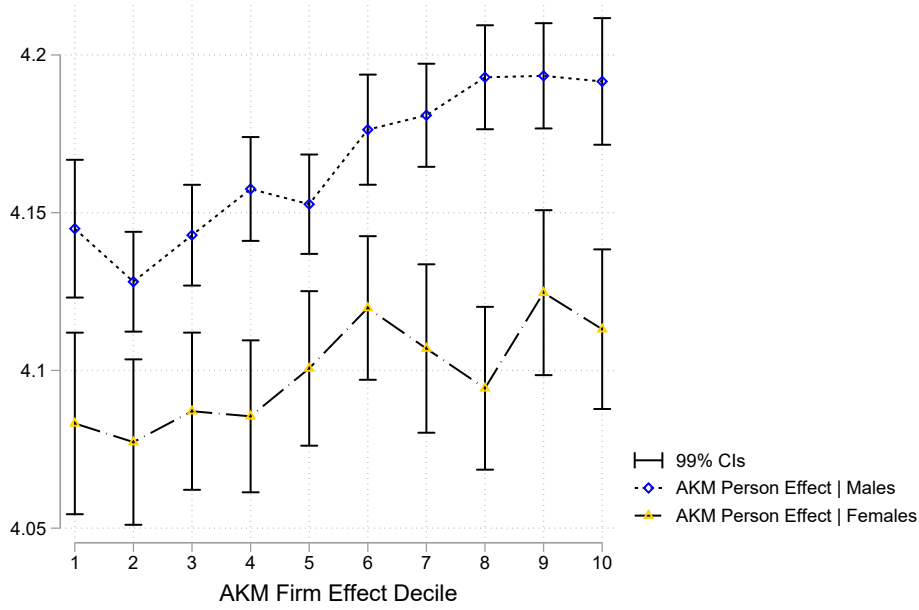
We have established that men are more likely than women to apply to high-wage firms, while firms select both genders roughly equally. Next, we analyse whether men and women who match at different wage premia differ considerably, as this may affect the selection behaviour. If only women with higher ability than men apply to high-wage firms, the similar selection behaviour of firms could mask gender bias. To this end, we make use of workers' estimated person fixed effects from the AKM wage regression. These fixed effects are often interpreted as a combination of (time-invariant) skills and other factors that are rewarded equally across employers (see Card et al., 2013).²⁴

firm-specific ratio aggregated). As the results are very similar, they are available on request. Multiplying these two probabilities gives the gender-specific hiring probability, e.g., male hires divided by overall hires.

²³Due to the cross-sectional nature of our data, we construct the second selection measure on the firm wage premium decile level. In this case, we bootstrap standard errors with replacement and 100 replications.

²⁴Worker fixed effects are an imperfect proxy for worker ability as they may capture all unobserved time-invariant factors, including preferences for non-wage amenities.

Figure 4: *Worker and firm fixed effects*



Note: This figure shows the residualised average worker fixed effects for matches within different firm fixed effect deciles. Full-time jobs only. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

Figure 4 shows how the AKM person fixed effects of new hires are allocated across the corresponding firm fixed effect distribution.²⁵ We observe that workers who match with high-wage firms tend to have higher worker fixed effects. This finding is in line with the positive assortative matching literature.²⁶ We find that the estimated person fixed effects are greater for men than for women across the entire firm fixed effect distribution. The average difference amounts to 6.2 percentage points at the lowest deciles and 7.9 at the highest decile. This speaks against the idea that high-wage firms only hire women at the same probability as men if women exhibit higher ability than men, though non-measured quality differences may still exist. Women appear to be less sorted into high-wage firms based on their wage fixed effects. However, as we demonstrate in the following sections, there is a clear pattern of women sorting more strongly toward non-wage characteristics, namely employer-side flexibility requirements.

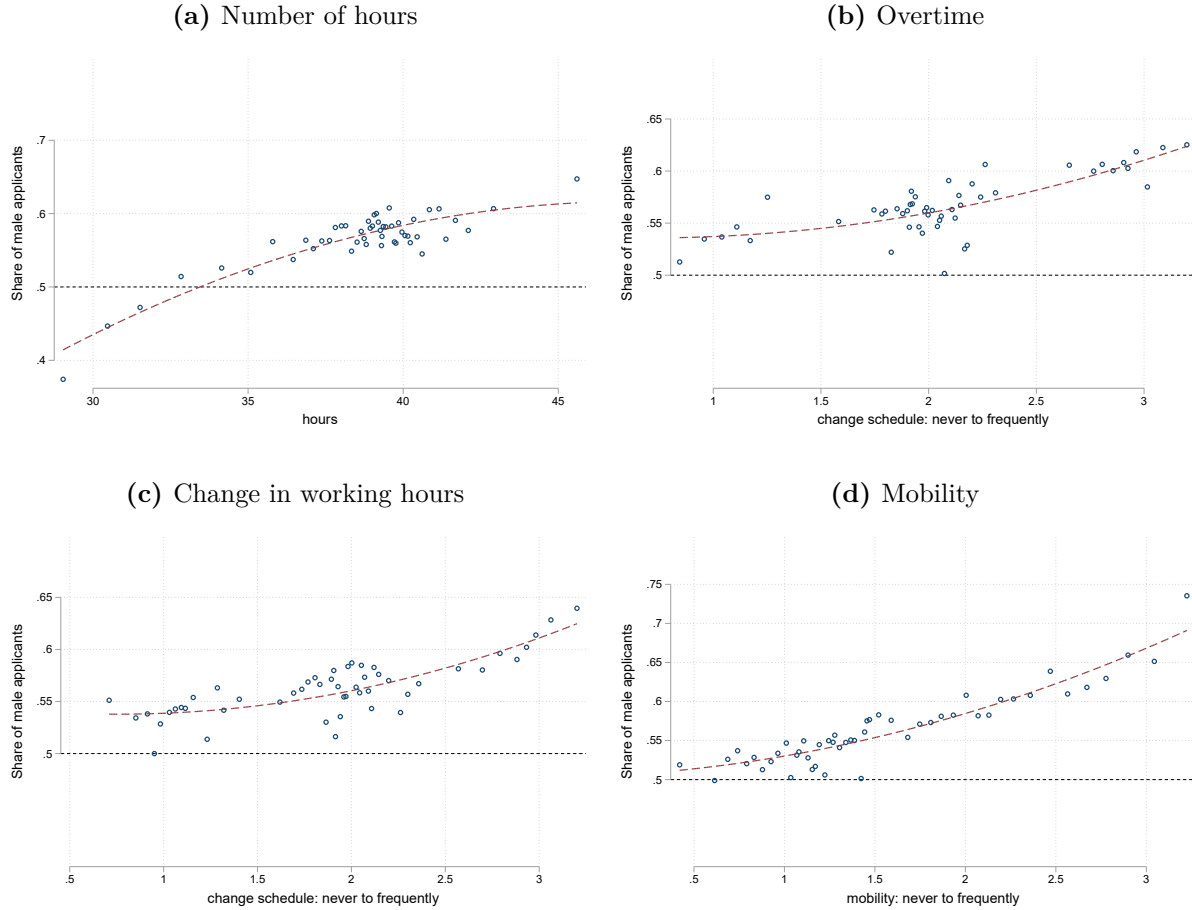
²⁵As our data are a cross-section of hires, we cannot directly estimate person fixed effects. However, we can use the person fixed effects estimated in the universe of German administrative data and link them to our cross-section. Note that we observe only the AKM person fixed effect of the actual match but not that for the entire pool of applicants. Figure B6 in the Appendix shows the corresponding plot when the full-time restriction is dropped.

²⁶For Germany, see [Lochner and Schulz \(2024\)](#) for a discussion. These authors also discuss why the wages at the very top of firm rankings are somewhat lower than those lower in the rankings.

4.3 Applications, Selection, and Employer-Side Flexibility Requirements

A notable feature of the JVS data is that it provides direct observations of several measures related to employer-side flexibility requirements. These data, which are available at the individual job level, allow for the study of correlations between these measures and workers' application behaviours within specific occupations, sectors, and firm size categories.

Figure 5: *Share of male applicants and flexibility requirements*

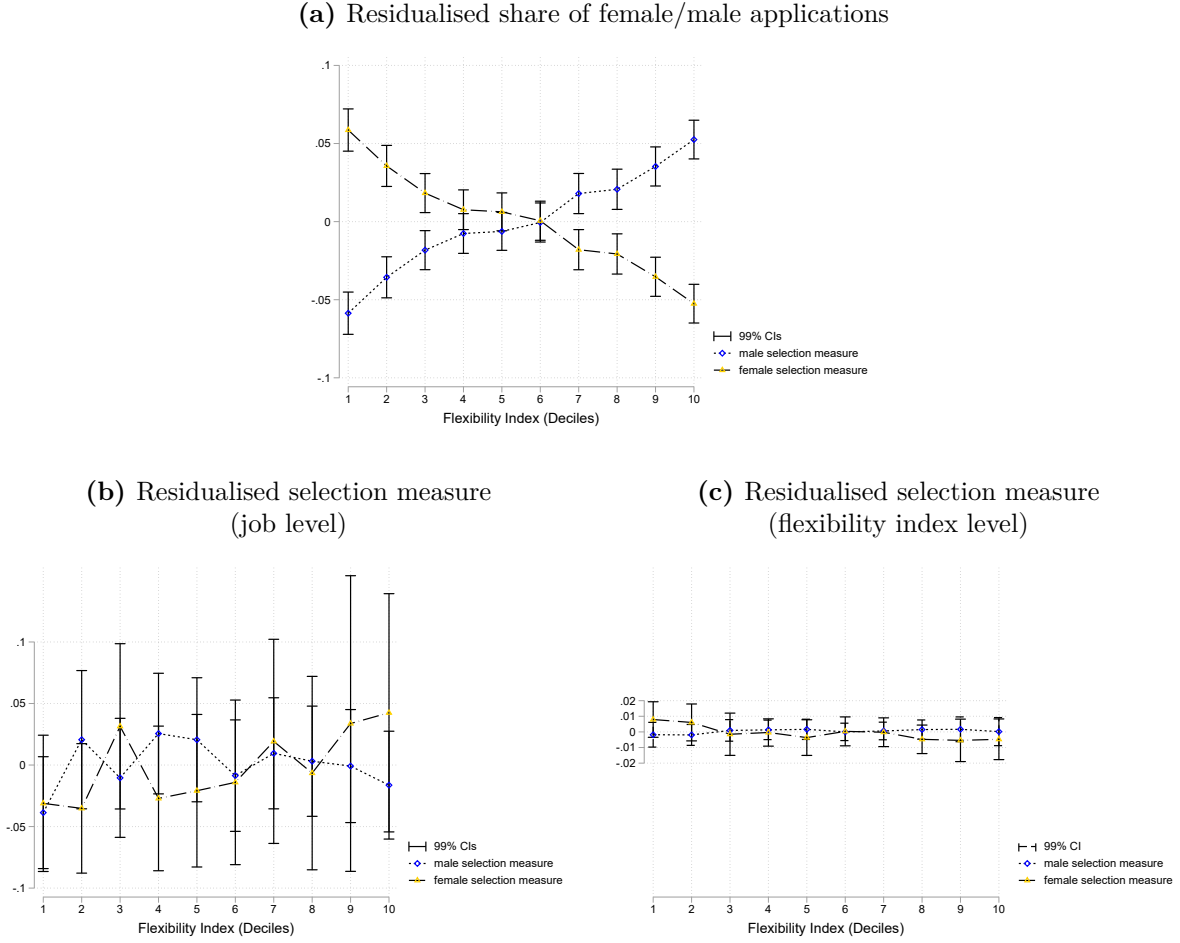


Note: These figures show binned scatterplots with 50 bins and quadratic fit lines. To residualise the x and y variables, we regress each variable on the controls, generate the residuals, and add the sample mean of each variable back to its residuals. We then group the x-axis variable into equal-sized bins, compute the means of the x- and y-axis variables within each bin, and create a scatterplot of these data points. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits); full-time jobs only. Source: IEB, JVS.

We use four job-specific flexibility requirements from the IAB JVS: the number of hours worked, the requirement to work overtime, the need to change working hours on short notice, and the necessity for workplace mobility (e.g., business travel).²⁷ In Figure 5, we plot these four employer-side flexibility requirements against the residualised share of male applicants.

²⁷Employers provide responses on whether a particular job is subject to these flexibility requirements, with possible answers being “often,” “rarely,” or “never.” Though we examine additional survey questions, these four dimensions seem to best represent the flexibility requirements. We remove observations that exceed the 99.9% percentile in hours.

Figure 6: Application rates and selection measures by gender and flexibility requirement index



Note: Full-time jobs only. The variables are defined as follows: a) share of male appl.=number of male appl./number of all appl., share of female appl.=number of female appl./number of all appl., b) see Equation (2), c) see Equation (3). Standard errors in c) are bootstrapped (with replacement, 100 replications). Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

All four flexibility requirements co-move positively with the share of male applicants for these particular jobs. Thus, these figures show that higher employer-side flexibility requirements are associated with a larger share of male applicants.²⁸ Figure B5 shows these plots without the full-time restriction.

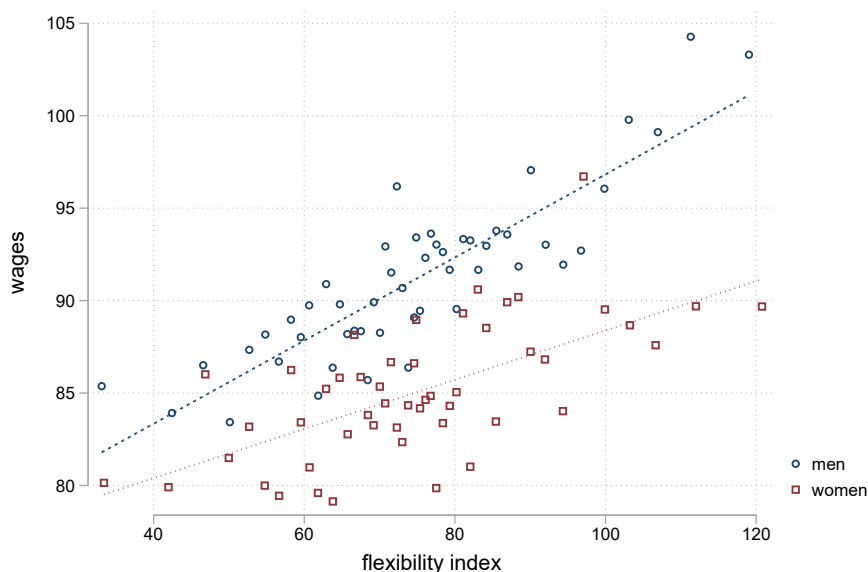
Next, we construct a composite employer-side flexibility requirement index. This index is defined as the number of working hours multiplied by the average of the three used flexibility requirement observed at the job level. Specifically, it accounts for required overtime, changes in working hours, and workplace mobility, with each measure ranging from 1 (never required) to 3 (often required).²⁹

²⁸The observed patterns might be influenced by differences in the overall number of applications submitted by men and women. However, in the IAB PASS worker survey, we find very small and statistically insignificant gender differences in the number of applications (results available on request); this suggests that such differences should not substantially bias our results.

²⁹We first winsorise the composite index at the first and ninety-ninth percentiles and then create deciles. See Figure A1 for distributional properties.

Analogous to our approach in Sections 4.2.1 and 4.2.2, we analyse how the flexibility requirement index interacts with workers' application behaviour and firms' selection behaviour. Panel a) of Figure 6 shows that gender differences in application behaviour are more pronounced for firms with different flexibility requirements than for those with different firm fixed effects (see Figure 2 for comparison). The application share difference is approximately 6 percentage points at the highest-paying firm decile, whereas it is 11 percentage points at the decile with the highest flexibility requirements. Panels b) and c) show no significant gender differences in residualised selection measures, regardless of the selection measure used.³⁰

Figure 7: *Wages and flexibility requirement index*



Note: Dependent variable: imputed daily earnings. Independent variables: total number of applicants, worker age fully interacted with education attainment (measured by five categories), experience in years and its squared term, an indicator variable for the previous labour market status (non-employed, unemployed, or employed), formal job requirements (four categories), year dummies, a full set of dummies for industries, occupations, and establishment size categories. Estimates for full-time workers aged 20-60. Source: IEB, JVS.

Finally, we analyse the relationship between flexibility requirements and wages at the job level. Figure 7 shows that, on average, employers pay higher wages for jobs with greater flexibility requirements. The widening differences between the fitted lines indicate that the relationship between the flexibility index and wages appears to be stronger for men compared to women, controlling for both individual worker and job characteristics.

In reality, flexibility requirements are multidimensional. Although the survey questions in the IAB JVS provide more detail on this dimension than many other surveys do, we believe that employer-side flexibility requirements can only be partially captured.³¹

³⁰We apply Equation (3) to the flexibility index decile instead of the AKM firm effect decile.

³¹This concept aligns with Goldin (2014, p. 1104): "By job flexibility, I mean a multitude of temporal

4.4 Wages and Flexibility Requirements

We analyse the role of flexibility requirements and the gender-specific application behaviour for wages. We start by looking at their role for the residual gender-earnings gaps. Next, we look at the interaction of flexibility requirements and gender-specific applications behaviour with motherhood.

4.4.1 Residual Gender Earnings Gap and Applications

We start by estimating a standard wage regression and then add directly measured employer-side flexibility requirements. Given the strong connection between observed flexibility requirements and the share of male applicants, we also estimate a specification where we add employer-side flexibility requirements or the share of male applicants as an additional explanatory variable. We view it as a general proxy for application behaviour, which is likely to capture other unmeasured multidimensional flexibility requirements.

Our benchmark Mincer-type regression is as follows:

$$\log wage_{i,t} = \alpha gender_{i,t} + \nu controls_{i,t} + error_{i,t}, \quad (4)$$

where i is the recruitment from the cross-sectional JVS in year t (2010 to 2016). We include a dummy for female hires (with male hires serving as the reference group), and α measures the residual gender earnings gap. The novel link between establishment survey data and high-quality administrative employment records allows us to control for a rich set of observables. The set of *controls* includes the total number of applicants, worker age fully interacted with educational attainment (measured by five categories), experience in years and its squared term, an indicator variable for previous labour market status (non-employed, unemployed, or employed), formal job requirements (four categories), year dummies, a full set of dummies for industries, occupations, and establishment size deciles. Recall that we observe new hires. Hence, we estimate the gap in hiring earnings without potential gender-specific tenure or promotion effects.

To assess the role of flexibility requirements and gender-specific application behaviour, we directly add i) the flexibility requirements and ii) the share of male applicants to Equation (4). In most other datasets, both job-specific flexibility requirements and application rates are absent. By adding these variables, we can assess how much of the residual gender earnings gap is due to omitted variable bias.

Table 3 shows the results of estimating Equation (4). The initial gender earnings gap for full-time jobs amounts to approximately 16%, which is on the same order of magnitude as that in the literature using IAB data for Germany (see, for example, [Fuchs et al., 2019](#)).

matters, including the number of hours, precise times, predictability, and the ability to schedule one's own hours."

Table 3: *Gender earnings gap*

	Coef.	Std. error	% Reduction	R^2	Obs.
Initial residual earnings gap	-0.163	0.007		0.59	13,991
+ Working hours (contractual)	-0.145	0.007	-11.04	0.6	13,991
+ Job mobility, overtime, change schedule	-0.132	0.008	-19.02	0.61	13,991
+ Distance residence-workplace	-0.122	0.006	-25.15	0.68	13,991
+ Flexibility requirement index	-0.138	0.007	-15.34	0.6	13,991
+ Distance residence-workplace	-0.119	0.007	-26.99	0.67	13,991
Initial residual earnings gap	-0.166	0.007		0.59	12,755
+ Share of male applicants	-0.078	0.009	-53.01	0.6	12,755

Notes: This distance is approximated by the beeline distance between the district of a worker’s main residence and workplace. Robust standard errors. Estimates for full-time workers aged 20-60. Source: IEB, JVS.

Adding contractual working hours to the regression narrows the gender gap by 11%. Further adding the other flexibility requirements (indicators for the need for job mobility, overtime, and a change in working schedule) shrinks the gap by 19% in total. Another variable that is known to be an indicator of worker preference for providing flexibility is commuting distance (see [Le Barbanchon et al., 2020](#)). Adding commuting distance leads to a total reduction in the residual gender earnings gap of roughly 25%. Adding the composite flexibility requirement index instead of each separate requirement also narrows the earnings gap, although at a slightly smaller magnitude.

The last block of Table 3 shows the reduction in the initial gender earnings gap when the share of male applicants is added to the regression. Given that we observe similar gender-specific selection measures across all AKM firm fixed effect deciles, the application rate appears to be a primary factor influencing pay differences. We consider the share of male applicants as a general proxy for gender-specific application behaviour, as it may also reflect job heterogeneity that may not be captured by our rich set of observables. We observe that the earnings gap narrows substantially, by more than 50%.³²

Table 3 indicates that the share of male applicants plays a significant role in explaining the gender earnings gap. Next, we examine whether the gender composition of the application pool has heterogeneous effects on wages within each gender, as already indicated by Figure 7. Specifically, we investigate whether men or women experience an earnings boost when hired for jobs with male-dominated application pools. To do this, we construct categorical variables for the share of male applicants and regress log earnings on these variables interacted with gender and controls.

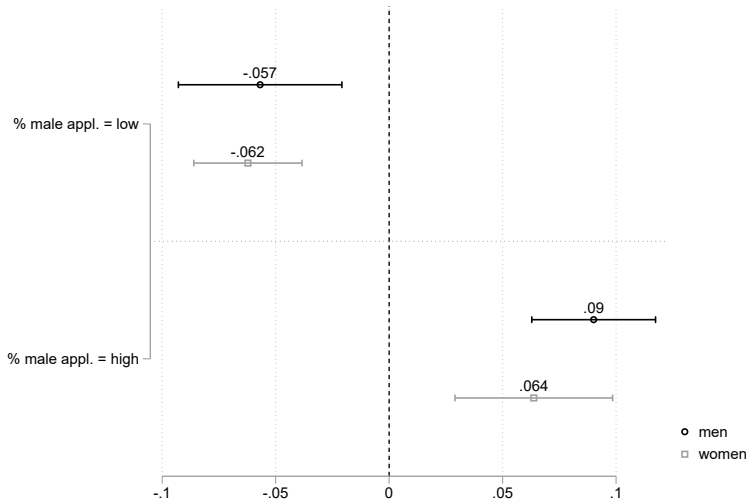
Figure 8 illustrates the marginal effects of the share of male applicants (categorised) on earnings by gender. Men matched with jobs featuring a low share of male applicants earn 5.7 percentage points less than those matched with jobs with a medium share. Similarly, women

³²Table B1 in the Appendix shows the corresponding table after dropping the full-time restriction.

in jobs with a low share of male applicants earn 6.2 percentage points less than women in jobs with a medium share. Conversely, men in jobs with a high share of male applicants earn 9.0 percentage points more than their counterparts in medium-share jobs, while women in high-share jobs earn 6.4 percentage points more than women in medium-share jobs.

These patterns in the data provide further evidence for the hypothesis that jobs with high flexibility requirements (a high share of male applicants) differ from those with low flexibility requirements (a low share of male applicants). Employers appear to provide compensating differentials for a higher degree of employer-side flexibility requirements. The observed patterns are consistent with the notion that firms pay compensating differentials for workers who are able and willing to provide the requested employer-side flexibility, which we discuss in greater detail in Section 5.

Figure 8: *Coefficients for categories of the share of male applicants*



Note: The plot shows the marginal effects of the share of male applicants by gender. There are five categories for the number of male appl. (only women, low male share, medium male share (reference), high male share, and only men). Dependent variable: imputed log daily earnings. Independent variables: total number of applicants, worker age fully interacted with education attainment (measured by five categories), experience in years and its squared term, an indicator variable for the previous labour market status (non-employed, unemployed, or employed), formal job requirements (four categories), year dummies, a full set of dummies for industries, occupations, and establishment size categories. Estimates for full-time workers aged 20-60. Source: IEB, JVS.

In further robustness checks, we restrict our sample to only female-dominated jobs and use an alternative occupational classification. The pattern in which the residual gender earnings gap decreases substantially when the share of male applicants is added holds in all specifications. These results are available upon request. Notably, adding the share of the stock of male workers at the firm level (instead of the share of male applicants) as a control variable to the earnings regressions changes the gender earnings gaps very little (see Appendix B.7). Thus, it is the share of male applicants for a given job, not the composition

of the existing workforce at the firm, that is important.

Against this background, we conduct another robustness check in the Appendix. As we find no meaningful gender differences in firms' residualised selection measures, the gender-specific hire shares should contain similar information as the gender-specific application rates. Therefore, in the Appendix B.8, we analyse the relationship between the gender-specific hire shares (calculated from the administrative data) and the firm wage premium. We find a similar pattern as for the gender-specific application rates. Furthermore, when we add the share of male hires at the firm level as an explanatory variable to the wage regression, the gender earnings gap decreases by 20%.³³ This result complements recent findings by Gobillon et al. (2015), who show that the hiring probability difference between men and women is increasing in wages (men are more likely to be hired in high-wage jobs). Our results indicate that gender-specific application behaviour might be the dominant driver.

4.4.2 Wages, Flexibility, and Motherhood

In our final empirical step, we analyse how the share of male applicants and the flexibility index interact with motherhood and the gender earnings gap. Therefore, we use the established proxy for being a mother in the administrative data (Müller and Strauch, 2017) and analyse how flexibility requirements interact with the residual gender earnings gap relative to men for mothers and for women without children. We interact our two flexibility requirement proxies with dummies for mothers and women without children. Figure 9 shows the (predicted) earnings discount for mothers and women without children (relative to men) divided according to the shares of male applicants and the flexibility requirement index at the respective jobs.³⁴ The average effects can be found in Appendix B.9.

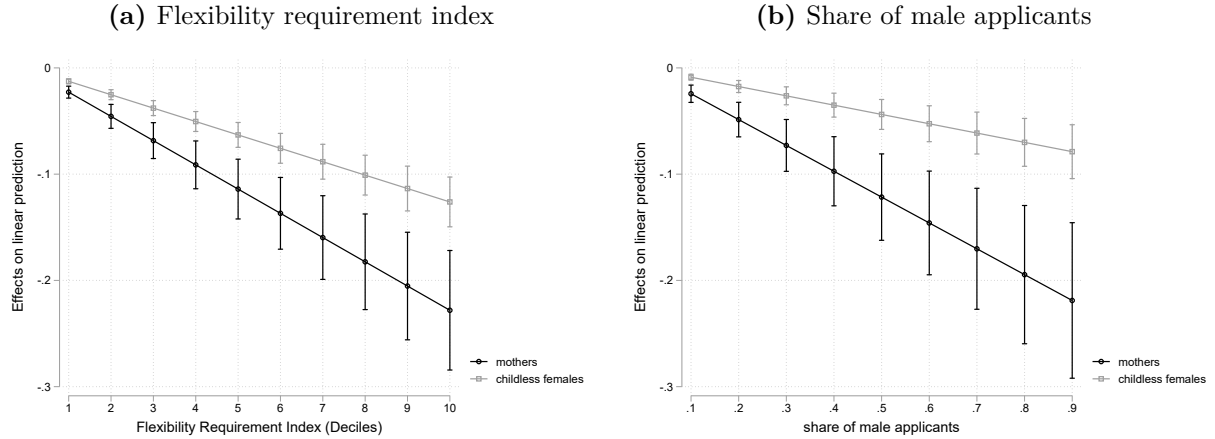
Figure 9 shows that the wage discount is increasing given the flexibility requirements of jobs. Mothers face only a small wage discount in the low deciles of the flexibility requirement index or a low share of male applicants. In contrast, when mothers match with a job with a 90% share of male applicants or with a high flexibility requirement index, they face a more than 20% residual gender earnings gap relative to men.³⁵ It is also striking that the wage

³³Gender-specific hire shares differ from application shares because the former are observed at the firm level, whereas the latter are at the job level. Calculating hire shares at a more disaggregated level — the intersection of firm and task complexity — and including them in the wage regression reduces the gender earnings gap by 28%, bringing it closer to the reduction achieved by the share of male applicants. Despite their differences, hire shares and application shares convey related information and outperform the male employment share (stock) in explaining the gender earnings gap, providing a valuable alternative when application data are unavailable in administrative datasets.

³⁴We include an interaction term of the share of male applicants as a continuous variable or the flexibility requirement index with a dummy variable that takes distinct values for mothers and women without children, relative to men, in our regression. Based on this regression, we then calculate marginal effects over the grid from 0.1 to 0.9 of the share of male applicants, as shares of 0 and 1 have to be excluded because only one gender matches at those jobs. Similarly, we use deciles of the flexibility requirement index.

³⁵Note that the weighted average of these estimates corresponds to the point estimates in Columns (2) and (3) of Table B2 in the Appendix. Figure B7 shows the corresponding table after dropping the full-time

Figure 9: Mothers and women without children



Note: This figure shows the earnings gap (marginal effects) for mothers and women without children compared with men as a reference group at various levels of the flexibility index/ the share of male applicants. Dependent variables: the flexibility index/ the share of male applicants interacted with a dummy for mothers and women without children (men=reference), the total number of applicants, a set of worker age dummies fully interacted with education dummies, experience in years and its squared term, a dummy for the previous labour market status (non-employed, unemployed, or employed), dummies for formal job requirements, year dummies, industry categories, occupation categories, and establishment size deciles. Estimates for full-time workers aged 20-60. Source: IEB, JVS.

discount differential between mothers and women without children increases with the share of male applicants or the level of the flexibility requirement index. While the differences in the point estimates are economically very small for matches with small shares of male applicants or low flexibility requirements, they are roughly 14 percentage points for matches with 90% male applicants and roughly 10 percentage points for matches with very high flexibility requirements.³⁶

Maybe surprisingly in an economic sense,³⁷ the earnings discount for women without children also increases with respect to the share of male applicants and the flexibility requirement index. This finding may be because having children is an incomplete proxy for the ability and willingness of women to provide flexibility and can be partly related to other care activities (e.g., eldercare activities) or to intertemporal considerations (e.g., plans to become a mother later). The cross-sectional nature of our data limits our ability to analyse this situation further. However, in Appendix B.2, we show that the gender earnings gap is largest for women of child-rearing age than for women of other ages.

In Appendix B.10, we show that, on average, higher firm wage premia are associated with longer commuting distances. In this vein, we find that women, on average, have shorter commuting distances than men do. On average, women without children have a restriction.

³⁶The confidence intervals are larger at the right side of the distributions because the number of observations is smaller there for two reasons. First, due to the matching of the IAB JVS and administrative data, the sample size is reduced. Second, at jobs with a larger share of male applicants/higher flexibility requirements, the absolute number of women and, even more so, mothers, is small.

³⁷Statistically, this is in line with Figure 7 where the gender gap widens for larger flexibility requirements.

commuting distance that is roughly 5 kilometers shorter, whereas mothers have a distance that is roughly 10 kilometers shorter than that of men. Although the commuting distance is not a job attribute in the narrow sense, it is a measure of workers' preferences to trade a larger amenity value (in this case, a shorter commuting distance) for a lower wage.

5 Theoretical Considerations

In this section, we discuss the components that a theoretical model would require to be in line with our results. We then compare these components to the existing theoretical literature.

Our paper finds that women apply at a significantly lower rate to high-paying firms than men do, even within the same occupations, industries, and size categories. We show that this application behaviour is connected to employer-side flexibility requirements, such as irregular work schedules or business travel demands. In contrast, firms' selection behaviour appears to be gender neutral within the same occupation, industry, and size categories: women who apply to high-paying firms have approximately the same probability of being hired as men do. Furthermore, we document that a substantial portion of the residual gender earnings gap is connected to gender-specific application behaviour and employer-side flexibility requirements. Women who match at firms with high flexibility demands earn more than comparable women who match at firms with low flexibility demands do (i.e., they earn compensating differentials). However, if mothers match these high-demand firms, then they earn significantly less than men or women without children do.

To align with our empirical findings, a search model would need to incorporate heterogeneity in terms of the demand and supply of employer-side flexibility requirements. On the one hand, firms need to offer jobs that differ in a margin beyond just wages, i.e., nonwage characteristics or (dis)amenities. On the other hand, workers may have different preferences for these (dis)amenities or different gender-specific abilities to meet these employer-side flexibility requirements. We discuss this in more detail below.

5.1 Job Heterogeneity: Employer-Side Flexibility Requirements

Our empirical work documents an important dimension of job heterogeneity, namely, employer-side flexibility requirements (such as irregular work schedules or business travel). This provides empirical evidence for the theoretical literature that models jobs as a combination of wages and nonwage characteristics/amenities (see, among others, [Lamadon et al., 2022](#); [Hall and Mueller, 2018](#); [Taber and Vejin, 2020](#); [Sorkin, 2022](#); [Sorkin, 2018](#)). In a theoretical model, there are at least two potentially complementary foundations for such heterogeneity. First, amenity provision may be associated with heterogeneous costs for different jobs (see

e.g., [Rosen, 1986](#); [Goldin and Katz, 2011](#)). Second, in the spirit of [Goldin \(2014\)](#), there may be jobs with two different types of production functions (nonlinear and linear jobs). In nonlinear jobs, it is necessary to provide input levels above a certain threshold to generate high output levels. For those jobs, only workers that are able to provide a high level of employer-side flexibility may be particularly profitable.³⁸ In such an environment, firms with nonlinear production functions or firms with higher costs of providing certain amenities (e.g., no overtime work) have to pay compensating differentials for workers who are able and willing to provide the requested employer-side flexibility. Consistent with such a framework, Figure 7 shows that higher employer-side flexibility requirements are associated with higher wages. Furthermore, substantial wage differences for matches of the same gender, depending on the job flexibility requirements, are documented in Figure 8. This evidence supports the notion that jobs with high employer-side flexibility requirements are associated with compensating differentials.

5.2 Worker Heterogeneity: Meeting Employer-Side Requirements

On the worker side, a model would need to account for the heterogeneity of workers in terms of their ability or willingness to meet employer-side flexibility requirements. We show that women are less likely to apply for high-flexibility jobs (see Figure 6). We also document that mothers have shorter commuting distances than men do (see Figure B16 in the Appendix). We also show that mothers face a large wage discount at jobs with high employer-side flexibility requirements (see Figure 9).

While the JVS is very rich in terms of firm information, there is less information on the worker side. However, gender differences in this dimension are well documented in the literature. [Wiswall and Zafar \(2017\)](#) and [Mas and Pallais \(2017\)](#) show that women have a greater willingness to pay for jobs with flexible work schedules such as part-time options. [Le Barbanchon et al. \(2020\)](#) show, for example, that women have shorter commuting distances to work and that this is important for the gender pay gap. [Maestas et al. \(2023\)](#) show that individuals tend to sort into jobs with attributes that they disproportionately value.

5.3 Matching and Sorting

We observe that men and women apply to specific jobs, indicating a labour market matching mechanism that is not completely random.³⁹ Workers who cannot meet employer-side

³⁸While [Goldin \(2014\)](#) provides different occupations as examples (lawyers as nonlinear jobs and pharmacists as linear jobs), our empirical results suggest that similar patterns should exist within occupations (e.g., medical doctors in the emergency room versus those in private practice).

³⁹Unlike the standard contact function in the spirit of [Mortensen and Pissarides \(1994\)](#), workers do not seem to be assigned randomly in terms of employer-side flexibility requirements.

flexibility demands should generate a lower surplus for employers, i.e., if they apply, they would face a lower hiring rate. However, we observe that if women apply for jobs with high employer-side flexibility requirements, they have the same probability of being hired as men do. This suggests a strong segmentation of the labour market where women who cannot meet these flexibility requirements rarely apply for these jobs in the first place.

Since our dataset does not include the characteristics of all applicants, we cannot specifically test whether the segmentation in application behaviour is primarily due to women with children. However, we do observe that matched mothers have on average shorter commuting distances and face a large wage discount in jobs with high employer-side flexibility requirements.

On this basis, we believe that in a suitable theoretical model, women with children should be modeled as having a lower ability to meet employer-side flexibility demands; this would result in a lower probability of them sorting into these jobs. Thus, a suitable model would incorporate some directedness of gender-specific search or segmentation of the labour market, leading to sorting along the employer-side flexibility margin.

5.4 The Role of Unmeasured Amenities

The JVS has only information on very specific nonwage attributes, namely, the employer-side flexibility requirements that we have described. However, our documented patterns may be convoluted by other non-measured amenities.

Whether firms that pay high wages offer better or worse amenities is ultimately an empirical question and is still debated.⁴⁰ Using data on many different nonwage characteristics from a U.S. online job platform, [Sockin \(2022\)](#) provides evidence that wages and amenities are complements. If this result would also be applicable for the firms in our sample, then this would mean that firms with high wages and large employer-side flexibility requirements also provide a bundle of other positive amenities (e.g., larger offices, company cars) that are not visible to the econometrician (at least not in the JVS).

What would this imply for the interpretation of our empirical results? If men and women value these non-measured amenities equally, then it would not affect our findings, as the unmeasured amenities would be orthogonal to the gender-specific application behaviour. However, if men value certain amenities (e.g., company cars) more than women do, then this may additionally contribute to gender-specific application behaviour. In this case, our conclusion that gender-specific application behaviour is a key driver of the gender earnings gap remains valid. However, we would not be able to disentangle the relative importance of

⁴⁰Theoretically, both are possible: In a standard competitive labour market, better amenities are associated with lower wages ([Rosen, 1986](#)). In a labour market with search frictions, higher wages may be associated with better amenities, as more productive firms can provide higher wages and better amenities at the same time ([Mortensen, 2003](#)).

our measured employer-side flexibility requirements from unmeasured amenities for gender-specific application behaviour. Therefore, the results of our wage regressions should be interpreted with caution. Due to the lack of more detailed data, we leave the analysis of this issue for future research (when more detailed data or field experiments are available).

If men and women value certain amenities differently, then firms may have an incentive to offer specific wage and amenity combinations to attract applicants from a certain gender (see [Iacopo and Moser, 2024](#), for a similar mechanism). Although this may lead to unequal treatment of men and women, we consider this to be a different mechanism from classical [Becker \(1971\)](#)-type taste-based discrimination. Under taste-based discrimination, employers' have a distaste to employ women and have to be compensated for this by higher profits. In contrast, when employers offer certain combinations of wages and nonwage characteristics to attract certain worker types, even without any distaste, women may be matched at different jobs as men. More generally, although we acknowledge that classical taste-based discrimination may be prevalent in the labour market, we consider it an unlikely key driver for our empirical results. Two facts speak against it. First, once a woman applies to high-paying firms, she has approximately the same probability of being selected as a man. Second, we find no evidence that gender differences in worker productivity—measured by worker fixed effect differentials at firms with high fixed effects (Figure 4)—explain this observation. However, if wage discrimination exists, worker fixed effects may fail to accurately reflect productivity when assessing selection discrimination.⁴¹

5.5 Comparison with Existing Theoretical Literature

The empirical patterns in the German data call for two-sided heterogeneity (in terms of demand and supply of amenities), search frictions with market segmentation or non-random search that leads to sorting. The existing theoretical literature already contains some of these elements.

[Sorkin \(2018\)](#) presents a model with firm heterogeneity in terms of the provision of amenities. However, his model does not contain any worker heterogeneity. In accordance with our results, his work underlines the importance of compensating differentials, where wages and amenities are substitutes. [Lamadon et al. \(2022\)](#) build a model with firm heterogeneity in amenities and productivity. In addition, they allow for worker heterogeneity in productivity and preferences. These features generate sorting between firms and workers. The authors find evidence supporting the idea that wages and amenities are complements (i.e., more productive firms offer better amenities). However, their model does not contain any search

⁴¹In a previous version of this paper, we provided a simple two-stage search model and discussed the role of worker heterogeneity in the context of taste-based discrimination. See [Lochner and Merkl \(2023\)](#).

frictions.⁴² Neither [Lamadon et al. \(2022\)](#) nor [Sorkin \(2018\)](#) provide an explicit analysis of the interaction of amenities and gender.

A closely related theoretical paper with an explicit gender analysis is [Iacopo and Moser \(2024\)](#). They model two-sided heterogeneity and amenity provision by firms (with multiple heterogeneities at the firm level, such as different preferences over gender or different amenity costs). The authors analyse the interaction of amenities, gender, and sorting for Brazil. In line with our empirical analysis, they find that compensating differentials can explain an important part of the gender pay gap. While markets in [Iacopo and Moser \(2024\)](#) are segmented by gender and ability, workers cannot direct their search to particular firms with particular wage and amenity combinations. We, however, document that men and women direct their applications to particular jobs, with women applying a lot less for jobs with high employer-side flexibility requirements.

Based on the rich JVS dataset, our paper empirically analyses the interaction between one specific type of disamenity (employer-side flexibility requirements), wages, and gender-specific application behaviour. In line with [Sorkin \(2018\)](#) and [Iacopo and Moser \(2024\)](#), we show that more employer-side flexibility demands are generally associated with higher wages for both genders, which supports the notion of compensating differentials. Furthermore, our results are consistent with those of [Sorkin \(2017\)](#) who shows that women work in firms with more desirable amenities. In his model, men and women receive offers from different exogenous distributions. He states: "In a random search model, the exogenous offer distribution is a reduced-form representation of the complicated process by which workers direct their search toward particular firms" ([Sorkin, 2017](#), p. 386). In line with this statement, we show that men and women have distinctively different application behaviours that are targeted at employer-side flexibility requirements.⁴³

Our empirical results highlight several additional dimensions that may be useful reference points for future modeling exercises. Many of the existing papers emphasize the interaction between observable characteristics (e.g., sector) and amenities. Beyond this, our paper shows that employer-side flexibility requirements matter even once we control for occupation, industry, and firm size. Furthermore, we show that sorting is driven by gender-specific application choices, not firm-specific selection choices. Finally, we show the importance of the interaction of employer-side flexibility requirements and motherhood.

⁴²[Taber and Vejlín \(2020\)](#) analyse different sources of wage differentials with a model that combines the Roy model, a search model, compensating differentials, and human capital accumulation.

⁴³The absence of measures for other amenities in our dataset prevents us from making general statements about the driving firm motives for providing amenities and wages. We have discussed the implications of the different scenarios above.

6 Conclusions

This paper shows that gender-specific application behaviour is crucial for understanding differences in the earnings of newly created jobs. Even within the same industries, firm size categories, and occupations, women are less likely to apply to the highest wage firms than are men.

Once we include proxies for employer-side flexibility requirements in standard Mincer regressions (beyond standard observable variables such as occupation, sector, and worker characteristics), the residual gender earnings gap decreases substantially. These findings suggest that these flexibility requirements, which are typically omitted in standard wage regressions, are important explanatory variables.

By combining IAB JVS data with administrative information on the most recent hire, we can use the proxy of whether women have children. We find that earnings discounts are particularly greater for mothers than for women without children, and this discount increases with our proxies for employer-side flexibility requirements. This finding supports the hypothesis that mothers are less able to meet high employer-side flexibility demands, resulting in a significant earnings discount.

We believe that the future provides an interesting test laboratory. The increase in work-from-home arrangements may challenge the necessity of rigid employer-side flexibility routines. Additionally, as the German labour force shrinks, firms may find it harder to hire qualified labour, making unnecessary flexibility requirements more detrimental. Future waves of the IAB JVS may provide further insights.

Our paper also offers policy-relevant lessons. Policy interventions that increase women's access to jobs with high flexibility requirements, such as improved childcare access or incentives for equitable sharing of caregiving responsibilities, can change application behaviour and reduce the gender earnings gap.

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Appendix

A Descriptive Details

Table A1: *Share of male/female hires and applicants across industries*

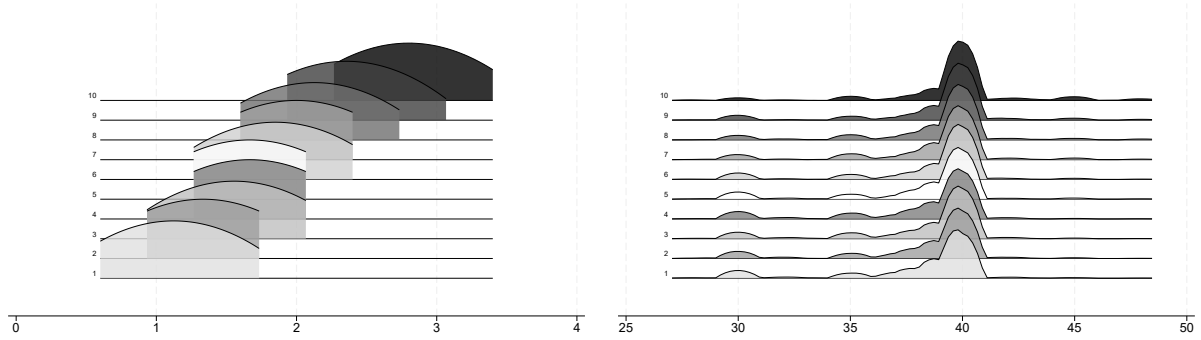
NACE Rev. 2	Share of hires			Share of applicants	
	Total Hired	Men (%)	Women (%)	Men (%)	Women (%)
A - Agriculture, forestry and fishing	1,028	67.8	32.2	66.19	33.81
+ B - Mining and quarrying					
C - Manufacturing	5,370	72.36	27.64	70.55	29.45
D - Electricity, gas, etc.	1,694	69.01	30.99	69.93	30.07
+ E - Water supply, sewerage					
F - Construction	913	88.39	11.61	85.2	14.8
G - Wholesale and retails trade, etc.	1,750	68.4	31.6	65.75	34.25
+ H - Transportation and storage					
I - Accommodation and food	722	41.69	58.31	38.98	61.02
J - Information and communic.	4,786	51.92	48.08	52.81	47.19
+ K - Financial and insurance					
+ L - Real estate					
+ M - Professional, scientific and technical					
+ N - Administrative and support service					
O - Public administration	2,023	35	65	37.59	62.41
P - Education	5,233	26.14	73.86	27.62	72.38
+ Q - Human health and social work					
+ R - Arts, entertainment and recreation					
+ S - Other services					
+ T - Households as employers					
+ U - Extraterritorial organis.					
Total	23,519	53.65	46.35	53.56	46.44

Note: Columns 3 (4) shows the average share of men (women) among newly hired workers in a given industry. Columns 4 (5) shows the average share of men (women) among applicants for newly filled positions in a given industry. Source: IEB, JVS.

Figure A1: *Flexibility index: details*

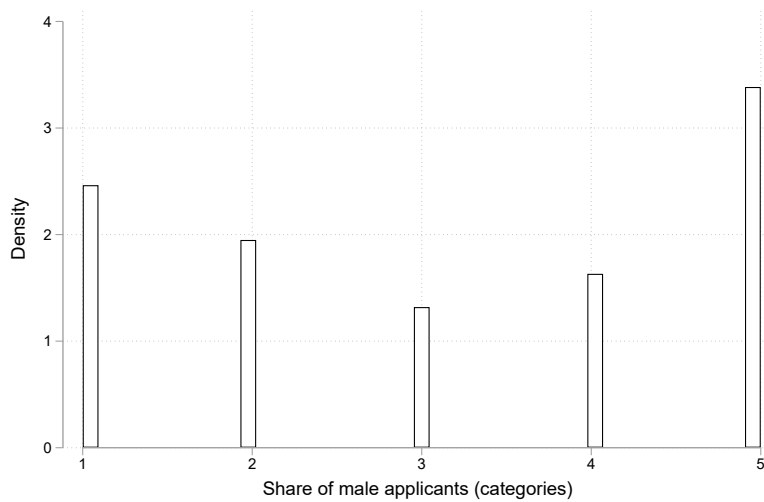
(a) Average overtime, job mobility, schedule changes

(b) Hours



Note: These figures show distribution plots of the main ingredients of the flexibility index by deciles of the index (winsorised at the 0.5/99.5%-level). a) shows the average demand for overtime, job mobility, and changes in the working schedule, where 1 refers to "never", 2 to "rarely", and 3 to "often." b) shows the working hours. Full-time jobs only. Source: IEB, JVS.

Figure A2: *Share of male applicants: categories*



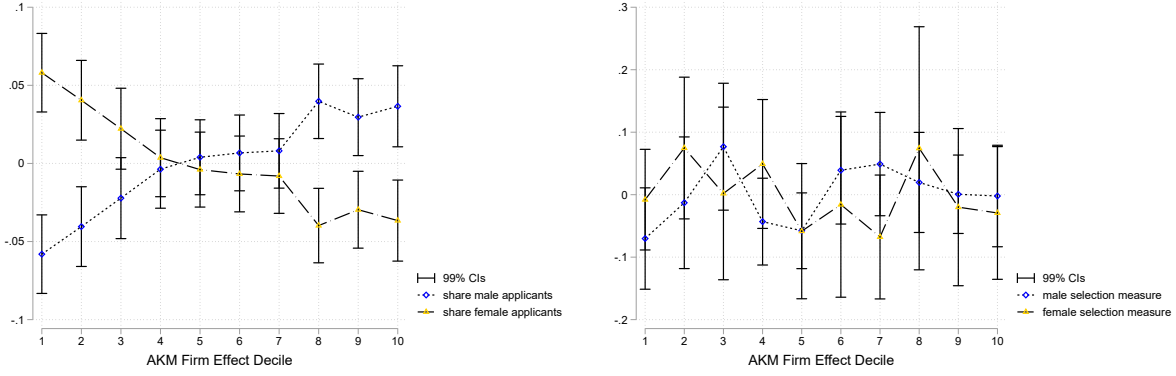
Note: This figure shows a histogram of the share of male applicant categories (from no male applicants (1) to only male applicants (2)). Source: IEB, JVS.

B Additional Empirical Results

B.1 Application and Selection Behaviour and Bargaining

Figure B1: *Application and selection behaviour by gender and AKM firm effect deciles, with organised bargaining*

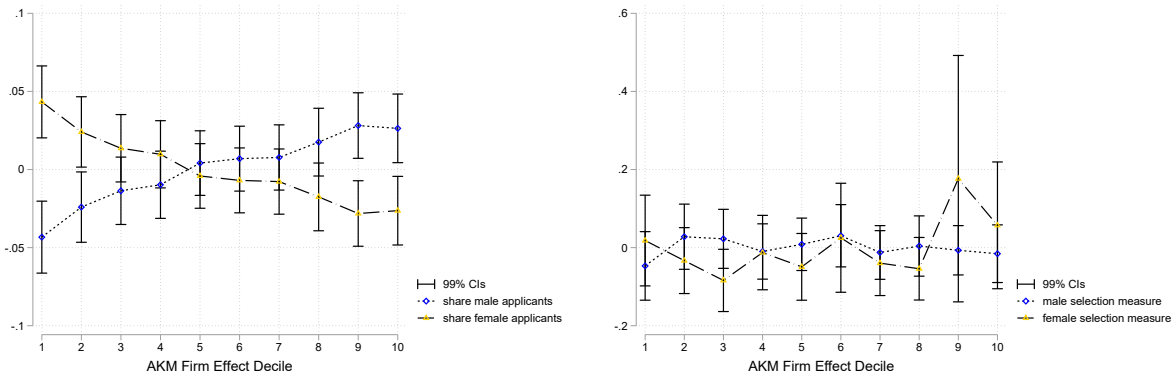
(a) Residualised share of female/male applications (b) Residualised female/male selection measure



Note: Full-time jobs with organised bargaining only. Firm effects estimate for women only. The variables are defined as follows: a) share of male appl.=number of male appl./number of all appl. and share of female appl.=number of female appl./number of all appl. b) male selection measure=1/share of male appl. if a man is hired and in this case, the female selection measure equals zero, and the female selection measure=1/share of female applicants if a woman is hired, and in this case, the male selection measure equals zero. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

Figure B2: *Application and selection behaviour by gender and AKM firm effect deciles, without organised bargaining*

(a) Residualised share of female/male applications (b) Residualised female/male selection measure



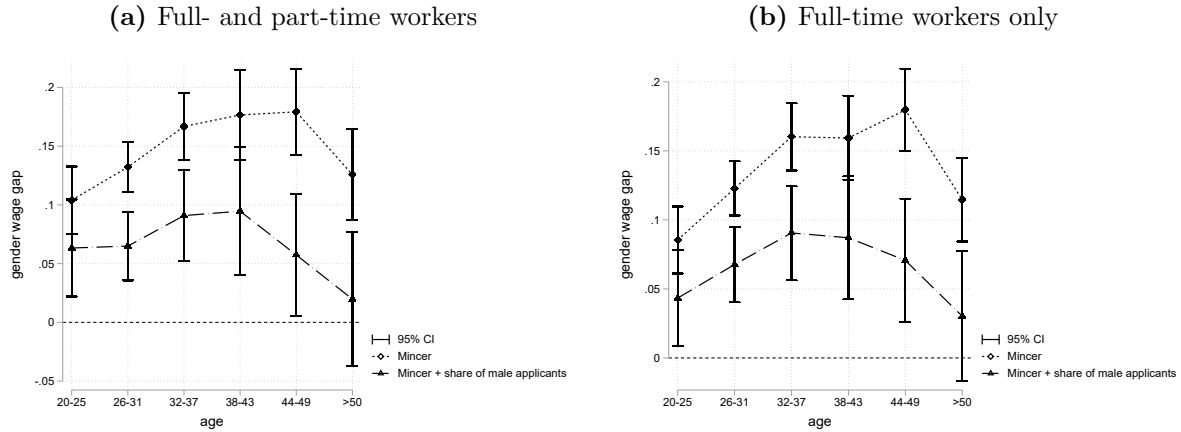
Note: Full-time jobs without organised bargaining only. Firm effects estimate for women only. The variables are defined as follows: a) share of male appl.=number of male appl./number of all appl. and share of female appl.=number of female appl./number of all appl. b) male selection measure=1/share of male appl. if a man is hired and in this case, the female selection measure equals zero, and the female selection measure=1/share of female applicants if a woman is hired, and in this case, the male selection measure equals zero. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

Figures B1 and B2 show the application and selection behaviour across AKM firm effect

deciles separately for firms that are subject to a collective or firm-level bargaining agreement (denoted by organised bargaining) and those that are not, respectively. Although the application rates differ somewhat in the raw data, once we include our full set of controls, the quantitative results are very similar to those from our baseline sample.

B.2 Age Cohorts

Figure B3: *Gender earnings gap estimates by 5-year cohort*



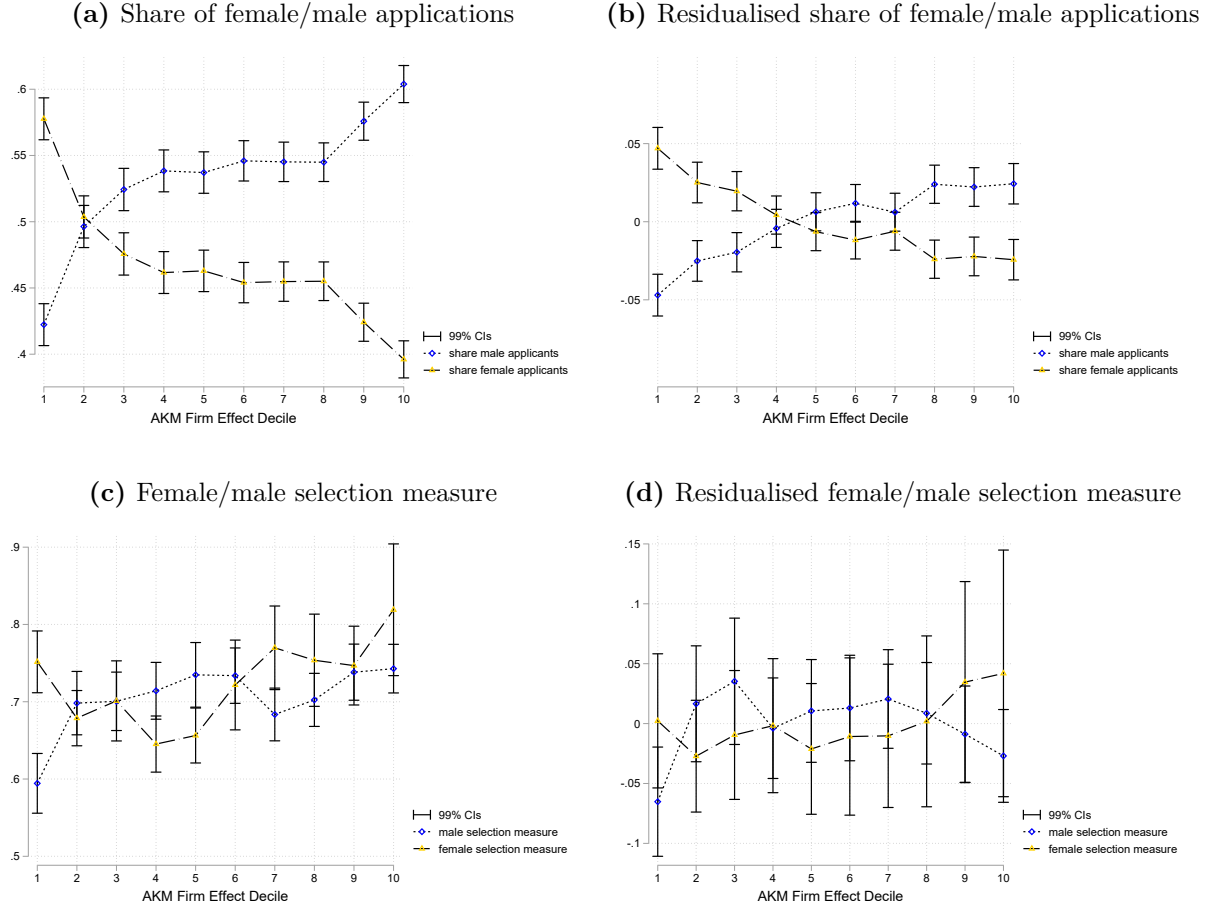
Note: This figure shows the estimates for the gender gap in hiring earnings by age group, as laid out on the x-axis.

Dependent variable: imputed log daily earnings. Default independent variables: gender dummy, total number of applicants, worker age fully interacted with educational attainment (measured by five categories), experience in years and its squared term, an indicator variable for the previous labour market status (non-employed, unemployed, or employed), contractual working hours of the new job, formal job requirements (four categories), and year dummies. Source: IEB, JVS.

B.3 Alternative Sample Restriction

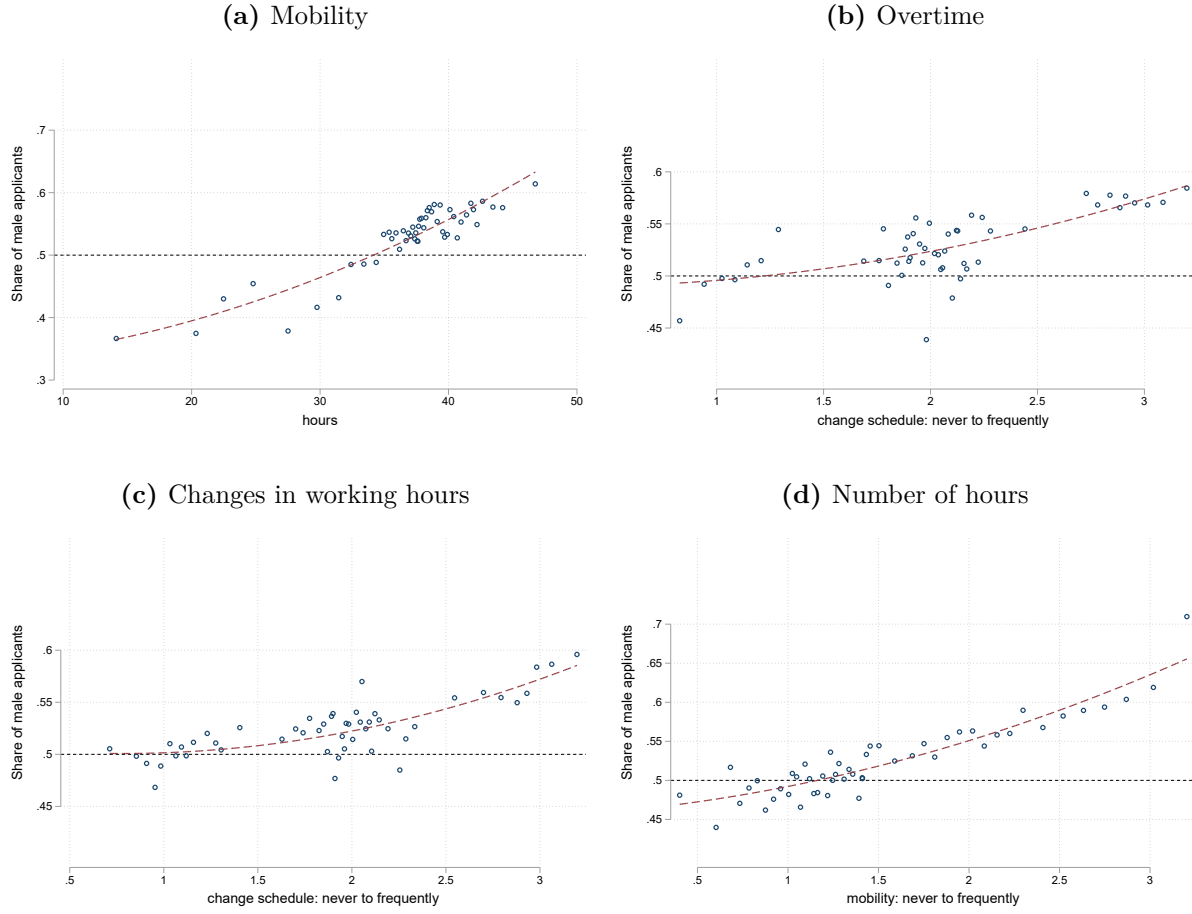
This appendix replicates all the main results without imposing the full-time restriction (i.e., confining the sample to only workers with more than 25 hours of working time). All our key insights are unaffected by the chosen sample restrictions, although the quantitative numbers differ somewhat.

Figure B4: *Application and selection behaviour by gender and AKM firm effect deciles*



Note: Full-time and part-time jobs. The variables are defined as follows: a) and b) share of male appl.=number of male appl./number of all appl. and share of female appl.=number of female appl./number of all appl. c) and d) male selection measure=1/share of male appl. if a man is hired and in this case, the female selection measure equals zero, and the female selection measure=1/share of female applicants if a woman is hired, and in this case, the male selection measure equals zero. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

Figure B5: *Share of male applicants and flexibility requirements*



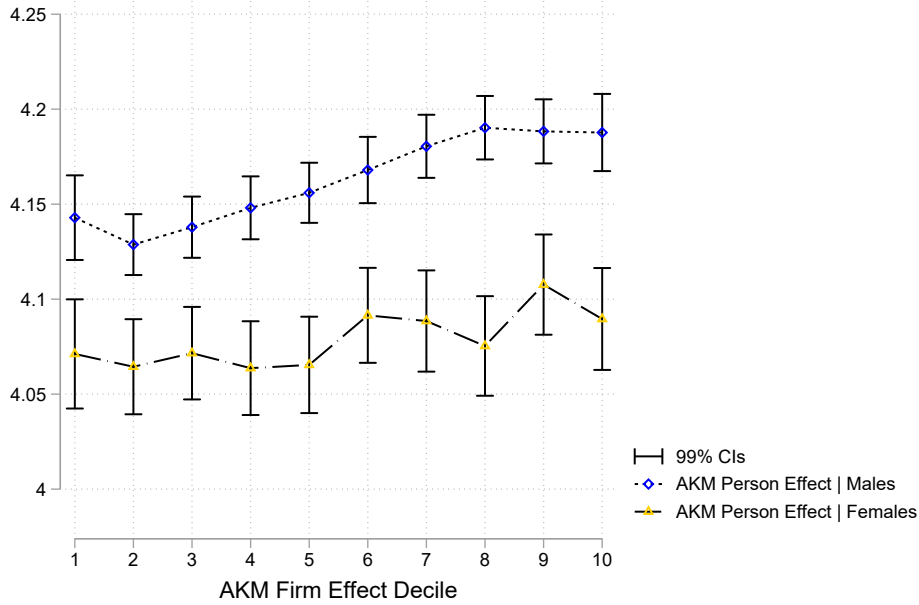
Note: These figures show binscatters with 50 bins and quadratic fit lines. To residualise the x and y variables, we regress each variable on the controls, generate the residuals, and add the sample mean of each variable back to its residual. We then group the x-axis variable into equal-sized bins, compute the mean of the x-axis and y-axis variables within each bin, and create a scatterplot of these data points. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Full-time and part-time jobs. Source: IEB, JVS.

Table B1: *Gender hiring earnings gap*

	Coef.	Std. error	% Reduction	R^2	Obs.
Initial residual earnings gap	-0.202	0.007		0.56	15,512
+ Working hours (contractual)	-0.141	0.007	-30.2	0.65	15,512
+ Job mobility, overtime, change schedule	-0.127	0.008	-37.13	0.66	15,512
+ Distance residence-workplace	-0.121	0.006	-40.1	0.7	15,512
+ Flexibility requirement index	-0.15	0.008	-25.74	0.6	15,512
+ Distance residence-workplace	-0.14	0.007	-30.69	0.64	15,512
Initial residual earnings gap	-0.205	0.008		0.56	14,169
+ Share of male applicants	-0.096	0.01	-53.17	0.57	14,169

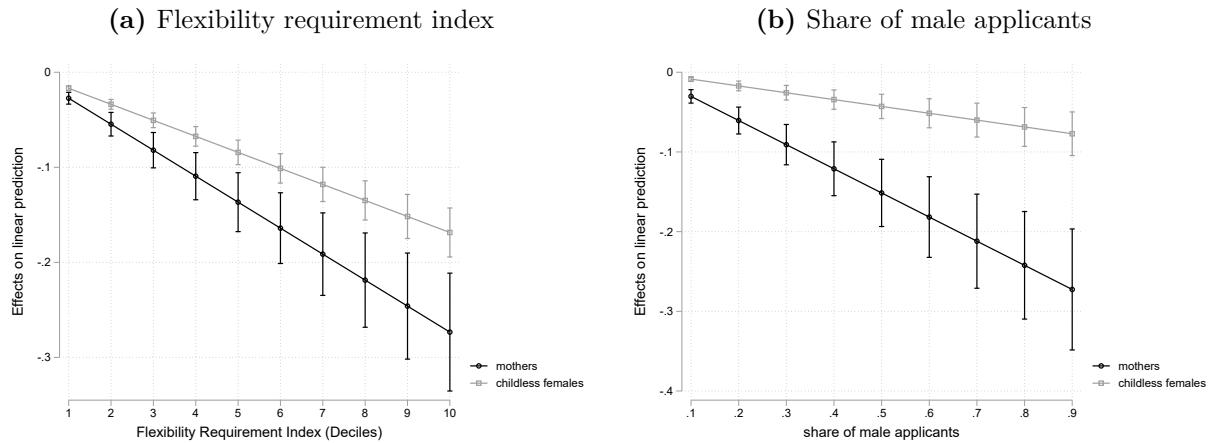
Note: This distance is approximated by the beeline distance between the district of a worker's main residence and workplace. Robust standard errors. Estimates for full-time and part-time workers aged 20-60. Source: IEB, JVS.

Figure B6: Worker and firm fixed effects



Note: This figure shows the residualised average worker fixed effects for matches within different firm fixed effect deciles. Full-time and part-time jobs. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

Figure B7: Mothers and women without children



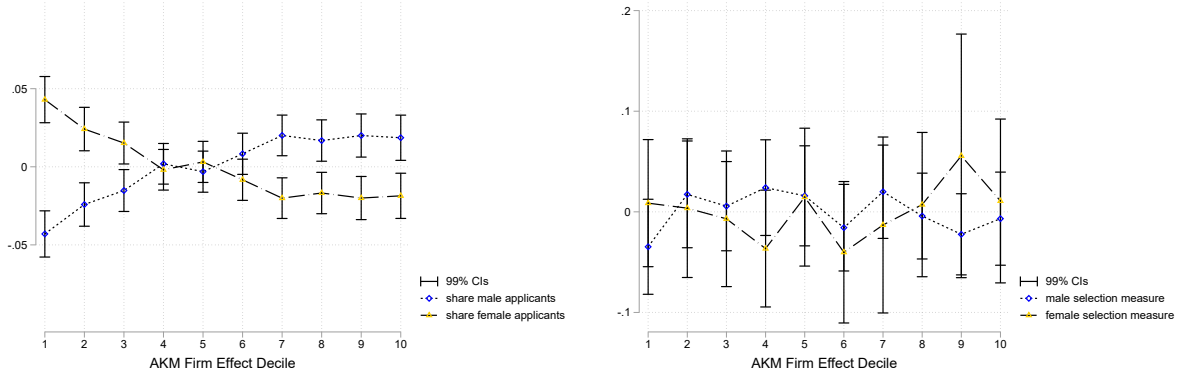
Note: These figures show the earnings gap (marginal effects) for mothers and women without children compared to men as a reference group at various levels of the share of male applicants. Controls: share of male applicants interacted with a dummy for mothers and women without children (men=reference), total number of applicants, a set of worker age dummies fully interacted with education dummies, experience in years and its squared term, a dummy for the previous labour market status (non-employed, unemployed, or employed), dummies for formal job requirements, year dummies, industry categories, occupation categories, and establishment size deciles. Estimates for full-time and part-time workers aged 20-60. Source: IEB, JVS.

B.4 Application and Selection behaviour with Alternative Firm Fixed Effects

Figures B8 and B9 show the patterns in the data with differently estimated firm fixed effects. In this case, the firm fixed effects are gender specific; that is, they are estimated separately for men and women (i.e., each firm has two types of wage premia: one for men and one for women).

Figure B8: *Application and selection behaviour by gender and AKM firm effect deciles (estimated for men only)*

(a) Residualised share of female/male applications (b) Residualised female/male selection measure



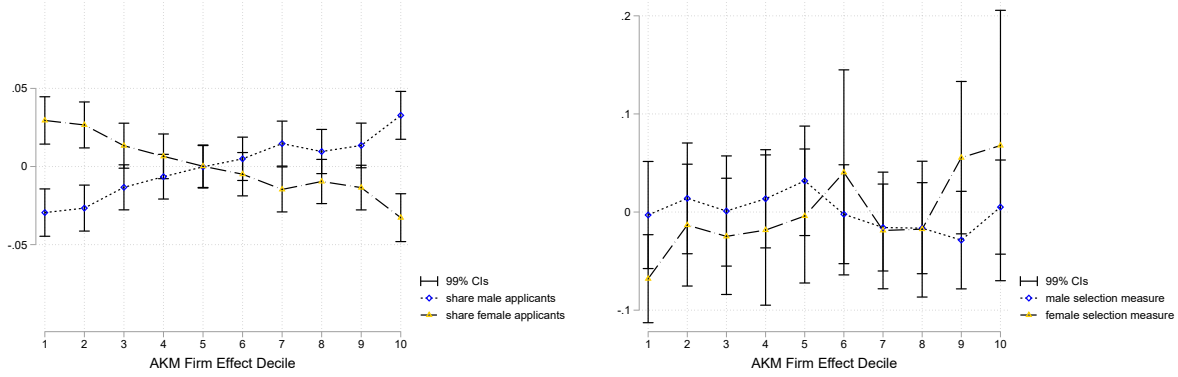
Note: Full-time jobs only. Firm effects estimate for men only. The variables are defined as follows: a) share of male appl.=number of male appl./number of all appl. and share of female appl.=number of female appl./number of all appl. b) male selection measure=1/share of male appl. if a man is hired and in this case, the female selection measure equals zero, and the female selection measure=1/share of female applicants if a woman is hired, and in this case, the male selection measure equals zero. Control variables: industry categories, firm size categories, and occupation categories. Source: IEB, JVS.

Note that the comparison of these separately estimated rankings with the ranking based on gender-pooled firm fixed effects itself is informative in terms of taste-based discrimination. An AKM firm effect ranking based only on men should show discrimination-free wages. However, if discrimination plays a role, then a ranking based on both women and men should yield lower average wages for women in discriminating firms than for those in nondiscriminating firms. Hence, discriminating firms should have a lower rank than should nondiscriminating firms.

Figure B10 shows the comparison of the AKM firm effect rankings estimated for men only and for both men and women. Consistent with our main results, we do not find major deviations in the rankings. The overall Spearman rank correlation coefficient is 0.94. This result is consistent with that of Bruns (2019), who show that the sorting effect (gender segregation across firms) dominates the bargaining effect (differences in wage premia within the same firm).

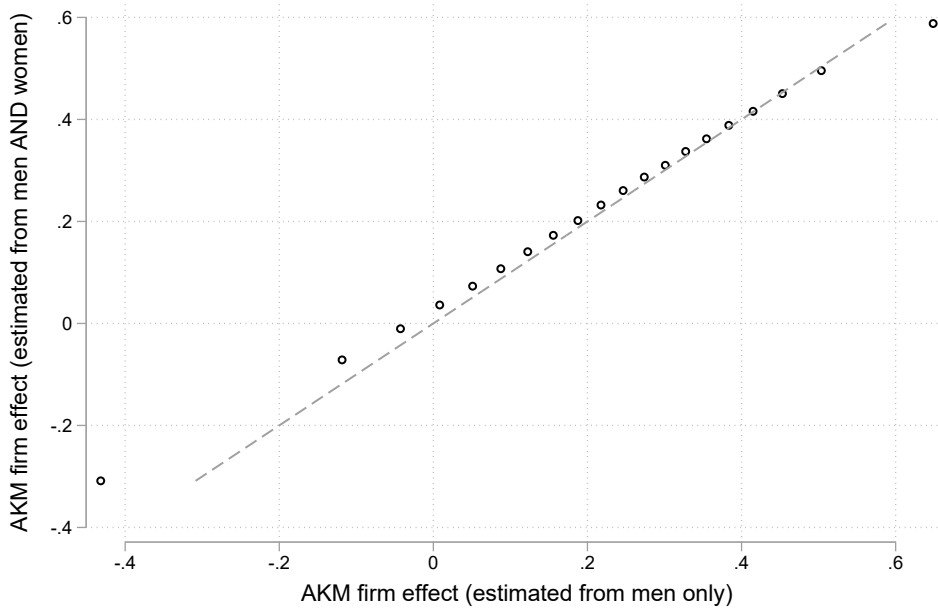
Figure B9: *Application and selection behaviour by gender and AKM firm effect deciles (estimated for women only)*

(a) Residualised share of female/male applications (b) Residualised female/male selection measure



Note: Full-time jobs only. Firm effects estimate for women only. The variables are defined as follows: a) share of male appl.=number of male appl./number of all appl. and share of female appl.=number of female appl./number of all appl. b) male selection measure= $1/\text{share of male appl.}$ if a man is hired and in this case, the female selection measure equals zero, and the female selection measure= $1/\text{share of female applicants}$ if a woman is hired, and in this case, the male selection measure equals zero. Control variables: industry categories, firm size categories, and occupation categories. Source: IEB, JVS.

Figure B10: *AKM ranking comparison*

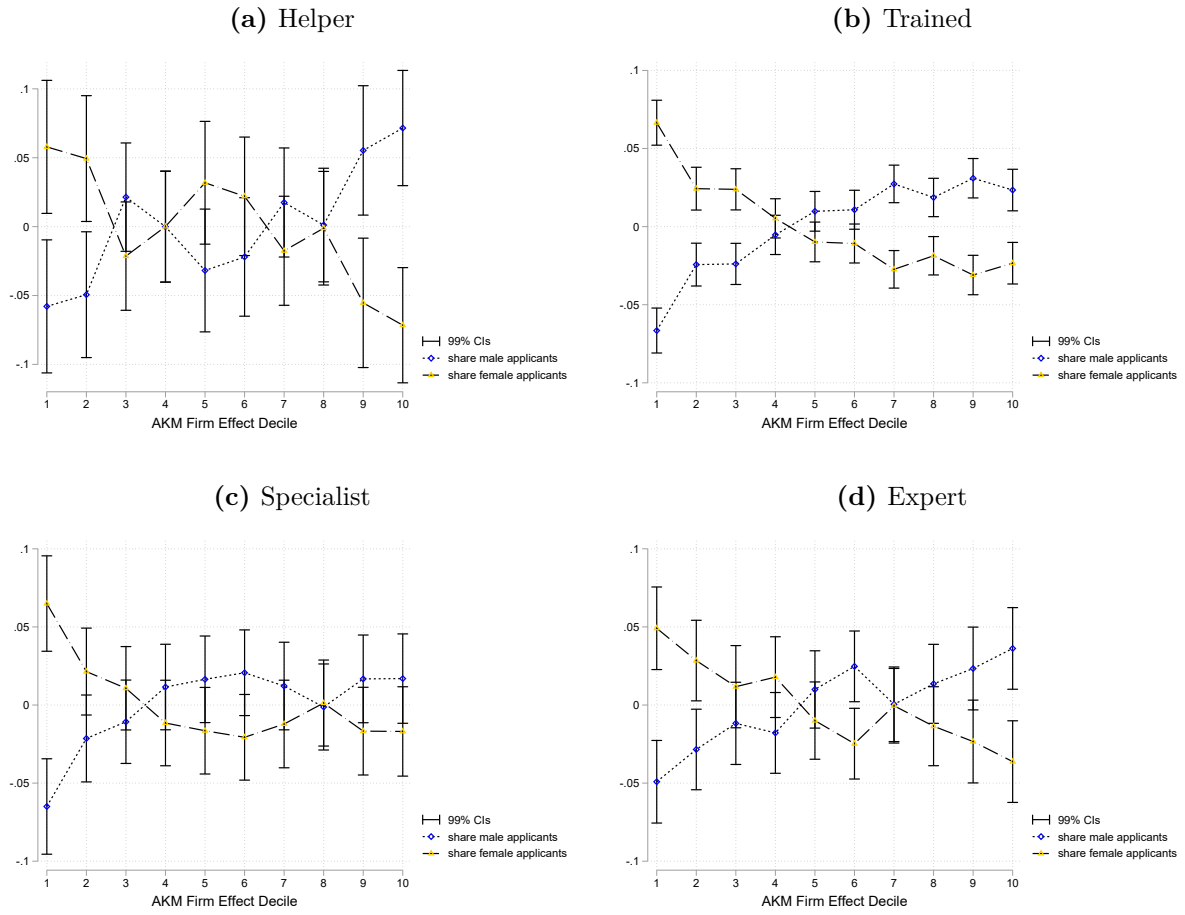


Note: This figure shows a binscatter that compares the AKM firm effects estimated from a sample with men only with the AKM firm effects estimated from a sample with men and women (as in the remaining paper). Source: IEB, JVS.

B.5 Application and Selection behaviour within Task Complexities

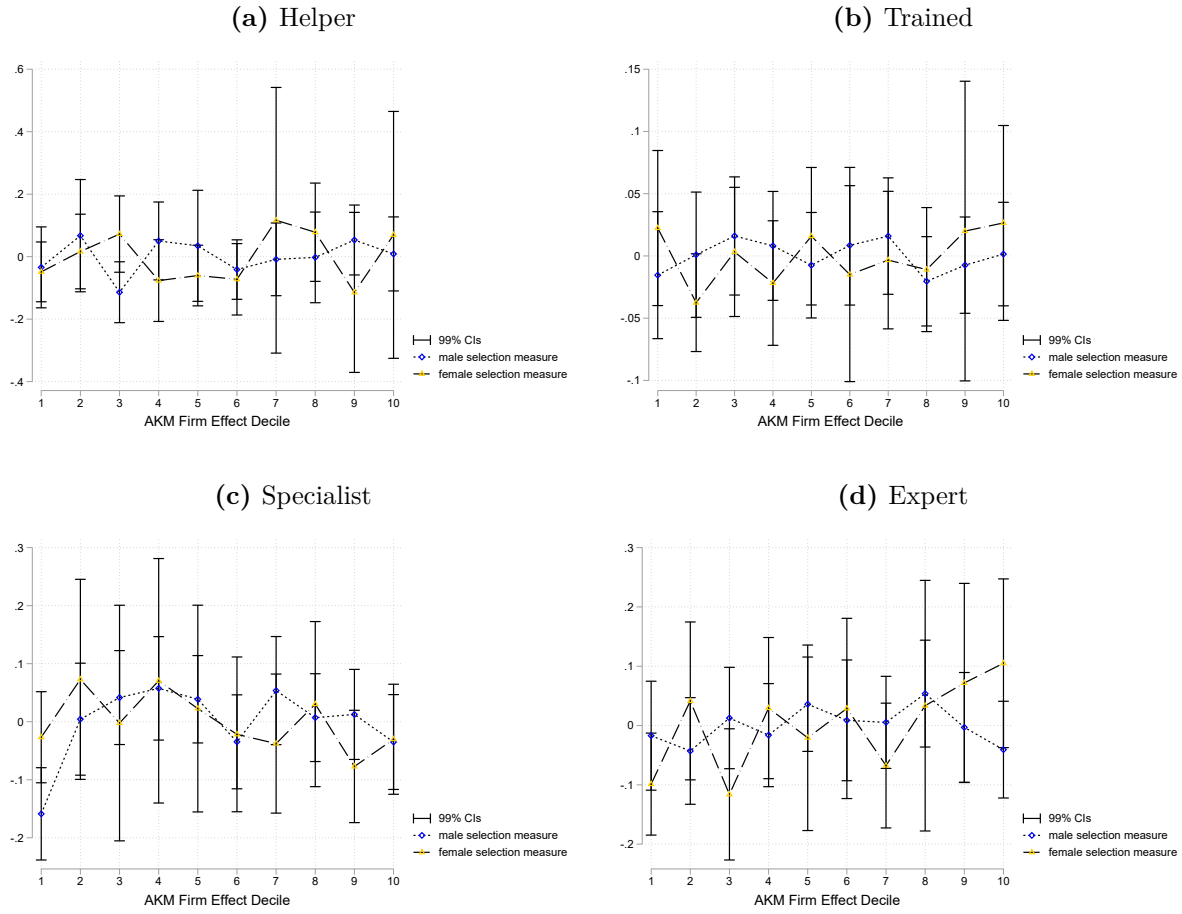
Figures B11 and B12 show the gender-specific residualised application and selection measures within different task complexity groups (unskilled, trained, expert, and specialist), which are defined based on the fifth digit of the occupational code (KldB2010).

Figure B11: *Residualised share of male applicants across the grid of AKM firm effect deciles by task complexity*



Note: Full-time jobs only. The variables are defined as follows: a)–d) share of male appl.=number of male appl./number of all appl. and share of female appl.=number of female appl./number of all appl. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

Figure B12: *Residualised selection measures across the grid of AKM firm effect deciles by job level*



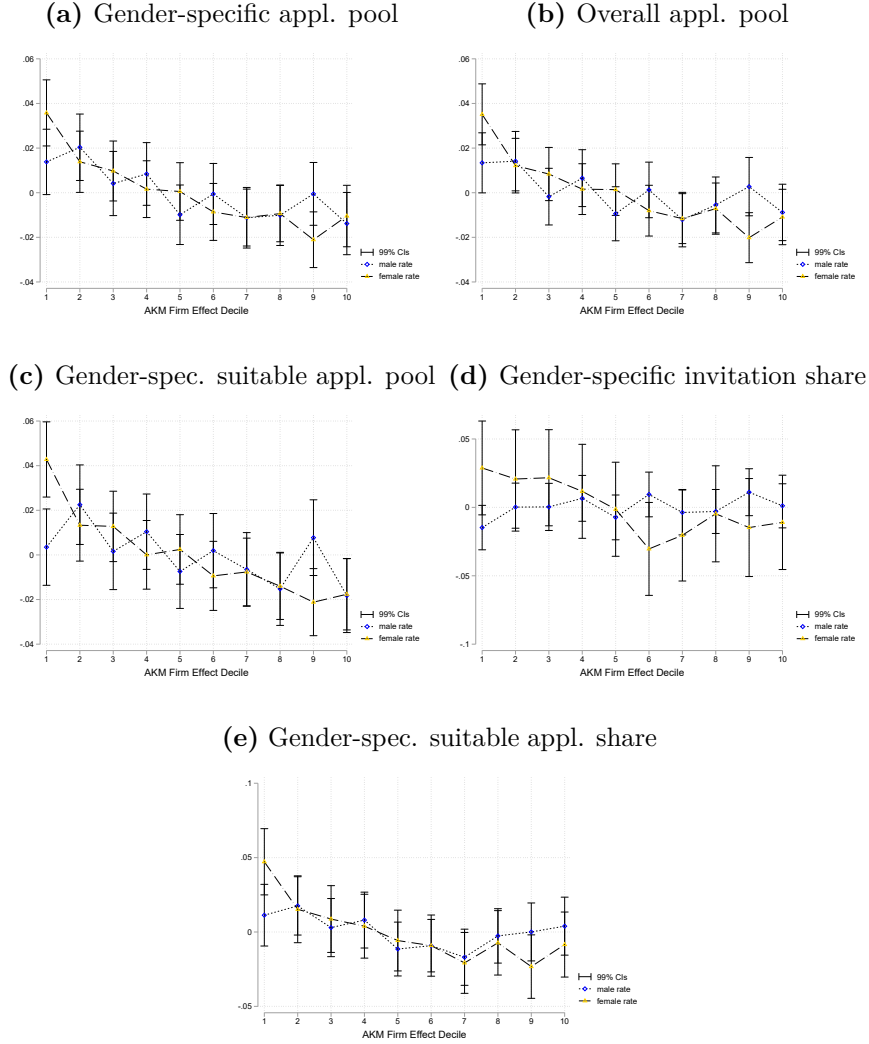
Note: Full-time jobs only. The variables are defined as follows: a)–d) male selection measure=1/share of male appl. if a man is hired and in this case, the female selection measure equals zero, and the female selection measure=1/share of female applicants if a woman is hired, and in this case, the male selection measure equals zero. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

B.6 Alternative Selection Measures

Figure B13 shows the residualised version of differently defined selection measures. Panel (a) defines the selection measure as 1 divided by the gender-specific number of applications. This represents the probability of a man or woman to be selected from the gender-specific pool of applicants, which we used in a prior working paper version. Panel (b) defines the selection rate as 1 divided by the overall number of applicants (instead of the gender-specific number of applicants). Thus, this version represents the probability of an individual being selected from the overall pool of applicants. Panel (c) uses the number of gender-specific suitable applicants instead of all applicants. Panel (d) uses the number of invited applicants instead of suitable applicants. Panel (e) uses the measure proposed by Carrillo-Tudela et al. (2023), namely, the number of suitable (gender-specific) applicants divided by the overall number of (gender-specific) applicants. Firms may endogenously change their definition of which candidates are suitable (i.e., a larger number of candidates may be defined as suitable when firms want to hire more people).

Interestingly, in all three cases, once we control for observables, there are no meaningful differences between male and female selection measures, which confirms our results from the main section.

Figure B13: *Alternative residualised selection measures*

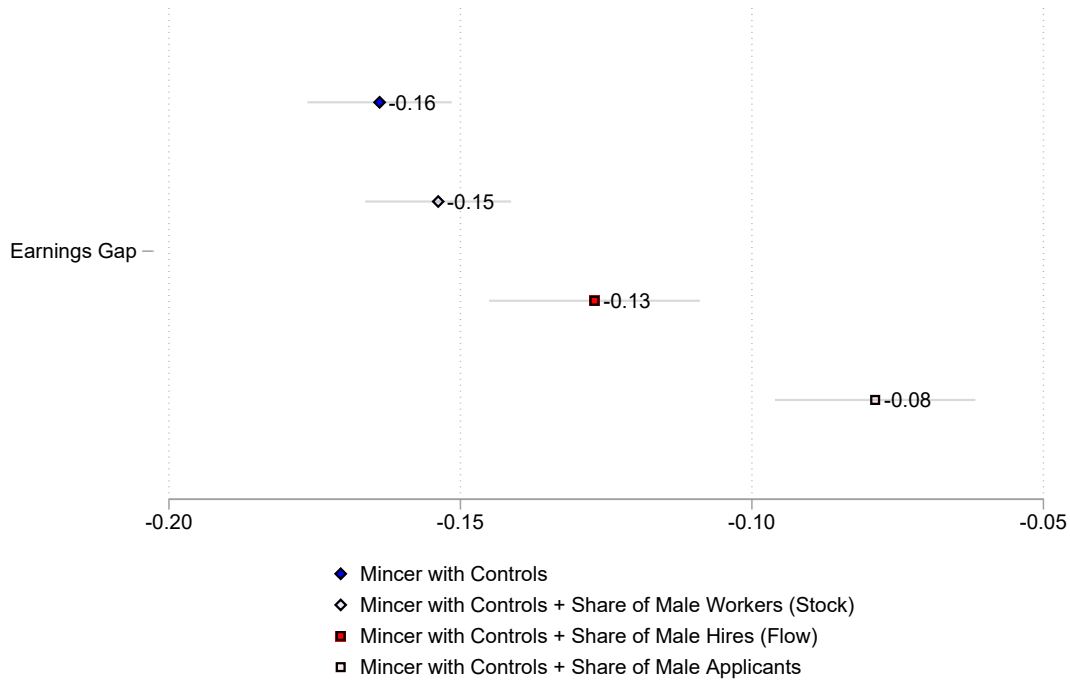


Note: Full-time jobs only. The variables are defined as follows. a) male selection rate=1/number of male appl. if a man is hired, and in this case, the female selection rate equals zero; female selection rate=1/number of female appl. if a woman is hired, and in this case, the male selection rate equals zero. b) male selection rate=1/number of all appl. if a man is hired, and in this case, the female selection rate equals zero; female selection rate=1/number of all appl. if a woman is hired; in this case, male selection rate equals zero. c) male selection rate=1/number of male suitable appl. if a man is hired; in this case, the female selection rate equals zero; female selection rate=1/number of female suitable applicants if a woman is hired. In this case, the male selection rate equals zero. d) male selection rate = 1/invited male applicants if a man is hired; in this case, the female selection rate equals zero; female selection rate = 1/invited female applicants if a woman is hired. In this case, the male selection rate equals zero. e) male selection rate=number of male suitable appl./number of male appl. if a man is hired. In this case, the female selection rate equals zero; female selection rate=number female suitable appl./number of female appl. if a woman is hired. In this case, the male selection rate equals zero. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

B.7 Wage Regressions

Figure B14 shows the estimated gender earnings gap. The first coefficient shows our benchmark estimate from Table 3. Next, we add the share of the stock of male workers at a particular firm. The estimated gender gap drops by roughly 10%. Then, we add the share of male hires instead of the stock, i.e., the inflow of male workers of a firm. The estimated gender gap drop by roughly 20%. Finally, we add the share of male applicants. The gender earnings gap decreases by roughly 50% as shown in Table 3. The aim of this comparison is to test whether gender-specific hire shares have similar explanatory power in explaining the gender earnings gap as gender-specific application rates, given that we find no significant gender differences in firms' (residualised) selection measures. The gender-specific hire share is not necessarily equivalent to gender-specific application shares, as application rates are observed at the job level while hire shares are observed at the firm level. In any case, in contrast to the share of men in firms' employment stock, both measures exhibit substantial explanatory power in the gender earnings regression.

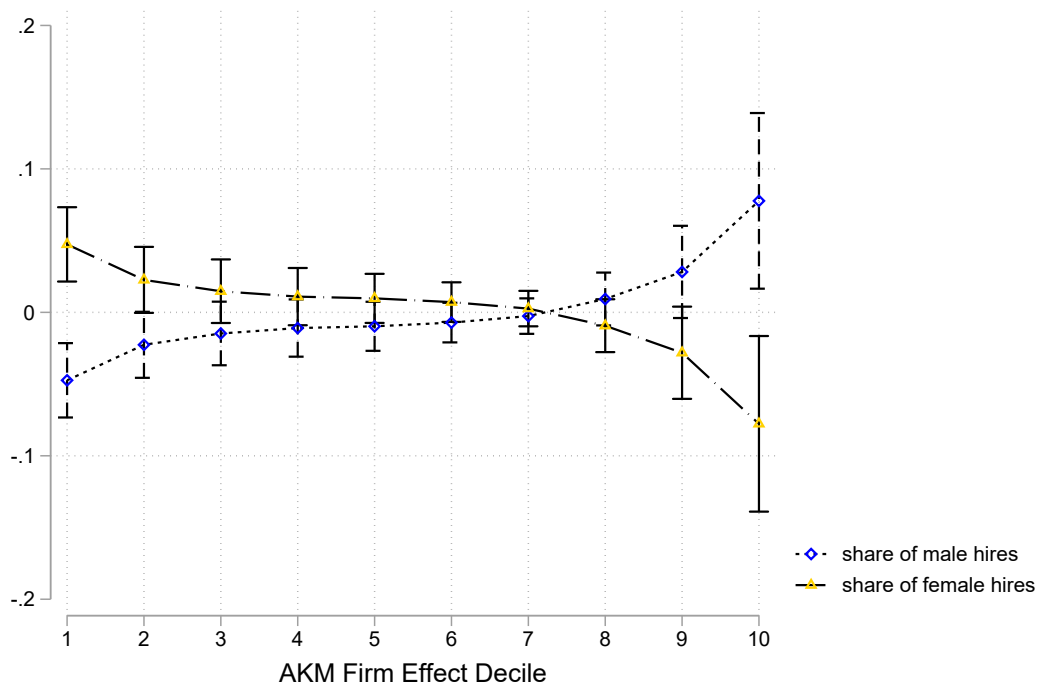
Figure B14: *Gender earnings gap*



Note: The figure shows the estimates of the gender gap (α) in hiring earnings. We add i) the firm-specific share of employed men (stock), ii) the firm-specific share of hired men (flow), and iii) the job-specific share of male applicants. Dependent variable: imputed log daily earnings. Independent variables: gender dummy, total number of applicants, worker age fully interacted with educational attainment (measured by five categories), experience in years and its squared term, an indicator variable for the previous labour market status (non-employed, unemployed, or employed), contractual working hours of the new job, formal job requirements (four categories), industry and occupation categories, firm size groups, and year dummies. Estimates for full-time workers aged 20-60. Source: IEB, JVS.

B.8 Firm-Specific Hire Shares

Figure B15: *Hire shares*



Note: The figure shows the relationship between the share of male hires, i.e., the inflow of male workers of a firm and the deciles of the AKM firm effects. The inflow measure is firm-specific and derived from administrative data. Estimates for full-time workers only. Source: IEB, JVS.

Figure B15 depicts the relationship between the share of male hires (i.e., the inflow of male workers at a firm) and the deciles of the AKM firm effects. Since we only observe the most recent hire in the JVS, the inflow measure is derived from administrative data for each firm and then merged with our JVS sample. The standard errors are bootstrapped (with replacement, 100 iterations). We find that, overall, relatively more men are hired at high-wage firms.

B.9 Gender Earnings Gap and Motherhood

Table B2 shows the estimated pay differences between men (reference category), mothers and women without children. The average differences are large. Note, however, that there are important interactions with different flexibility requirements at the job level. See Section 4.4.2 for these interactions.

Table B2: *Gender earnings gap and motherhood*

	<i>Default</i>	<i>With flex. req.</i>	<i>With share of male appl.</i>
Dep. variable	Log daily wage	Log daily wage	Log daily wage
Mothers (men=reference)	-0.20*** (0.01)	-0.13*** (0.02)	-0.12*** (0.01)
Women without children (men=reference)	-0.14*** (0.01)	-0.11*** (0.01)	-0.06*** (0.01)
Observations	14,020	8,783	12,625
Adjusted R^2	0.61	0.68	0.62

Note: Estimates for full-time workers aged 20-60. Standard errors are in parentheses. Controls: total number of applicants, a set of worker age dummies fully interacted with education dummies, experience in years and its squared term, a dummy for the previous labour market status (non-employed, unemployed, or employed), the working hours of the new contract, dummies for formal job requirements, year dummies, industry categories, occupation categories, and establishment size deciles. The regression in Column (2) adds the four flexibility requirements (hours, index for workplace mobility, overtime, and changes in the working schedule) plus the distance between the place of residence and the workplace. The regression in Column (3) adds the share of male applicants. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. Source: IEB, JVS.

B.10 Firm Fixed Effects and Commuting

We analyse how commuting distances differ for men and women (with or without children). According to French data, [Le Barbanchon et al. \(2020\)](#) show that women have shorter commuting times than do men. We do not know the (potential) commuting distances for each of the applicants. However, we can use the commuting distances for each realised match (see Section 4.4.1 for details). First, we estimate the difference in the commuting distances of women without children and mothers compared to those of men, controlling for individual and job characteristics (see the notes in Table B3). On average, women without children have a commuting distance that is 5.2 kilometers shorter than that of men, whereas mothers have a commuting distance that is 10.3 kilometers shorter.

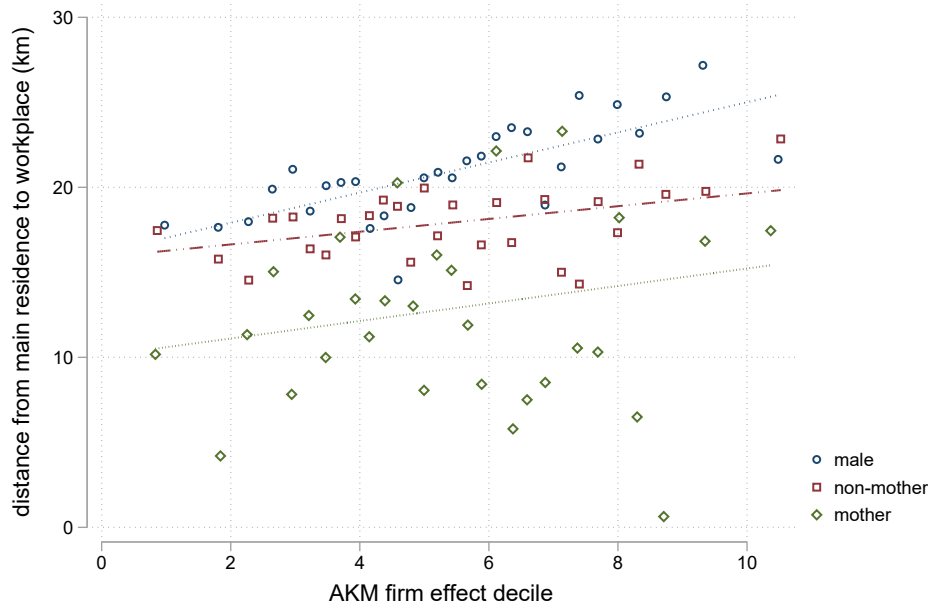
In the second step, we compare the commuting distances for the three groups over the firm fixed effect deciles. Figure B16 shows that workers who match with firms with larger firm fixed effects have, on average, longer commuting distances. This is the case for all three groups (although somewhat noisy for mothers). Commuting distances are another component where women (particularly mothers) appear to trade a larger amenity value (in this case, shorter commuting distances) for a lower wage.

Table B3: *Commuting distances*

	Distance (km)
Women without children	-5.2***
(men=reference)	(0.6)
Mothers	-10.3***
(men=reference)	(1.0)
Observations	18,821
Adjusted R^2	0.05

Note: Estimates for full-time workers aged 20-60.. Standard errors are in parentheses. Distance is winsorised at the 95 percentile level. Controls: total number of applicants, a set of worker age dummies fully interacted with education dummies, experience in years and its squared term, a dummy for the previous labour market status (non-employed, unemployed, or employed), working hours of the new contract, dummies for formal job requirements, year dummies, industry categories, and occupation categories. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. Source: IEB, JVS.

Figure B16: *Commuting and firm fixed effects*



Note: This figure shows binscatters with 50 bins and linear fit lines. Distance winsorised at the 95 percentile level. To residualise the x and y variables, we regress each variable on the controls, generate the residuals, and add the sample mean of each variable back to its residuals. We then group the x-axis variable into equal-sized bins, compute the mean of the x-axis and y-axis variables within each bin, and create a scatterplot of these data points. Control variables: total number of applicants, a set of worker age dummies fully interacted with education dummies, experience in years and its squared term, a dummy for the previous labour market status (non-employed, unemployed, or employed), working hours of the new contract, dummies for formal job requirements, year dummies, industry categories, and occupation categories. Estimates for full-time workers aged 20-60. Source: IEB, JVS.