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ABSTRACT

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

This paper analyzes the relationship between gender-specific application behavior, employer-side flexibility requirements, and the gender earnings gap using a unique combination of the German Job Vacancy Survey (JVS) linked to administrative employment records. We document that women have a substantially lower probability of applying to jobs with high flexibility requirements at high-wage firms than do men but have the same probability of being hired upon application. In our two-stage search model, these empirical patterns are rationalized by firms compensating workers for meeting employer-side flexibility requirements. Consistently, we empirically show that among women, mothers face the largest earnings discounts relative to men in jobs with high flexibility requirements.

JEL Classification: E24, J16, J31

Keywords: job search, application behavior, gender earnings gap

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1 Introduction

After several decades of gender convergence, substantial differences in earnings between men and women remain. 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 the literature has analyzed the role of gender-specific search behavior in gender earnings gaps, combining search theory and newly available microeconomic datasets (see, among others, Cortés et al., 2021; Faberman et al., 2017; Fluchtmann et al., 2024).

Our paper analyzes the interaction between gender-specific application behavior, firm-side flexibility requirements, and the gender earnings gap. To this end, we exploit detailed application and recruitment information from the German Job Vacancy Survey (JVS), which we link to administrative employment records. Both data sets are provided by the Institute for Employment Research (IAB). This unique combination allows us to observe important dimensions of the search and matching process, such as the 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] Guided by our two-stage search and matching model, we show that men and women tend to apply to different firms[2] and for different jobs. These differences can explain a large part of the residual gender earnings gap. Specifically, we show from a two-way fixed effects regression approach (Abowd et al., 1999; Card et al., 2013) that women in Germany are less likely to apply for jobs at firms with high wage premia than do men. However, the probability of being hired by these high-wage firms conditional on having applied is similar for men and women. We argue—through the lens of our theoretical model—that these patterns are not reconcilable with taste-based discrimination at the hiring stage. In contrast, these patterns can be explained by different job characteristics (Goldin, 2014), namely, more employer-side flexibility requirements at high-wage firms. At the job level, the share of male applicants[3] increases with various employer-side flexibility requirements (such as working irregular hours or at various locations). Adding these flexibility requirements or the share of male applicants as proxies for multidimensional flexibility requirements to standard Mincer earnings regressions leads to a sizable narrowing of the residual gender earnings gap. Women who match at jobs with a high share of male applicants earn substantially more than do women at comparable jobs with

[1] To 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.

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

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

only women in the applicant pool (netting out worker, firm, and job characteristics). These patterns are in line with the idea of nonlinear jobs that pay workers a premium for providing flexibility (Goldin, 2014). We show that the discount in earnings is particularly strong for mothers with children in jobs with high employer-side flexibility requirements. In line with our model, if mothers match at these nonlinear jobs, then they are more likely to be unable to satisfy the desired flexibility requirements and thereby have lower earnings compared to other women.

We motivate and structure our empirical exercise with a simple two-stage search and matching model. In the first stage, searching workers have to decide whether they want to apply for a particular job. Facing heterogeneous application costs, they apply whenever the expected returns from the application exceed the application costs. In the second stage, only those worker-firm pairs with a positive surplus form a match. Worker-firm pairs draw an idiosyncratic match-specific training cost shock. Only a certain fraction of workers are selected in the model.[4] In our model, male and female application behavior is a function of the expected match surplus. Thus, a large share of male applicants shows that men (on average) perceive a greater surplus for certain job types. We analyze two scenarios that may lead to different gender-specific applicant pools for different jobs. In the first scenario, we assume taste-based discrimination at the hiring stage. Employers recruit women only if they are compensated in the form of higher profits for their distaste. This scenario leads to lower female application rates at discriminating firms and lower selection rates at discriminating employers. In the second scenario, we assume nonlinear and linear jobs, as proposed by Goldin (2014). In nonlinear jobs, higher input (e.g., in terms of providing a larger number of working hours or meeting higher employer-side flexibility requirements) leads to a more than proportional increase in output. We assume that the desired input levels among men and women are heterogeneous. A smaller fraction of women able to provide a high input generates a sorting equilibrium, with a larger number of women applying for linear jobs and a larger number of men applying for nonlinear jobs. Under strong sorting (i.e., workers who are unable to provide a large input apply predominantly for linear jobs), firms with nonlinear production functions predominantly receive applications from workers who are willing and able to provide high input. Men and women who apply at these nonlinear firms have similar selection rates and wages.[5]

In the first step of the empirical analysis, we sort different hiring firms according to their Abowd–Kramarz–Margolis (AKM) firm wage effects, which we obtain from two-

[4]For details on selection models, see Chugh and Merkl (2016) or Carrillo-Tudela et al. (2023).

[5]Our baseline framework assumes the ex ante homogeneity of workers' aggregate productivity. In Appendix A, we discuss the potential implications of ex ante heterogeneity against the background of our empirical results.

way fixed effects regressions (Abowd et al., 1999; Card et al., 2013). We find that the probability of women applying for a job decreases almost monotonically with respect to the firm wage premium. After accounting for differences in sectors, occupations, and firm size, we find that women have a 10 percentage points higher probability of applying in the lowest AKM firm wage effect decile and a 7 percentage points lower probability of applying in the highest AKM firm wage effect decile. Importantly, we find indistinguishable selection rates between men and women in the second stage of the application process (after controlling for sector, occupation, and firm size), which is inconsistent with the taste-based discrimination hypothesis in our model. We also discuss whether taste-based discrimination may be compensated for by composition effects (i.e., more productive women matching at taste-based discriminating firms with higher firm productivity levels). When we proxy for worker productivity by worker fixed effects from the AKM wage regression, we find no support for this hypothesis. On average, women who match with the highest-paying firms have lower worker fixed effects than do their male counterparts, and the gender difference is similar in size for low-paying firms.

In the second step, we show at the job level that the (residualized) 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. In terms of gender-specific application and selection behavior, we observe the same patterns as those for different firm wage premia. Women have a considerably lower probability of applying to jobs with high flexibility requirements, while gender-specific selection rates are similar. In line with the model mechanism, we show that log wages increase with the composite index of flexibility requirements. Although the IAB JVS is richer in the employer-side flexibility requirements dimension than are other datasets, many additional flexibility requirements remain unmeasured. Therefore, we use the employer-side flexibility requirements that we observe in the data as a lower bound for our empirical analysis and the share of male applicants as an upper bound proxy, as they may also contain other driving sources.

In the third step of the empirical analysis, we estimate Mincer earnings regressions controlling for detailed worker, firm, and job characteristics. We add the flexibility requirements and the share of male applicants as proxies for employer-side flexibility requirements. We 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%). The proxies are also relevant for the level of earnings when we consider female matches only. Women who match in a pool with a large share of male applicants (at jobs with high flexibility requirements) earn 8.1 (5.3) percentage points more than do comparable women who match in a pool with a medium share of male applicants (medium-sized flexibility requirements). Women who match in jobs with no male applicants (at jobs with low flexibility requirements) earn 8.8 (7.2) percentage points less than do comparable women who match in a pool with a medium share of male applicants (medium-sized flexibility requirements).

Finally, 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 at jobs that require high degrees of flexibility, then they face substantially larger discounts relative to both men and women without children. Again, this finding is in line with our hypothesis of nonlinear production functions. Mothers tend to be less flexible than other women. Thus, if they match at nonlinear jobs, then they face particularly large wage discounts.

In the Appendix, we additionally 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.

The remainder of this paper proceeds as follows. Section 2 briefly reviews our contribution to the related literature. Section 3 describes the model framework and derives theoretical implications for taste-based discrimination at the hiring stage and for different production functions. Section 4 provides details on the datasets employed. Section 5 contains the empirical analysis of gender-specific application behavior, the estimated gender earnings gap, differences between male- and female-dominated jobs, and how flexibility requirements and being a woman with children interact. Section 6 briefly concludes the paper.

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 main source of firm wage premium differentials between genders is the underrepresentation of women in high-wage firms.[6] We complement this literature in several ways. First, we show that gender-specific behavior in applying to high-wage firms (not firms' selection behavior) is a key determinant of gender-specific sorting. Second, due to the rich information on flexibility requirements (which is absent in typical administrative data), we show the importance of these re-

[6]For 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.

quirements for application behavior 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 C.8 that the observed patterns are equally present for firms that have an organized bargaining regime (collective or firm-level bargaining).

Our findings complement a recent strand of the literature that analyzes 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 behavior (e.g., working longer hours or working night shifts), the gender wage gap decreases considerably. While these studies have very detailed information on the gender-specific behavior of workers within certain industries or firms, we have a dataset that represents the entire economy and contains information on application behavior and flexibility requirements that are both typically absent from standard datasets.

Our work is most closely related to another recent strand of literature that analyzes 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 behaviors of men and women and the implications for the gender wage gap. Moreover, Cortés et al. (2021) 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) analyzes the gender wage gap from a lifecycle perspective and finds that both statistical discrimination based on fertility concerns and different labor 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 tractable model and the IAB JVS with linkages to administrative data allows us to shed light on the intertwining of the gender-specific application of workers and the selection behavior of firms. Specifically, the data allow us to explore the role of job characteristics such as employer-side flexibility requirements while simultaneously 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 C.4, 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 that of Illing et al. (2021), 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 behavior can explain large parts of the traditional gender wage gap. The 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, which allows us to calculate the important measure derived from our model that help explain the gender earnings gap.

Our paper also contributes to the recent literature on compensating differentials. Sorkin (2018) shows for the U.S. that compensating differentials can explain approximately two-thirds of the variance in firm-level earnings. Morchio and Moser (2021) show that compensating differentials can explain up to one-fifth of the gender wage gap in Brazil. For Denmark, Taber and Vejlin (2020) show that preferences for nonpecuniary aspects are very important for job choices. Our empirical findings are in line with these findings. Women have a higher probability of applying for low-wage jobs and of being compensated in terms of low employer-side flexibility requirements compared to men. Consistently, Budig and Hodges (2010) show that mothers are more willing than are women without children to trade their wages for family friendly employment.

Based on experimental data, Wiswall and Zafar (2017) show that women have a higher willingness to pay for nonwage job features than do men. In the same vein, Le Barbanchon et al. (2020) analyze gender differences in terms of employees' willingness to commute and show for France that women commute much shorter distances than do men. Based on their search model, the above authors find that 14% of the residualized 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 do women in general and substantially longer distances than do mothers in particular. On average, matches that require longer commuting times can be expected to be disliked by women (particularly those women with care responsibilities). When we add commuting distances to our earnings regressions with the proxies for the required flexibility of a job (see Tables 3, the gender earnings gap is further narrowed. We further show that adding the share of male applicants as an encompassing measure for flexibility requirements reduces the residual gender earnings gap even more than the other proxies.

Our paper is also highly relevant from an economic policy perspective. In particular, working from home arrangements during the COVID-19 episode provided a laboratory in which to test whether a higher degree of flexibility on the employee side is possible. Barrero et al. (2020) argue that these working 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 Theory

We derive a theoretical model that allows us to interpret the patterns in the IAB JVS from a gender-specific labor market flow perspective.[7] In the data, we observe the application behavior of men and women for particular jobs (both in terms of pay and flexibility requirements) and the hiring behavior of firms for particular jobs. Accordingly, our model assumes a two-stage decision problem (i.e., application and hiring/selection). In the first stage, workers have to decide whether to apply for a particular job. In the second stage, only those worker-firm pairs with a positive match surplus form a match; i.e., only a certain fraction of workers are selected by firms.[8] We analyze the implications of two specific scenarios and compare them to the patterns in the data. First, some firms may engage in taste-based discrimination at the hiring stage; i.e., they may dislike hiring women. Second, following Goldin (2014), we assume that there are jobs with nonlinear production functions and jobs with linear production functions. At nonlinear jobs, the output increases more than proportionally with the input. Working hours are certainly an important dimension of input. However, we define input in a multidimensional sense (e.g., including the ability to travel for business or be available on short notice).

3.1 Model Environment

We assume that there are different job profiles, where $y_{p,j}$ denotes the output level when worker j matches with a certain job profile, p. For simplicity, we derive a static model and exclude the possibility of multiple vacant jobs for one worker, i.e., one random job is visible for each searching worker. We assume that workers learn about one particular job profile. In the first stage, they have to decide whether to apply for this particular job, which they do if the application costs e are lower than the expected return from this application.

In the second stage, worker j, who decides to apply for a particular job profile, p, draws a match-specific training cost shock upon contacting the firm. We denote this shock by $\varepsilon_{p,j}$. Only those worker-firm pairs with a positive joint surplus form a match.

3.1.1 Application Decision

Worker j applies for a particular job, p, whenever the expected returns from the match exceed the application costs:

[7] In line with the cross-sectional dataset, the model is silent on some other potentially important dimensions (e.g., the intertemporal lifecycle perspective).

[8] For other selection models, see Brown et al. (2016), Chugh and Merkl (2016), or Carrillo-Tudela et al. (2023).

$$E(\eta_{p,j}\bar{w}\left(\tilde{\varepsilon}_{p,j}\right)) - \xi_j \geq e_{p,j}. \tag{1}$$

The left-hand side of the equation shows the expected returns from a match, where $\eta_{p,j}$ is the hiring rate in the second stage and $\bar{w}\left(\tilde{\varepsilon}_{p,j}\right)$ is the expected wage conditional on being hired, which are defined below and is a function of the cutoff point in the second stage, $\tilde{\varepsilon}_{p,j}$. A searching worker faces uncertainty about the ex post realization of match-specific shocks in the second stage. Consequently, the worker has to form expectations, which are denoted by the expectations operator E.[9] Henceforth, we assume rational expectations.[10] ξ is the worker's value of unemployment (e.g., home production and benefits). Ex ante application costs e are drawn from a stable density function, $g\left(e\right)$. Application costs are sunk at the time of application; i.e., they play no role in determining the surplus in the second stage.

There is a certain cutoff point level, $\tilde{e}_{p,j}$, up to which workers apply for job type p:

$$\tilde{e}_{p,j} = E(\eta_{p,j}\bar{w}\left(\tilde{\varepsilon}_{p,j}\right)) - \xi_j. \tag{2}$$

Above the threshold $\tilde{e}_{p,j}$, the application costs exceed the expected returns. Below this threshold, workers apply for job p. The application rate of group j for a particular job, p, is the integral from the lower support of the distribution ($e_p^{\min}$) up to the cutoff point:

$$\alpha_{p,j} = \int_{e_p^{\min}}^{\tilde{e}_{p,f}} g\left(e\right) de. \tag{3}$$

3.1.2 Hiring Decision

Upon contact, each worker-firm pair draws an idiosyncratic match-specific cost shock, $\varepsilon_{p,j}$, which we interpret as training costs. To complete the same job, some workers require little training, while other workers require considerable training. The ex post training cost shock is drawn from a stable density function, $f\left(\varepsilon\right)$.

Once a match is formed, each job profile produces a certain output level, $y_{p,j}$, which may be dependent on the ability or willingness of the worker to provide input (to be discussed and specified below). In addition, taste-based discrimination by employers at

[9] In the first stage, workers do not know their shock realization in the second stage. However, they know the output level of the job $y_{p,j}$ and form expectations about the hiring probability and average training cost realization.

[10] Under rational expectations, workers know the average expected hiring probability and the average expected wage conditional on being hired. Although our model allows us to analyze the implications of worker overconfidence or underconfidence (e.g., men (women) systematically overestimate (underestimate) their wage and hiring prospects), we abstain from doing so, as we do not have any data on this dimension in our firm-level dataset.

the hiring stage against certain worker groups may exist, meaning that the firm hires from this group only if there is compensation in the amount of $t_{p,j}$. The joint match surplus between workers and firms is defined as follows:

$$\Pi_{p,j} = y_{p,j} - \varepsilon_{p,j} - t_{p,j} - \xi_j. \tag{4}$$

The next two equations define the worker and firm surpluses separately. Both surpluses have to be nonnegative for a match to take place.

$$w\left(\Pi_{p,j}\right) - \xi_j \geq 0, \tag{5}$$

$$y_{p,j} - w\left(\Pi_{p,j}\right) - \varepsilon_{p,j} - t_{p,j} \geq 0. \tag{6}$$

Equation (6) defines the condition under which the employer is willing to hire a worker and to produce. Under a bilaterally efficient wage formation process, there is a higher level of production when there is a nonnegative joint surplus, $\Pi_{p,j} \geq 0$. At the cutoff point for training costs, the joint surplus equals zero. Thus, by imposing bilateral efficiency, we can calculate the cutoff point for idiosyncratic match-specific costs up to which workers and firms are willing to match and produce.[11]

$$\tilde{\varepsilon}_{p,j} = y_{p,j} - t_{p,j} - \xi_j. \tag{7}$$

The selection rate of a worker from group j at job p is the integral from the lower support of the idiosyncratic cost function ($\varepsilon_p^{\min}$) up to the cutoff point:

$$\eta_{p,j} = \int_{\varepsilon_p^{\min}}^{\tilde{\varepsilon}_{p,j}} f\left(\varepsilon\right) d\varepsilon. \tag{8}$$

3.1.3 Wage Formation

To be able to define the wage and application rate, we need to consider wage formation. Without loss of generality,[12] we assume Nash bargaining between workers and firms, which delivers bilaterally efficient wages in our setting. Nash bargaining leads to the plausible outcome that wages are a function of firm-specific output, the realization of idiosyncratic training costs and workers' fallback options.

Under Nash bargaining, workers and firms maximize their joint Nash product, Λ, with respect to the wage as follows:

[11] Note that the wage does not appear in Equation (7) because of the imposed bilateral efficiency.

[12] Any match with a bilateral surplus is created in the second stage. Thus, the selection rate (which is important for testing taste-based discrimination) is unaffected by wage formation, as long as it is bilaterally efficient.

$$\Lambda = \left(w\left(y_{p,j}, \varepsilon_{p,j}, \xi_j\right) - \xi_j\right)^{\varrho} \left(y_{p,j} - w\left(y_{p,j}, \varepsilon_{p,j}, \xi_j\right) - \varepsilon_{p,j} - t_{p,j}\right)^{1-\varrho}, \tag{9}$$

where ϱ denotes workers' bargaining power.

This calculation yields the following wage:

$$w\left(y_{p,j}, \varepsilon_{p,j}, \xi_j\right) = \varrho\left(y_{p,j} - \varepsilon_{p,j} - t_{p,j}\right) + \left(1-\varrho\right)\xi_j. \tag{10}$$

Equations (5) and (6) establish the conditions under which wage formation is bilaterally efficient, and they hold under Nash bargaining.

Based on the wage formation mechanism, we calculate the expected wage conditional on being hired for a particular job, which we require for the first stage of the decision process, as follows:

$$\bar{w}\left(\tilde{\varepsilon}_{p,j}\right) = \frac{\int_{\varepsilon_{p,j}^{\min}}^{\tilde{\varepsilon}_{p,j}} w\left(\varepsilon\right) f\left(\varepsilon\right) d\varepsilon}{\eta_{p,j}}. \tag{11}$$

3.1.4 Production

We consider two scenarios in terms of production. There is either a fixed production level for each job profile, y_p, or two types of production functions. The second case is derived below.

Following Goldin (2014), we assume that there may be firms with different production functions and that workers can choose the amount of input provided λ_j.[13] Input may be working hours, but it may also be other employer-side flexibility requirements, such as working at different locations or being available on short notice.

For jobs with a nonlinear production function, nl, output is defined as follows:

$$y_{nl,j} = \lambda_j a_{nl} \text{ if } \lambda_j > \lambda^* \tag{12}$$

$$y_{nl,j} = \lambda_j a_{nl}\left(1-\delta\right) \text{ if } \lambda_j \leq \lambda^* \tag{13}$$

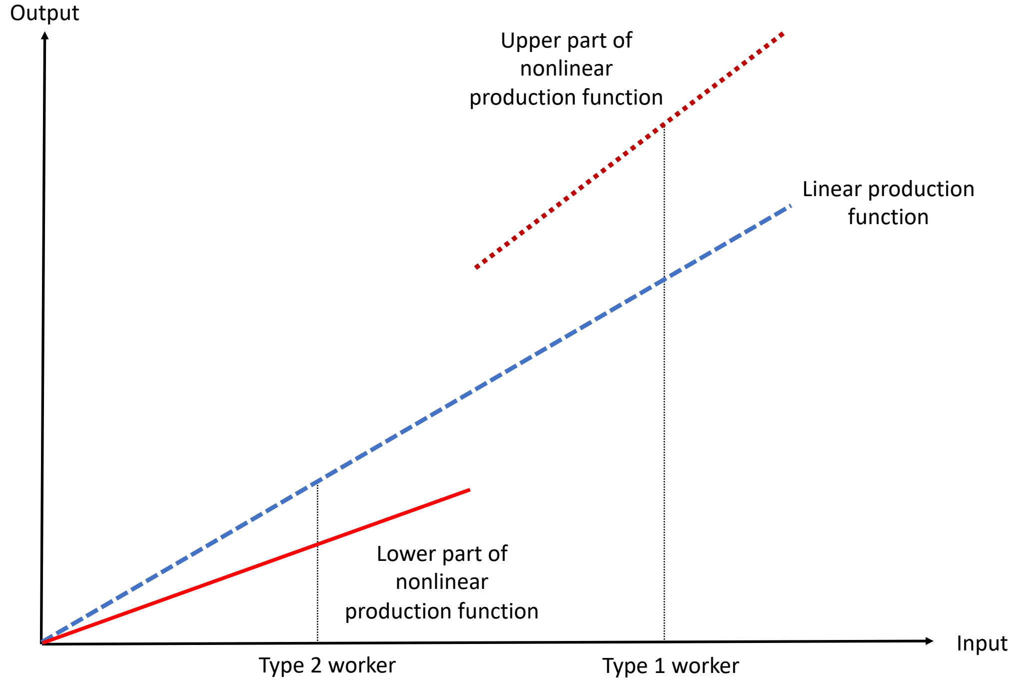
In addition, other jobs where the output is linear, l, exist as follows:

$$y_{l.j} = \lambda_j a_l \tag{14}$$

As in Goldin (2014), we assume that $\lambda_j a_{nl} > \lambda_j a_l$ for $\lambda_j > \lambda^*$ and $\lambda_j a_{nl} < \lambda_j a_l$ for $\lambda_j < \lambda^*$. Figure (1) illustrates the nature of the two production functions. A worker being

[13] As we focus on workers' application behavior in a partial equilibrium setting, we abstract from the question of the circumstances under which these nonlinear and linear firms coexist in a full general equilibrium setting.

Figure 1: Nonlinear and linear jobs



Note: The figure illustrates output as a function of input for a linear and nonlinear production function, showing the input-output connection for a worker who is willing to provide a high input (type 1) and for a worker who is willing to provide a lower input (type 2.)

willing to provide working hours/flexibility beyond the minimum threshold λ^* leads to a larger amount of production carried out at nonlinear firms than at linear firms. Otherwise, there is a larger amount of production at linear firms.

The underlying idea is that certain job profiles require a large degree of flexibility to deliver high output levels (nonlinear jobs). A surgeon in a hospital may, for example, have to be available on short notice, while he/she may have more reliable working times in a doctor's office. A sales manager at an internationally operating firm may have to travel long distances, while this may not be the case for a sales manager at a locally operating firm. As we control for occupation, sector, and firm size in our empirical specification, we consider different jobs in similar occupations or sectors.

3.1.5 Equilibrium

The labor market equilibrium is described by the application cutoff point in Equation (2), the application rate (3), the cutoff point for the idiosyncratic match-specific cost shock (7), the corresponding selection rate (8), the wage equation (10) and the wage expectations conditional on being hired (11). Either the output per job is exogenous or production may be governed by different types of (non)linear production functions and by the willingness of applicants to provide certain input levels.

3.2 Model Implications

Our model allows us to analyze how different scenarios affect the application rates, selection rates and wages for different worker groups j. We consider two scenarios. First, we analyze the scenario in which there is taste-based discrimination against women in the hiring stage for high-productivity jobs. The empirical observation that women earn systematically less than do men (when controlling for observables) may be driven by taste-based discrimination at firms that produce a large output level per worker. Second, we analyze the implications of our model with nonlinear and linear jobs.[14]

3.2.1 Taste-Based Discrimination

We start by assuming that workers are ex ante homogeneous and that production per job is exogenous, y_p. The exogenous production assumption is relaxed in the next subsection. The implications of a deviation from ex ante worker heterogeneity are discussed in Appendix A, in which we also analyze the case where application costs and training costs are positively correlated. Applicants differ only in terms of their gender. We assume that employers at certain firms/jobs discriminate against women in the hiring stage ($t_{p,f} > 0$, $t_{p,m} = 0$, where f stands for female workers and m for male workers).

Taste-based discrimination against women reduces the joint surplus in the event of a female match and thereby reduces the cutoff point for idiosyncratic shock realization as follows:

$$\tilde{\varepsilon}_{p,f} = y_{p,f} - t_{p,f} - \xi_f. \tag{15}$$

This situation leads to a lower selection rate in the second stage of the application process.

As women anticipate selection behavior and wages in the second stage, only a smaller fraction of them apply to discriminating firms in the first place; i.e., the cutoff for application costs is lower. This situation can be understood best by substituting the wage conditional on hiring (Equation (11)) into the application cutoff point condition (Equation (2)) as follows:

$$\tilde{e}_{p,f} = E \int_{\varepsilon_{p,j}^{\min}}^{\tilde{\varepsilon}_{p,j}} w(\varepsilon) f(\varepsilon) d\varepsilon - \xi_f. \tag{16}$$

Overall, taste-based discrimination in the hiring stage leads to lower female application and selection rates. These implications can be tested with the data used in our paper.

[14] As a third potential mechanism, we could analyze the different bargaining powers of men and women. However, we do not have any direct proxy for the level of bargaining power in our dataset. In addition, we show in Appendix C.8 that our empirical results are very similar for firms with and without an institutionalized bargaining agreement (e.g., collective bargaining).

3.2.2 (Non)Linear Production Functions and Sorting

Next, we analyze the implications of two types of production functions (linear and non-linear). Let us assume, for illustration purposes, that there are two types of workers (see also Figure (1)). Type-1 workers are willing/able to provide a larger input, λ_j, than are type-2 workers. In addition, we assume that type-1 workers are above the threshold $\lambda_1 > \lambda^*$, while type-2 workers are below the threshold $\lambda_2 < \lambda^*$.

Under these assumptions, we obtain the following four different cutoff points:

$$\tilde{\varepsilon}_{nl,1} = \lambda_1 a_{nl} - \xi_1, \tag{17}$$

$$\tilde{\varepsilon}_{l,1} = \lambda_1 a_l - \xi_1, \tag{18}$$

$$\tilde{\varepsilon}_{nl,2} = \lambda_2 \left(1 - \delta\right) a_{nl} - \xi_2, \tag{19}$$

$$\tilde{\varepsilon}_{l,2} = \lambda_2 a_l - \xi_2. \tag{20}$$

Under our assumptions, the following ranking holds:

$$\tilde{\varepsilon}_{nl,1} > \tilde{\varepsilon}_{l,1}, \tag{21}$$

and

$$\tilde{\varepsilon}_{l,2} > \tilde{\varepsilon}_{nl,2}. \tag{22}$$

Thus,

$$\eta_{nl,1} > \eta_{l,1}, \tag{23}$$

$$\eta_{l,2} > \eta_{nl,2}. \tag{24}$$

Intuitively, type-1 workers generate the largest output at nonlinear production firms and thereby face the highest selection rate at these firms. In contrast, type-2 workers generate the largest output at firms with linear production functions. The same ranking is true for wages and thus for the probability of applying it to the respective firms.

Under certain parameterizations (large differences in production between linear and nonlinear jobs and the small dispersion of idiosyncratic application costs), our model generates a complete sorting equilibrium of the following type:

$$\eta_{nl,1} > \eta_{l,1} = 0 \tag{25}$$

$$\eta_{l,2} > \eta_{nl,2} = 0 \tag{26}$$

In this case, type-1 workers have no surplus at linear jobs, and type-2 workers have no surplus at nonlinear jobs. As a consequence, in such a case, type-1 workers do not apply for linear jobs, and type-2 workers do not apply for nonlinear jobs. Although this example appears to be extreme, it is very useful for illustration purposes.

How can different production functions and input provisions interact with gender? Even at present, women bear greater responsibility in terms of childcare and other family-related responsibilities than do men. Therefore, a larger fraction of women may be less flexible in terms of input provision than men (i.e., they may have more difficulty working long hours, being available on short notice, or traveling for business). Let us assume that a larger share of men are type-1 workers (relative to women). In this case, we observe that the average application rate of women at high-wage firms (those with nonlinear production functions) is lower than that of men. Note that under complete sorting, women who match with nonlinear firms (only type-1 women) have the same selection rate and the same wages as those of men.

We are unable to directly observe type-1 and type-2 individuals in the data. However, one of the key data innovations is that we have proxies for the required flexibility for specific job vacancies (e.g., working hours or other flexibility requirements) and a proxy for the flexibility that can be provided on the worker side (whether women are mothers).

3.2.3 Model and Data

Our simple theoretical model provides useful guidance regarding which outcome variables we should consider. Hence, it provides a roadmap for empirical analysis.

Given that we have AKM firm fixed effects for each firm and observe the exact number of applicants for each job, we can calculate the share of female applicants and their probability of being selected (upon application) for jobs with different wage premia. As low female application rates at high-wage firms are consistent with both predictions (taste-based discrimination and nonlinear production functions), we need both measures to differentiate between them.

In the first step, we test our hypothesis of taste-based discrimination in the hiring stage by checking whether the probability of women being hired (upon application) is generally lower than that of men (while controlling for observables). In addition, we check whether such a pattern is prevalent in high-wage premium firms. If high-wage firms discriminate more than do low-wage firms, then this situation leads to a gender earnings gap, as women apply to these firms with a lower probability and are thus hired with a lower probability by these firms. Overall, this situation depresses the share of women in firms with the highest earnings. To analyze potential composition effects in terms of heterogeneity in worker productivity that may drive the application and selection patterns, we check whether we find differences in worker fixed effects in terms of the gender of those workers who match at different firms.

In the second step, we analyze the connection between female application behavior and employer-side flexibility requirements at the job level. This approach helps us understand whether these flexibility requirements (potentially driven by nonlinear production functions) may be important drivers of gender differences. In addition, this approach helps us understand whether the share of male applicants may be a suitable proxy for these flexibility requirements.

In the third step, we analyze whether flexibility requirements are important for realized earnings. Moreover, we analyze whether women who match at jobs that require considerable flexibility or in a pool with a larger share of male applicants earn more than do women who match at jobs that require less flexibility or in a pool with a large share of female applicants.

Finally, we directly check whether having children affects certain outcomes for women at the person level, which provides a direct test of the question of whether nonlinear production functions and inflexibility interact for mothers.

4 Data

4.1 Data Sources

We use the IAB JVS (Moczall et al., 2015) as our primary source of data. The JVS covers up to 14,000 establishments per year and is a representative survey of establishments in Germany from all sectors and includes all establishment size classes. Each year, the survey collects information on the hiring process of German establishments.[15]

An important component of the JVS is an array of questions regarding the recruitment process for the most recent new hire.[16] 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

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

[16] Specifically, establishments are asked to report their most recent hire (regular part- or full-time worker and not marginally employed or apprentice worker) within the last 12 months.

hours and certain job-specific flexibility requirements, such as the need to work overtime, changes in working schedules on short notice, and work-related mobility.

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). The identification is based on overlapping information such as the hiring date 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. Table 2 in Lochner (2019) shows that the identified JVS hires are similar to new hires in terms of observable worker characteristics.[17] The IEB encompasses labor market information for the majority of workers in Germany.[18] Combining the survey data with the 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 D, we additionally show that all our results are robust when abandoning this restriction and also considering part-time jobs.

4.2 Administrative Data Linkages and Imputations

Social security data report the total wage sum over workers' employment spell. 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.[19]

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). Then, we 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

[17] The 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.

[18] The IEB covers approximately 80% of the German working population, excluding only civil servants and self-employed individuals.

[19] First, 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. The administrative data lack detail on working hours, and thus, only the wages of full-time workers can be estimated. However, the share of part-time observations with censored wages is negligibly small (less than 1%).

or university degree.

To identify the role of children, we use established proxies for motherhood (Müller and Strauch, 2017).[20] 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 unemployment and benefits. Since this procedure is suitable for all of the administrative data, we can run it on our linked JVS-IEB sample and hence identify mothers among the identified JVS hires.

4.3 Final Sample

For our analysis, we use the JVS from 2010-2016.[21] We then link the administrative data to the survey information. Ultimately, our estimation sample consists of 21,694 distinct new hires for which we obtain further 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	35.86	10.75	36.46	10.91
Share with college or university degree*	18.45		14.74	
Experience (years)	8.19	8.19	9.67	8.38
Match characteristics	Mean	Std. dev.	Mean	Std. dev.
Working hours (contractual)	34.40	7.69	38.85	4.20
Share jobs requiring college degree**	2.86		2.97	
Firm size decile	5.47	2.92	5.44	2.88
Firm wage premium decile	5.47	2.89	5.58	2.84
Log daily earnings	4.13	0.47	4.36	0.44
Log daily earnings if full-time	4.20	0.43	4.37	0.43

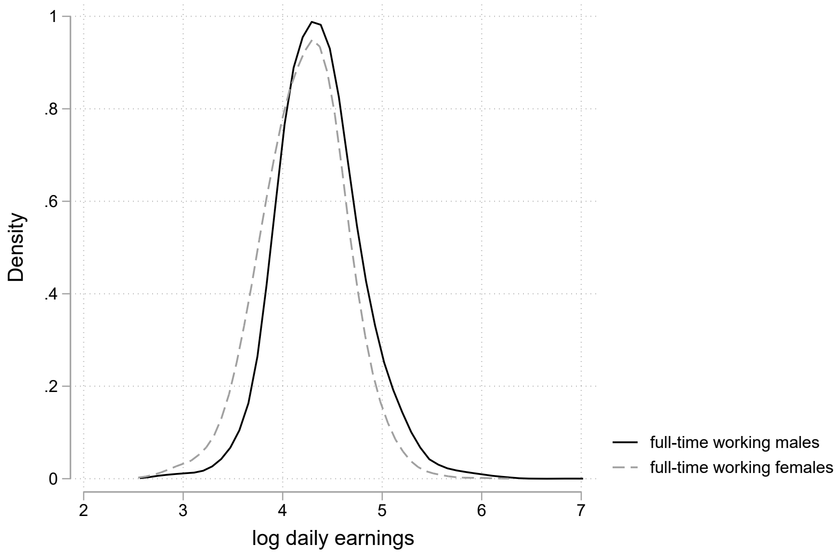
Note: * based on the education variable with five categories: 1) intermediate school exit certificate without vocational training, 2) intermediate school exit certificate with vocational training, 3) upper secondary school exit certificate without vocational training, 4) upper secondary school exit certificate 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.

[20] The use of administrative data allows us to use a proxy for marriage (Bächmann et al., 2021). We experimented with this proxy. However, motherhood appears to be a more meaningful variable.

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

On average, at the time of hire, men are approximately half a year older and approximately 0.6 years older than are the women in our sample. Women are somewhat more educated. On average, men work approximately 4 hours longer than do women. 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 amounts to 23 log points on average for all jobs in our sample and 17 log points for full-time jobs.[22] Figure 2 shows the distributions of the hiring earnings for women and men in full-time jobs.

Figure 2: 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.

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.[23] For example, women are more likely to apply for health care-related occupations than are men, while the opposite is the case in occupations related to construction and architecture. Table B.1 in the Appendix shows similarly distinct application patterns across industry sectors. For example, the share of male applicants is much larger in manufacturing than in certain service sectors (e.g., education).[24]

[22]We define hiring earnings as earnings within the first employment spell in the administrative data on the new hire.

[23]Note that the shares of female and male applications always sum to one for each hire and thereby also do so for each occupation.

[24]In 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.

Table 2: Share of male/female hires and applicants across occupations

Occupation in (KldB2010 1-digit)	Total hires	Share of hires Men (%)	Share of hires Women (%)	Share of applicants Men (%)	Share of applicants Women (%)
1 Agriculture, forestry, farming, etc.	701	68.47	31.53	66.46	33.54
2 Production of raw materials, manufacturing etc.	4,785	84.91	15.09	82.65	17.35
3 Construction, architecture, techn. building services etc.	1,601	90.82	9.18	88.90	11.10
4 Natural sciences, geography, informatics etc.	894	77.85	22.15	75.80	24.20
5 Traffic, logistics, etc.	1,910	80.00	20.00	76.16	23.84
6 Commercial services, trading, sales, hotels, etc.	1,814	40.24	59.76	40.26	59.74
7 Business organization, accounting, law, etc.	5,643	30.96	69.04	34.82	65.18
8 Health care, the social sector, teaching, education etc.	3,679	17.75	82.25	19.44	80.56
9 Philology, humanities, soc. sciences, media, etc.	574	41.99	58.01	43.48	56.52
Total	21,604	53.67	46.33	58.66	41.34

Source: IEB, JVS.

5 Empirical Results

5.1 Application and Selection Patterns at the Firm Level

We start by investigating the application and selection behavior at particular firms through the lens of our theoretical model with the ex ante homogeneity of applicants. For this purpose, we use the information on the pool of applicants for different jobs from the IAB JVS. We know the gender composition of the pool of applicants, i.e., the number of male and female applicants. However, we do not know any other characteristics of these applicants. In addition, we use information on the characteristics of the individual who is actually hired and the characteristics of the job.

In the theoretical model, higher firm-specific wages may be driven by either a larger output per worker or wage formation.[25] As there is no direct output measure such as value added or sales in the IAB JVS, we analyze how gender-specific application behavior differs across firm fixed effects through two-way fixed effects regressions, as described in Bellmann et al. (2020) and Lochner et al. (2020).[26] Specifically, we obtain gender-pooled firm effects by simultaneously including men and women in the two-way fixed effects

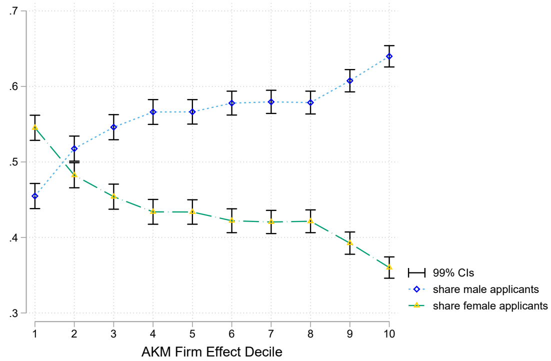
[25]We do not model different wage formation mechanisms. However, in the Appendix, we show that our key results on application and selection behavior are robust to considering different wage formation regimes.

[26]We run an AKM wage regression on the universe of German administrative data for 2010-2017 in the spirit of Abowd et al. (1999). The specification largely follows that of Card et al. (2013), where we assume that workers' log real daily wages are an additive separable function of the time-invariant worker fixed effect, the firm fixed effect, an index of time-varying observable characteristics, and an error component.

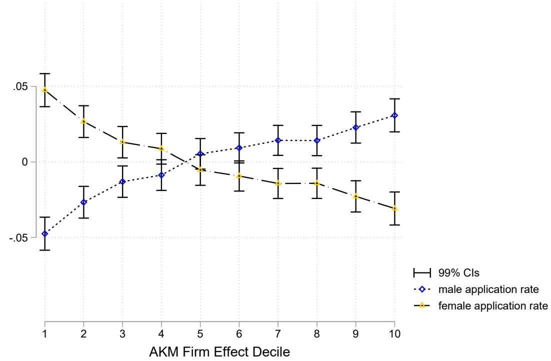
regression. Hence, we restrict gender gaps in the firm wage premia to segregation across firms. In Appendix C.7, we present additional results from gender-specific firm fixed effects and discuss them in the context of our theoretical model.

Figure 3: Application and selection rate by gender and AKM firm effect deciles

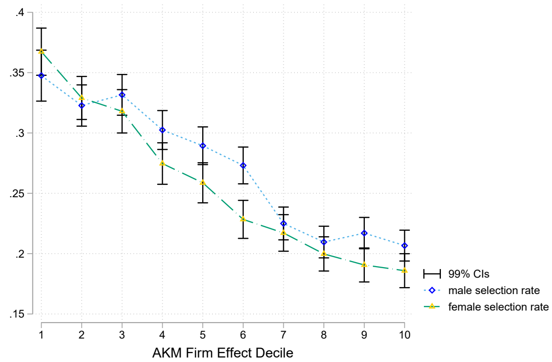
(a) Share of female/male applications



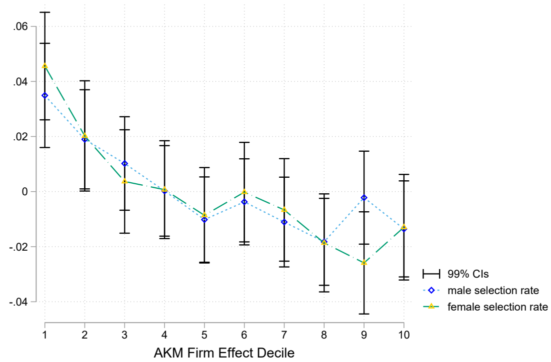
(b) Residualized share of female/male applications



(c) Female/male selection rate



(d) Residualized female/male selection rate



Note: Full-time jobs only. 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 rate=1/number of male appl. if hired, and in this case, the female selection rate equals zero, and female selection rate=1/number of female appl. if hired, and 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.

Panel (a) of Figure 3 shows the share of male and female applicants for each of these firms, ranked according to AKM firm fixed effect deciles (with the firms that pay the largest average discount on the left-hand side and those with the largest premium on the right-hand side). At the highest earnings premia, the share of male applicants is more than 20 percentage points larger than the share of female applicants. At the bottom of the earnings premium distribution, the opposite is true, with a 10 percentage points larger application share for female applicants at firms that pay the lowest premia.

A sizable part of these patterns is driven by women and men applying in different sectors and occupations, as is visible in Tables 2 and B.1. Therefore, we control for occupation, industry, and firm size in Panel (b) of Figure 3. Although the differences between male and female application behavior are quantitatively less pronounced when these controls are added, the striking insight is that a substantial gap in application behavior remains. There is an approximately 7 percentage points higher probability of men applying at the highest wage firms and a 10 percentage points higher probability of women to applying at the lowest wage firms. Through the lens of our model, this large difference in gender-specific application behavior may be driven by either taste-based discrimination at the hiring stage or by different employer-side flexibility requirements at different jobs.

In the Appendix, we show that higher female application rates at low-paying firms and lower female application rates at high-paying firms are very robust results (both for the raw data and the residualized data). This situation is true within different task complexity groups (see Appendix C.6), when firm fixed effects are estimated separately for men and women (see Appendix C.7), for different wage formation regimes (see Appendix C.8), or when dropping the full-time restriction (see Figure D.1 in Appendix D).

To analyze the second stage of the matching process, we use a model-based measure for the gender-specific selection rate of firms conditional on application. We define the gender-specific selection rate (analogous to the selection rate from the model; see Equation (8)) as follows: if a woman (man) is hired, then the female (male) selection rate is 1 over the number of female (male) applicants and 0 for the gender that is not hired (if there are applicants from this gender). Let us assume that a firm has 5 applicants, two women and three men. Assume further that a woman (man) is hired. In this case, the probabilities of a woman and a man being selected from the pool of women and men are 50% (0%) and 0% (33%), respectively. Our selection measure follows the proposition by Hochmuth et al. (2021) and Lochner et al. (2021) in terms of defining the selection rate as the inverse of the number of applicants based on the JVS.[27]

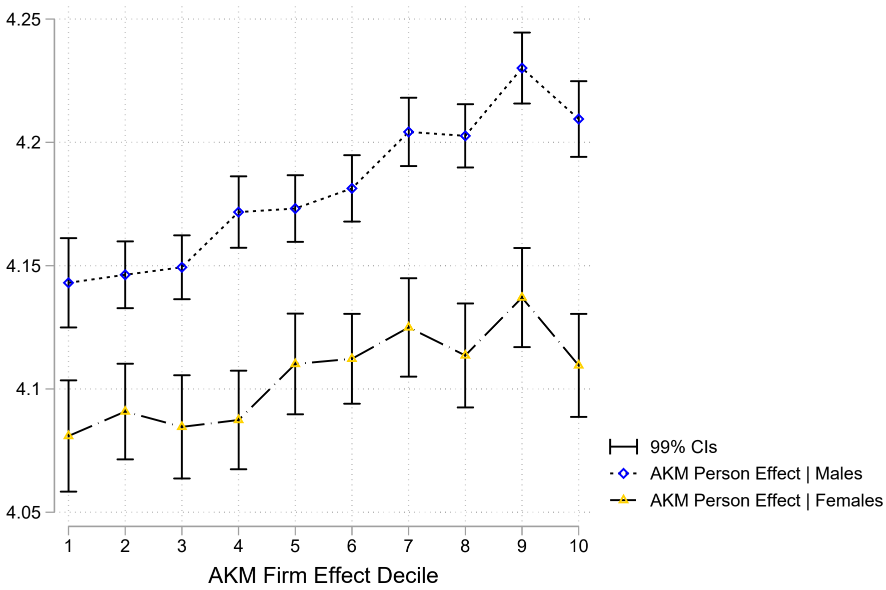
Panel (c) of Figure 3 shows that the (uncontrolled) selection rate for men and women is remarkably similar across AKM deciles. Most importantly, at firms with the highest wage premia, the probabilities of men and women being hired/selected (conditional on applying) are nearly identical (with confidence bands overlapping). When we control for sector, occupation, and firm size in Panel (d), the male and female selection rates are very similar in all deciles. The confidence bands overlap in all deciles.

In the Appendix, we show that the indistinguishable female and male selection rates at different AKM deciles are very robust (after controlling for observables). In Appendix

[27] This definition of the selection rate yields several realistic properties that are in line with model predictions. Hochmuth et al. (2021) show that the aggregate selection rate is procyclical over the business cycle (i.e., firms become less selective during booms). Lochner et al. (2021) show that the selection rate is positively correlated with employment growth distribution (for growing firms). In other words, growing firms are less selective than are firms with a constant workforce. In addition, firms that engage in considerable replacement hiring are less selective than are other firms.

C.6, we show that our results also hold for other selection measures. Furthermore, our results are robust within different task complexity groups (see Appendix C.6), when firm fixed effects are estimated separately for men and women (see Appendix C.7), for different wage formation regimes (see Appendix C.8), or when relaxing the full-time restriction (see Figure D.1 in Appendix D).

Figure 4: Worker and firm fixed effects



Note: This figure shows the residualized average worker fixed effects for matches within different firm fixed effect deciles. The AKM personfixed effect is estimated as explained in Section 5.1. Full-time jobs only. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

According to our model with ex ante homogeneity, similar gender-specific selection rates are not reconcilable with taste-based discrimination. However, we show in Appendix A that under ex ante heterogeneity, taste-based discrimination may be compensated for by a composition effect. Let us assume, for the sake of argument, that high-wage firms disfavor women. Intuitively, this situation means that only high-productivity women apply to these high-wage firms, as the expected surplus is too low for an application for low-productivity women due to taste-based discrimination. As these high-productivity women have higher ex ante selection rates, this effect and taste-based discrimination can cancel each other out in terms of the observed selection rates.

To check whether this mechanism may be a key driver of our results, Figure 4 plots the AKM person fixed effects of matches against the corresponding firm fixed effect deciles.[28]

[28] As our data are a cross-section of hires, we cannot directly estimate person fixed effects. However, we can use the person fixed effects estimated on the basis of 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

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.[29] Based on Figure 4, we find no evidence that ex ante heterogeneity may compensate for taste-based discrimination. Women have lower person fixed effects than do men at high-wage firms. Obviously, person fixed effects are driven not only by productivity but also by other factors, such as an individual's bargaining ability. However, if similar gender-specific selection rates are compensated for by composition effects, then we expect women to have larger person fixed effects than men at high-paying firms.

Given the stark differences in gender-specific application rates and the strong similarities in selection rates across AKM firm effect deciles, the model mechanism whereby high-paying firms discriminate more strongly against women than do low-paying firms (and thereby drive up the earnings gap) is not supported by the empirical gender-specific selection patterns. In contrast, the patterns are reconcilable with the second hypothesis that high-paying firms offer different jobs (namely, nonlinear jobs) and predominantly attract workers who are willing to provide the necessary flexibility. Therefore, women who apply to these high-paying firms may have the same probability of being selected as men. We analyze this hypothesis in greater detail in the following subsections.

5.2 Application Behavior and Firm-Side Flexibility Requirements

While our previous analysis is at the firm level, we now move to the job level. The IAB JVS offers several proxies for firm-side flexibility requirements. These variables serve as proxies for Goldin (2014)'s hypothesis on different production functions. As flexibility requirements are available at the job level, we do not have to rely on a flexibility definition based on occupation codes and can use the variation within occupations (by adding fixed effects).

We use four job-specific flexibility requirements from the IAB JVS, namely, the number of hours worked, the need to work overtime, the need to change working hours on short notice, and the need to be mobile in terms of the workplace (e.g., due to business travel).[30] In Figure 5, we plot these four employer-side flexibility requirements against the (residualized) share of male applicants.[31] In line with the second model hypothesis

match but not that for the entire pool of applicants. Figure D.3 in the Appendix shows the corresponding plot when the full-time restriction is dropped.

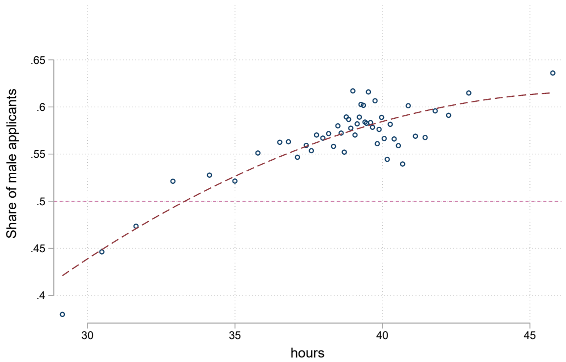
[29] For Germany, see Lochner and Schulz (2024) for a discussion. These authors also discuss why the wages at the very top of firm rankings are somewhat lower than those lower in the rankings.

[30] Employers respond regarding whether a particular job is subject to these flexibility requirements. Possible answers are "often," "rarely, " or "never." We experiment with further questions from the survey. These four selected dimensions seem to best reflect the flexibility requirements dimension.

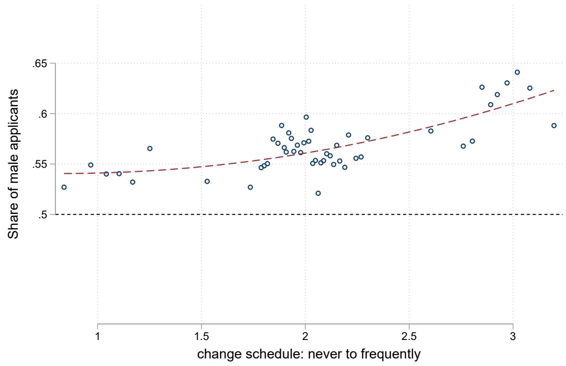
[31] Both the horizontal and vertical axes are residualized by sector, occupation, and firm size.

Figure 5: Share of male applicants and flexibility requirements

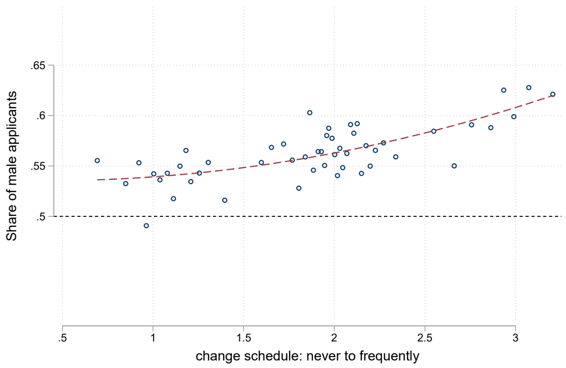
(a) Number of hours



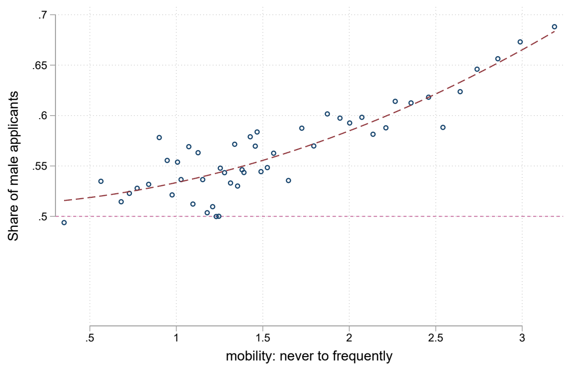
(b) Overtime



(c) Change in working hours



(d) Mobility



Note: These figures show binscatters with 50 bins and quadratic fit lines. To residualize 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- 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.

that there are different types of jobs, all four flexibility requirements comove 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.[32]

In line with the idea that the flexibility requirements satisfied by employees are inputs for a production function, we construct a composite employer-side flexibility requirement index. We define the index as working hours multiplied by the average flexibility requirement that we observe at the job level. Specifically, we consider required overtime, changes in working hours, and workplace mobility, where all the measures vary between 1 ("never require") and 3 ("often required").[33]

Analogous to our approach in Section 5.1, we analyze how the flexibility requirement index interacts with workers' application behavior and firms' selection behavior. Qualitatively, the patterns are the same for different flexibility requirements at the job level as for different firm fixed effects at the firm level. In both cases, there are pronounced differences in residualized gender-specific application behavior. Moreover, in both cases, the residualized selection rates are similar for men and women across the distribution.

Figure 6 shows that the gender differences in application behavior are quantitatively even more pronounced for firms with different flexibility requirements than for those with different firm fixed effects (compare to Figure 3). While the difference in the application shares is approximately 7 percentage points at the decile with the highest-paying firms, the difference is approximately 16 percentage points at the decile with the highest flexibility requirements.

Finally, we analyze the interaction effect between flexibility requirements and wages at the job level. Figure 7 shows that jobs with greater flexibility requirements are associated with a higher wage. In line with the idea of nonlinear jobs in the theoretical model, we show that wages increase with higher flexibility requirements.[34]

In reality, flexibility requirements are multidimensional. Although the survey questions in the IAB JVS are considerably more detailed in this dimension than are many other surveys, we believe that employer-side flexibility requirements can be captured only partially.[35] Given the strong connection between observed flexibility requirements and the share of male applicants, we regard the share of male applicants as an upper-bound

[32]Figure D.2 shows these plots when dropping the full-time restriction.

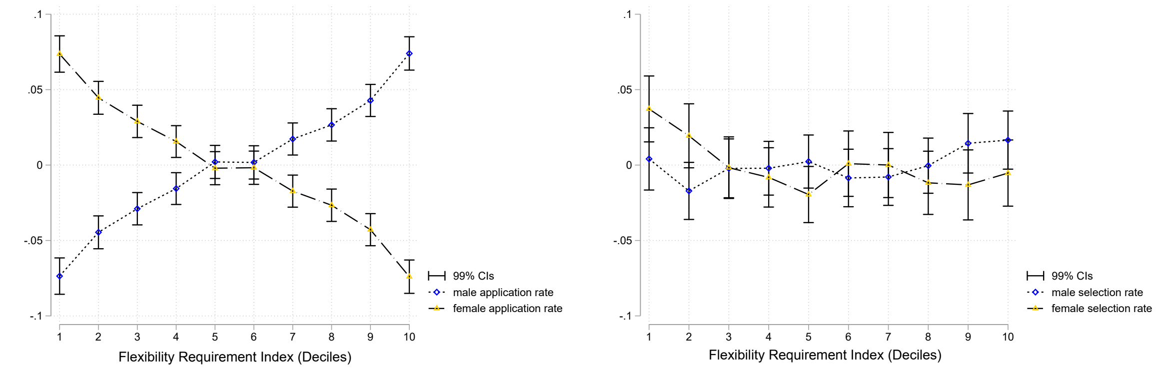
[33]We first winsorize the composite index at first and one hundredth percentiles and then create deciles. See Table B.2 for distributional details.

[34]Figure 7 plots these wages at different levels. If we plot both variables in logs, then the convex relationship is also clearly visible.

[35]This concept follows the idea of Goldin (2014, p.1104): "By job flexibility, I mean a multitude of temporal matters, including the number of hours, precise times, predictability and ability to schedule one's own hours."

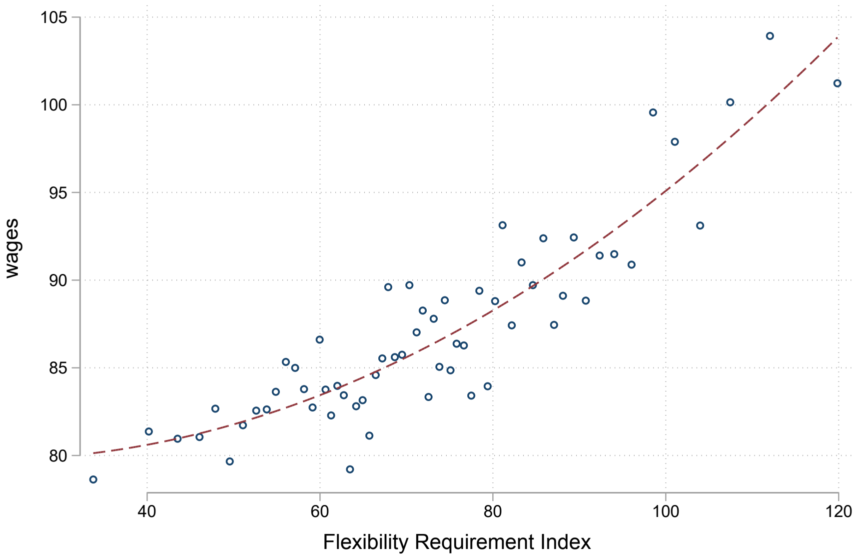
Figure 6: Application and selection rate by gender and flexibility requirement index

(a) Residualized share of female/male applications **(b)** Residualized female/male selection rate



Note: Full-time jobs 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, and b) male selection rate=1/number of male appl. if hired, and in this case, the female selection rate equals zero, and female selection rate=1/number of female appl. if hired, and 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.

Figure 7: Wages and flexibility requirement index



Note: Full-time jobs only. The Y-axis shows the daily wages of new hires. The flexibility requirement index is defined as the working hours multiplied by the average requirement (overtime, changes in working hours, and workplace mobility). Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

proxy for multidimensional flexibility requirements, as it may be correlated with other amenities. In addition, we use our survey-based flexibility requirements directly. We consider them to be lower bounds, as they probably do not measure all dimensions of flexibility requirements. In the next step, we analyze how the residual gender earnings gap is affected by employers' flexibility requirements.

5.3 Residual Gender Earnings Gap

To quantify the gender earnings gap, we estimate Mincer-type wage regressions. Our benchmark Mincer-type regression is as follows:

$$Log\ wage_{i,t} = \alpha\ gender_{i,t} + \gamma\ controls_{i,t} + error_{i,t}, \tag{27}$$

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 labor market status (nonemployed, 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 in the context of our model predictions, we directly add i) the flexibility requirements and ii) the share of male applicants to Equation (27). 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 (27). 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). Adding contractual working hours to the regression narrows the gender gap by 10.6%. Further adding the other flexibility requirements (indicators for the need for job mobility, overtime, and a change in working schedule) shrinks the gap by 18.6% 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 decreases the total reduction in the residual gender earnings gap to 24.2%. This

Table 3: Gender earnings gap

		Coef.	Std. error	Reduction	R^2	Obs.
	Initial residual earnings Gap	-0.163	0.007		0.578	12,920
+	Working hours (contractual)	-0.146	0.007	-10.6%	0.594	12,920
+	Job mobility, overtime, change schedule	-0.133	0.009	-18.6%	0.606	12,920
+	Distance residence-workplace	-0.124	0.007	-24.2%	0.666	12,920
+	flexibility requirement index	-0.139	0.008	-14.6%	0.595	12,920
+	Distance residence-workplace	-0.121	0.007	-26.1%	0.663	12,920
	Initial residual earnings gap	-0.165	0.009		0.588	11,749
+	Share of male applicants	-0.078	0.009	-52.7%	0.602	11,749

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 only. Source: IEB, JVS.

distance is approximated by the beeline distance between the district of a worker's main residence and that of his or her workplace.[36] 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 rates in all AKM firm fixed effect deciles, through the lens of our model, the share of male applicants is an encompassing measure for flexibility requirements. In our empirical analysis, we consider the share of male applicants as an upper-bound measure, as it may also capture effects that may not be captured by our rich set of observables. We observe that the earnings gap narrows drastically, by more than 50%.[37]

Recall that under the second theoretical hypothesis, jobs with a high share of male applicants differ from those with a low share of male applicants. Both men and women (and not only men) should earn more than men and women with comparable observable characteristics, respectively. To test this idea, we construct categorical variables for the share of male applicants and the flexibility requirement index and regress the log earnings on these variables and controls, conditioning on men and women being hired, respectively. Figures C.1 and C.2 in the Appendix show that men who match with a job with a high share of male applicants earn 7.5 percentage points more than do men who match with a job with a medium share of male applicants. Analogously, women who match at a job with a high share of male applicants earn 8.1 percentage points more than do women

[36]This measure is based on the distance between the respective center of the district and is zero when the first residence and the workplace are in the same district.

[37]Table D.1 in the Appendix shows the corresponding table when dropping the full-time restriction.

who match with a job with a medium share of male applicants. In our exercise using categories of the flexibility requirement index, we find that men (women) who match with a job with high flexibility requirements earn on average 5.8 (5.3) percentage points more than do men (women) who match with a job with medium-sized flexibility requirements. 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.

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. It is also worth emphasizing that 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 Figure C.3 in the Appendix). 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.

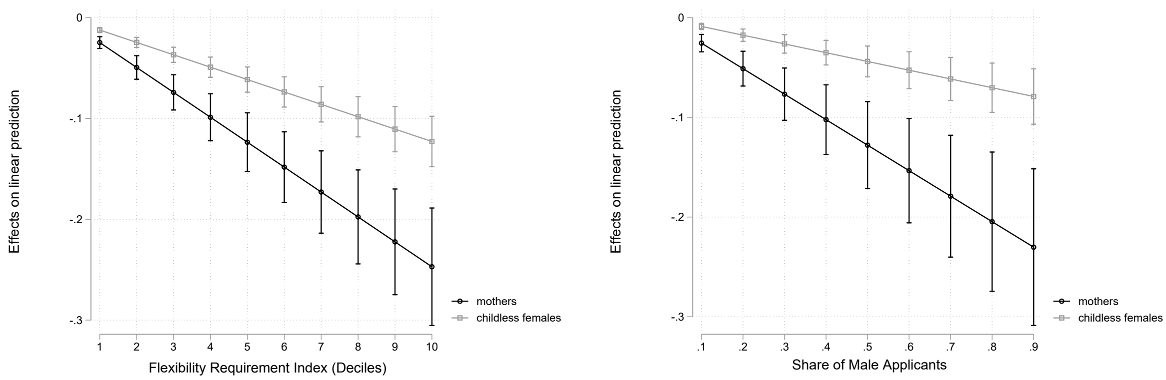
5.4 Evidence for a Flexibility Amenity at the Person Level

Thus far, our empirical results suggest that jobs with high flexibility requirements (i.e., those with a larger share of male applicants or directly measured higher flexibility requirements) are associated with disamenity and thereby pay compensation differences. At the person level, we can also test the hypothesis of whether these patterns are driven by different production functions. Let us assume that a person who is unable to provide high flexibility matches with a firm with a nonlinear production function. In this case, our model predicts low output at this job and a particularly large earnings discount for the matched person. Although we do not have any information on the degree of flexibility that a person can provide, we consider motherhood a suitable proxy. Mothers in Germany still bear a larger fraction of childcare than do fathers and thereby tend to be less flexible.

Therefore, we use the established proxy for being a mother in the administrative data (Müller and Strauch, 2017) and analyze 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 8 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.[38] The average effects can be found in Table C.1 in the Appendix.

Figure 8: Mothers and women without children

(a) Flexibility requirement index (b) Share of Male Applicants



Note: This figure shows 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: 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 labor market status (nonemployed, unemployed, or employed), working hours of the new contract, dummies for formal job requirements, year dummies, industry categories, occupation categories, and establishment size deciles; full-time jobs only. Source: IEB, JVS.

Through the lens of our model, we expect that workers earn a similar wage at linear jobs independent of their ability to provide input. In contrast, we expect a wage discount at nonlinear jobs with high flexibility requirements when workers do not provide enough input. Figure 8 is in line with these predictions. 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.[39] This finding is in line with our interpretation that jobs with a high share of male applicants or a high flexibility requirement index tend to be nonlinear jobs. From the perspective of our model, as mothers are unable to provide employer-side (desired) flexibility, they produce less and thereby face a larger earnings discount than do women without children. It is also striking that the wage discount differential between

[38]We 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.

[39]Note that the weighted average of these estimates corresponds to the point estimates in Columns (2) and (3) of Table C.1 in the Appendix. Figure D.4 shows the corresponding table when dropping the full-time restriction.

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 more than 15 percentage points for matches with 90% male applicants and more than 10 percentage points for matches with very high flexibility requirements.[40]

It may appear surprising that 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 due to the fact that 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 analyze this situation further. However, in Appendix C.4, we show that the gender earnings gap is largest for women of childbearing age compared to women of other ages.

In Appendix C.3, 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 do men. On average, women without children have a commuting distance that is 5.4 kilometers shorter, whereas mothers have a distance that is 10.6 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.

6 Conclusions

This paper shows that gender-specific application behavior is key for understanding differences in hiring earnings. Even within industries, firm size categories, and occupations, women are 7 percentage points less likely to apply to the highest-wage firms than are men. Our theoretical labor market flow model rationalizes this behavior based on different production functions at different jobs, where the highest-paying jobs are nonlinear in terms of input, as defined by Goldin (2014).

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 illustrate that these proxies are important explanatory variables that are typically omitted

[40]The confidence intervals are larger at the right part of the distributions because the number of observations is smaller there due to 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.

in Mincer-type wage regressions, as they are not included in standard datasets.

Our paper combines information from the IAB JVS with administrative information on the most recent hire. This combination allows us to use the proxy of whether women have children. We show that earnings discounts are particularly larger for mothers compared to women without children. This earnings discount increases in our proxies for employer-side flexibility requirements. Again, this finding is in line with the nonlinear jobs hypothesis. When mothers match with nonlinear jobs, they are less able to provide a high degree of employer-side flexibility requirements and thereby face a large earnings discount.

Our paper offers various policy-relevant lessons. Policy interventions that allow women to access jobs with high flexibility requirements (such as better access to childcare or incentives for different intrafamily sharing of care responsibilities) change the application behavior of these women and can thereby reduce the gender earnings gap. Furthermore, during the COVID-19 pandemic, it was shown that a different organization of work is possible (e.g., a larger number of working from home arrangements). An open question is whether this new work environment will persist and whether it will improve women's ability to secure better access to jobs with high flexibility requirements.

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A Taste-Based Discrimination and Ex Ante Heterogeneity

In this Appendix, we discuss the effects of taste-based discrimination in a model with ex ante heterogeneity. First, we analyze what happens in our model when we introduce a negative correlation in the degree of worker-specific disutility between job search and productivity. Second, we discuss how to interpret similar empirical selection rates for men and women with ex ante heterogeneity.

A.1 Extended Model: Search Effort and Productivity

In a model extension, we allow the idiosyncratic disutility of search to be correlated with the productivity of the match. This approach is a parsimonious way in which to introduce worker heterogeneity.

In this scenario, the search decision remains a function of the future expected returns from the search. However, the expectations on the selection rate and wage differ as follows:

$$\tilde{e}_{p,j} = E(\eta_{p,j}\bar{w}\left(\tilde{\varepsilon}_{p,j}\right)) - \xi_j. \tag{A.1}$$

$$\alpha_{p,j} = \int_{e_p^{\min}}^{\tilde{e}_{p,f}} g\left(e\right) de. \tag{A.2}$$

In the second stage, we assume that productivity is a function of the worker-specific draw of the disutility of search, $\mu(e_{p,j})$. We analyze the case where $\mu'(e_{p,j}) < 0$; i.e., a worker with lower search costs is more productive.

$$\Pi_{p,j} = y_{p,j} + \mu(e_{p,j}) - \varepsilon_{p,j} - t_{p,j} - \xi_j. \tag{A.3}$$

Thus, any worker-firm pair that fulfils the following condition generates a positive surplus and is thus hired:

$$\varepsilon_{p,j} - \mu(e_{p,j}) = y_{p,j} - t_{p,j} - \xi_j. \tag{A.4}$$

The left-hand side consists of two random variables, with $\mu(e_{p,j})$ being a truncated distribution, i.e., only those who sent out an application in the first place. Therefore, we define $h(\varepsilon_{p,j}, e_{p,j})$ as the joint density function of both random variables and κ as an auxiliary variable for joint realization; that is, $\kappa_{p,j} = \varepsilon_{p,j} - \mu(e_{p,j})$.

The cutoff in the second stage is a function of that in the first stage. If a smaller fraction of workers in a specific group (e.g., women) apply for a given job, then the average productivity level increases, as only the most productive workers are included in the pool of applicants.

$$\tilde{\kappa}_{p,j} = y_{p,j} - t_{p,j} - \xi_j. \tag{A.5}$$

$$\eta_{p,j} = \int_{\kappa_p^{\min}}^{\tilde{\kappa}_{p,j}} h(\kappa)\, d\kappa. \tag{A.6}$$

Nash bargaining yields the following result:

$$w(y_{p,j}, \mu(e_{p,j}), \varepsilon_{p,j}, \xi_j) = \varrho(y_{p,j} + \mu(e_{p,j}) - t_{p,j}) + (1-\varrho)\,\xi_j. \tag{A.7}$$

Thus, the average wage conditional on being hired is as follows:

$$\bar{w}(\tilde{\kappa}_{p,j}) = \frac{\int_{\min_{p,j}}^{\tilde{\kappa}_{p,j}} w(\kappa)\, h(\kappa)\, d\varepsilon}{\eta_{p,j}}. \tag{A.8}$$

In our extended framework, where a lower degree of disutility of search is associated with a higher level of match-specific productivity, the empirical observation that we have similar selection rates for men and women (despite different application rates) may be driven by a combination of taste-based discrimination and higher productivity for those who actually match with discriminating firms. Intuitively, when women face taste-based discrimination, it makes them less attractive for employers and reduces their selection rate (same direct effect as in the main part: $\partial\Pi_{p,f}/\partial t_{p,f} < 0$). However, as only those women with low search costs and thereby higher productivity apply for these jobs (indirect effect: $\partial^2\Pi_{p,f}/(\partial e_{p,f}\partial t_{p,f}) > 0$), this situation increases selection rates and may compensate for the first effect. Next, we discuss, in more general terms, whether taste-based discrimination is compensated for by ex ante heterogeneity when we observe similar selection rates in our empirical analysis.

A.2 Discussion: Same Selection Rates under Heterogeneity

According to our empirical analysis, the selection rates of men and women are indistinguishable across different AKM deciles:

$$\eta_{p,f} \approx \eta_{p,m}. \tag{A.9}$$

Under ex ante homogeneity ($\xi_f = \xi_m$, $y_{p,f} = y_{p,m}$), there cannot be any taste-based discrimination, as equal selection rates for men and women imply that the cutoff points are the same.

$$\tilde{\varepsilon}_{p,f} = \tilde{\varepsilon}_{p,m}. \tag{A.10}$$

Using the definition for the cutoff points,

$$y_{p,f} - t_{p,j} - \xi_j = y_{p,m} - \xi_j, \tag{A.11}$$

this can be true only if

$$t_{p,j} = 0. \tag{A.12}$$

However, under ex ante worker productivity heterogeneity (where $y_{p,j}$ may be drawn from a distribution and the mean of this distribution varies by gender), only the most productive women (i.e., those with a large $y_{p,f}$ value) apply to and match with firms with taste-based discrimination (same argument as in the previous subsection). A higher level of ex ante worker productivity compensates for employers' distaste for women. Although women earn a lower wage than men given the same productivity level, they may apply for this job and form a match. Due to high degrees of individual ex ante productivity, there may still be a surplus. Under equal selection rates, it is then true that

$$t_{p,j} = y_{p,f} - y_{p,m} \tag{A.13}$$

Under ex ante heterogeneous productivity, taste-based discrimination and similar selection rates, the difference in the degree of productivity between men and women compensates for discrimination. Thus, female matches at discriminating firms are more productive than are male matches. In the main section, we use worker fixed effects to analyze whether this situation is the case in reality.

To the extent that estimated worker fixed effects are driven mainly by productivity, we can check whether they are larger for women than for men at high-paying firms , which can provide evidence in favor of the above channel. Obviously, women who move between different discriminating employers may also have lower worker fixed effects. However, we believe that this effect should be of the second order, as women match not only with discriminating employers but also with nondiscriminating employers. In addition, we expect the dispersion of productivity across workers to be much greater than the wage cuts triggered by taste-based discrimination.

In our empirical analysis, we find no evidence that women who match with high-wage firms have systematically greater worker fixed effects than men. In fact, the opposite is the case. This finding does not support the hypothesis that the combination of taste-based discrimination and ex ante heterogeneity is the key driver of similar selection rates among men and women.

While we find no evidence for taste-based discrimination through the lens of our theoretical model (e.g., in terms of different selection rates for different shares of male applicants), we find evidence for the nonlinear production hypothesis. The share of male applicants correlates with various employer-side flexibility requirements (such as overtime or the necessity to travel).

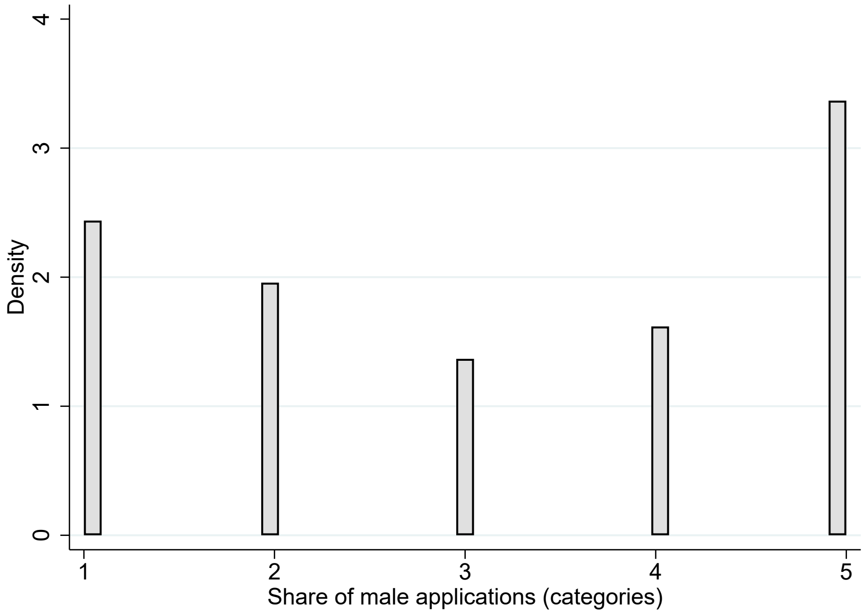
B Data Appendix

Table B.1: Share of male/female hires and applicants across industries

		Share of hires		Share of applicants	
NACE Rev. 2	Total hired	Men (%)	Women (%)	Men (%)	Women (%)
A - Agriculture, forestry and fishing + B - Mining and quarrying	941	67.59	32.41	66.13	33.87
C - Manufacturing	4,952	72.70	27.30	70.72	29.28
D - Electricity, gas, etc. + E - Water supply, sewerage	1,579	68.84	31.16	69.65	30.35
F - Construction	826	87.89	12.11	85.00	15.00
G - Wholesale and retails trade, etc. + H - Transportation and storage	1,613	68.20	31.80	65.36	34.64
I - Accommodation and food	664	41.27	58.73	39.03	60.97
J - Information and communication + K - Financial and insurance + L - Real estate + M - Professional, scientific and technical + N - Administrative and support service	4,470	52.24	47.76	52.99	47.01
O - Public administration	1,860	34.68	65.32	37.17	62.83
P - Education + Q - Human health and social work + R - Arts, entertainment and recreation + S - Other services + T - Households as employers + U - Extraterritorial organizations	4,789	26.12	73.88	27.87	72.13
Total	21,694	53.72	46.28	57.10	42.90

Source: IEB, JVS.

Figure B.1: Share of male applicants: Categories



This figure shows a histogram of the share of male applicant categories. Source: IEB, JVS.

Table B.2: flexibility requirement index: Distribution

Deciles	Mean	SD
1	40.61363	3.718717
2	51.62085	1.342513
3	55.23701	2.597408
4	64.04605	1.709363
5	66.66666	0
6	69.48661	3.44603
7	79.1861	1.099305
8	82.55626	3.956467
9	93.44968	1.524027
10	110.8735	6.904595

Note: We define the index as contractual working hours multiplied by the average flexibility requirement that we observe at the job level (overtime, changes in working hours, and workplace mobility). Source: IEB, JVS.

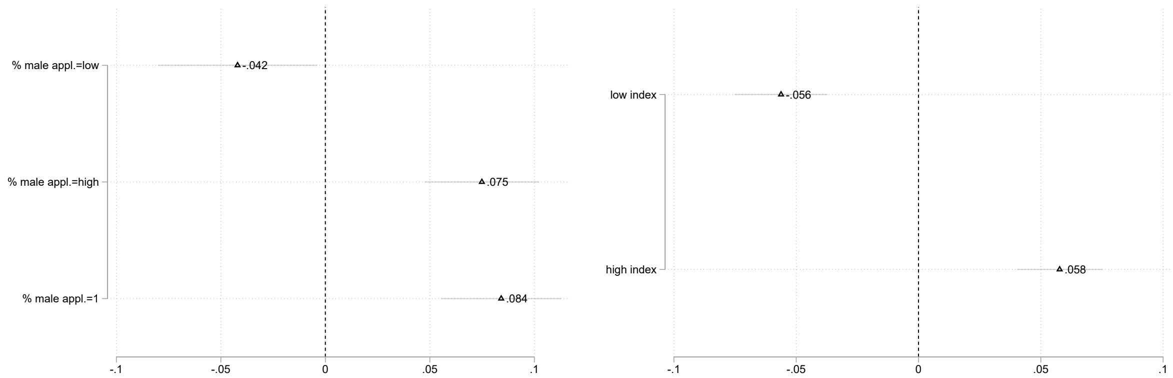
C Additional Empirical Results

C.1 Wage Regressions

In Section 5.3, we show that adding flexibility requirements to our wage regressions leads to a significant narrowing of the gender wage gap. Here, we construct a categorical variable instead of the continuous share of male applicants. We distinguish five categories: one if a vacancy has only female applications; five if there are only male applications; and two, three, and four fall somewhere in between.[41] Two refers to a low, three refers to a medium, and four to a high share of male applicants. We choose a medium share of male applicants as the reference group, which allows us to compare the coefficients across genders. Furthermore, we distinguish the terciles of the flexibility requirement index, with the category in the middle being the reference group.

Figure C.1: Coefficients for categories of the share of male applicants, **male** hires

(a) Share of male appl. **(b)** Flexibility requirement index



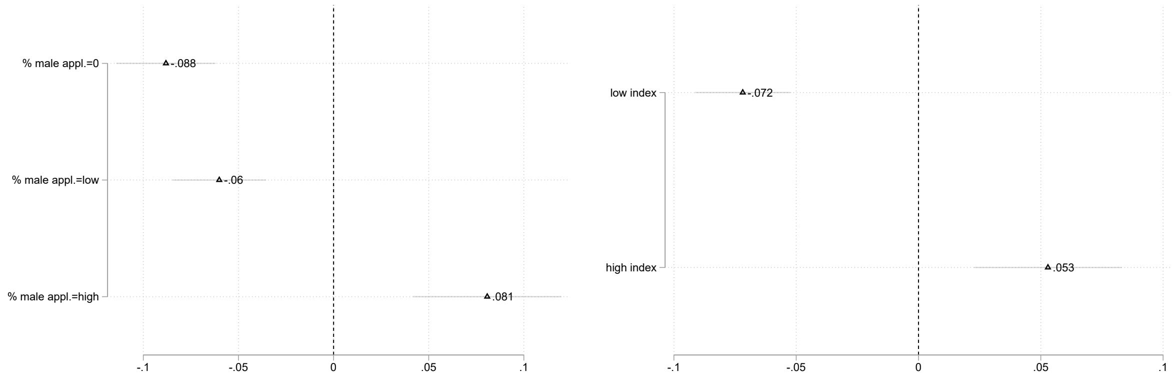
Note: These figures shows the regression coefficients of the share of male applicants (five categories; Panel (a)) and flexibility requirement index (three categories; Panel (b)). Dependent variable: imputed log daily earnings. Default independent variables: total number of applicants, worker age fully interacted with education attainment (measured by five categories), experience in years and its squared term, an indicator variable for the previous labor market status (nonemployed, unemployed, or employed), formal job requirements (four categories), and year dummies. 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) and three categories for the flexibility requirement index (terciles). Estimates for full-time male workers only. Source: IEB, JVS.

Figures C.1 and C.2 show the estimation results. As discussed in Section 5.3, both men and women who match in jobs with male-dominated application pools or at jobs with higher employer-side flexibility requirements earn substantially more than those in the reference category. The opposite is the case for jobs with female-dominated application pools and jobs with lower employer-side flexibility requirements.

[41] Figure B.1 in the Appendix shows the categories. We divide the inner part of the distribution into three parts. In the first part, the mean number of male applicants is 21%; in the second part, it is 48%; and in the third part, it is 80%.

Figure C.2: Coefficients for categories of the share of male applicants, **female** hires

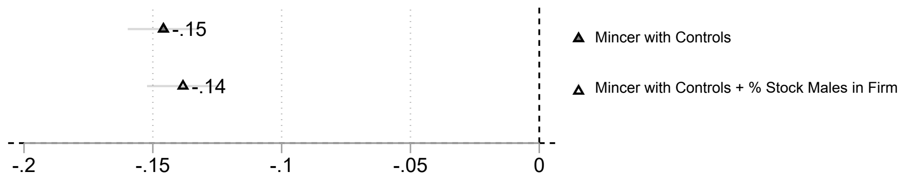
(a) Share of male appl. **(b)** Flexibility requirement index



Note: These figures shows the regression coefficients of the share of male applicants (five categories; Panel (a)) and flexibility requirement index (three categories; Panel (b)). Dependent variable: imputed log daily earnings. Default 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 labor market status (nonemployed, unemployed, or employed), formal job requirements (four categories), and year dummies. There are five categories for the number of male appl. (only women, low male share, medium male share (reference), high male share, or only men) and three categories for the flexibility requirement index (terciles). Estimates for full-time female workers only. Source: IEB, JVS.

We also add the share of the stock of male workers at the firm level instead of the share of male applicants. Figure C.3 shows that the residual gender earnings gap barely changes when we add the share of the stock of male workers in a particular firm instead of the share of male applicants. This finding provides further supporting evidence that the share of male applicants seems to provide information on employer-side flexibility. Whether the firm is male or female dominated is not very important for the residual gender earnings gap. In contrast, the attributes of the job seem to matter, i.e. whether the job is associated with high employer-side flexibility requirements and whether a large fraction of males applies for a specific job.

Figure C.3: Gender hiring earnings gap



Note: The figure shows the estimates of the gender gap (α) in hiring earnings. Instead of adding the share of male applicants, we add the share of the employed men (stock) at the firm. 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 labor market status (nonemployed, 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 only. Source: IEB, JVS.

C.2 Gender Earnings Gap and Motherhood

Table C.1 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 5.4 for these interactions.

	Default	*With flex. req.*	*With share of male appl.*
Dep. variable	Log daily wage	Log daily wage	Log daily wage
Mothers	-0.2024***	-0.1413***	-0.1231***
(men=reference)	(0.0142)	(0.0146)	(0.0158)
Women without children	-0.1389***	-0.1082***	-0.0637***
(men=reference)	(0.0071)	(0.0070)	(0.0093)
Observations	12945	10747	11631
Adjusted R^2	0.6038	0.6790	0.6126

Standard errors are in parentheses.
* $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table C.1: Estimates for full-time workers only. 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 labor market status (nonemployed, 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 (2) adds the share of male applicants. * $p < 0.10$, ** $p < 0.05$, and ***. Source: IEB, JVS. $p < 0.01$

C.3 Firm Fixed Effects and Commuting

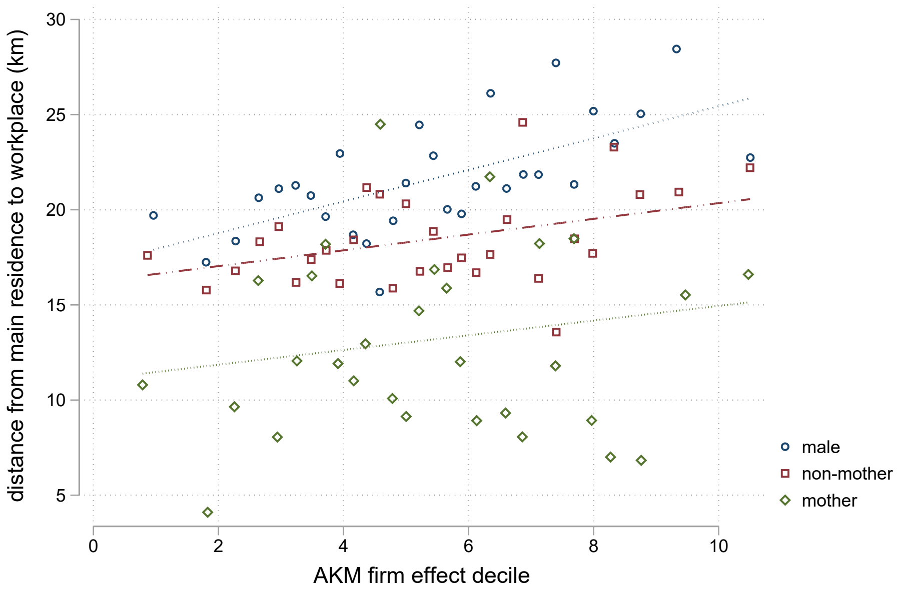
In this Appendix, we analyze how commuting distances differ for men and women (with or without children). According to French data, Le Barbanchon et al. (2020) show that women have shorter commuting times than do men. We do not know the (potential) commuting distances for each of the applicants. However, we can use the commuting distances for each realized match (see Section 5.3 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 C.2). On average, women without children have a commuting distance that is 5.4 kilometers shorter than that of men, whereas mothers have a commuting distance that is 10.6 kilometers shorter.

In the second step, we compare the commuting distances for the three groups over the firm fixed effect deciles. Figure C.4 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.

	Distance (km)
Mothers	-10.6111***
(men=reference)	(2.4327)
Women without children	-5.3873***
(men=reference)	(1.0658)
Observations	17,268
Adjusted R^2	0.0495

Table C.2: Estimates for full-time workers only. 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 labor market status (nonemployed, 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 ***. Source: IEB, JVS. $p < 0.01$

Figure C.4: Commuting and firm fixed effects

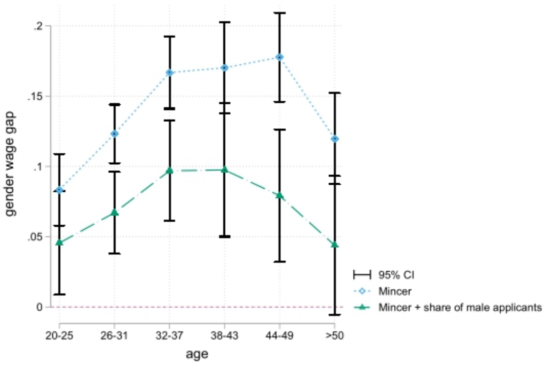


Note: This figure shows binscatters with 50 bins and linear fit lines. To residualize the x and y variables, we regress each variable on the controls, generate the residuals, and add the sample mean of each variable back to its residuals. We then group the x-axis variable into equal-sized bins, compute 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 labor market status (nonemployed, unemployed, or employed), working hours of the new contract, dummies for formal job requirements, year dummies, industry categories, and occupation categories; full-time jobs only. Source: IEB, JVS.

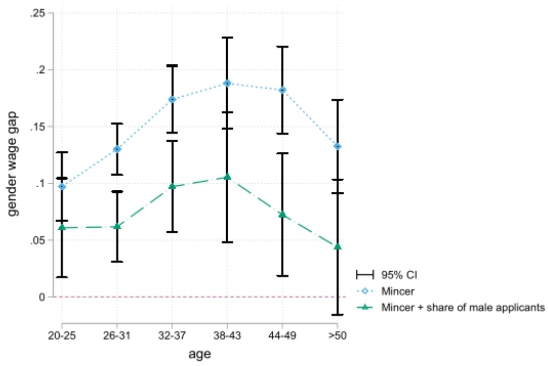
C.4 Age Cohorts

Figure C.5: GWG estimates by 5-year cohort

(a) Full- and part-time workers



(b) Full-time workers only



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 labor market status (nonemployed, unemployed, or employed), contractual working hours of the new job, formal job requirements (four categories), and year dummies. Source: IEB, JVS.

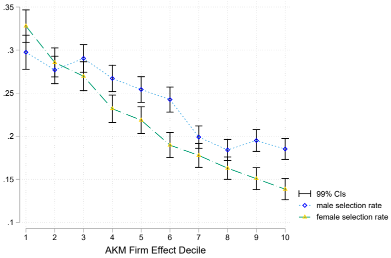
C.5 Alternative Selection Measures

Figure C.6 shows differently defined selection rates. Version 1 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. Version 2 uses the number of gender-specific suitable applicants instead of all applicants. Version 3 uses the number of invited applicants instead of suitable applicants. Version 4 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).

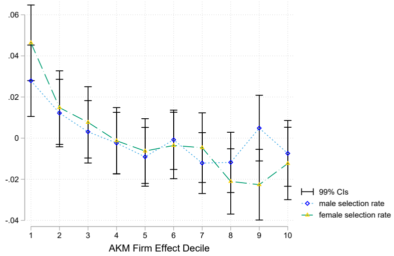
Interestingly, in all three cases, once we control for observables, there are no meaningful differences between male and female selection rates, which confirms our results from the main section.

Figure C.6: Alternative selection measures

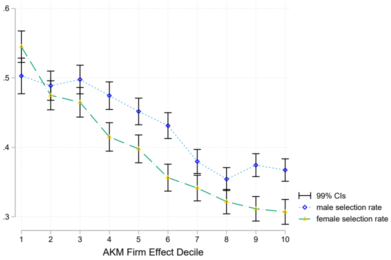
(a) Overall appl. pool



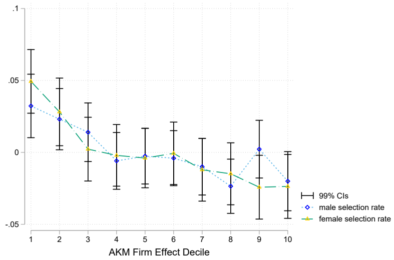
(b) Residualized version (a)



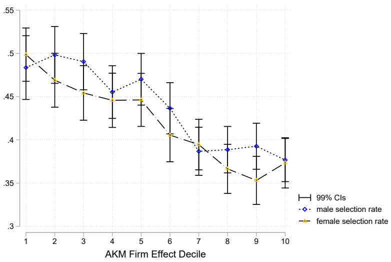
(c) Gender-specific suitable appl. pool



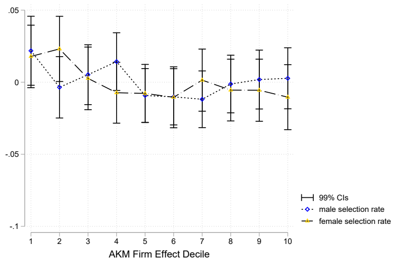
(d) Residualized version (c)



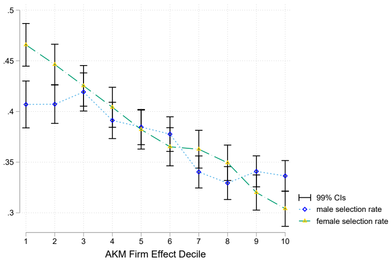
(e) Gender-specific invitation share



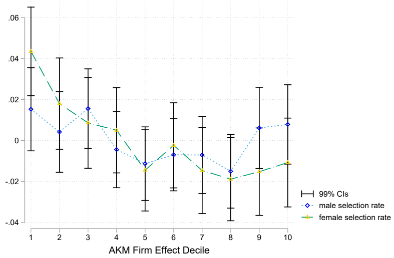
(f) Residualized version (e)



(g) Gender-specific suitable appl. share



(h) Residualized version (g)



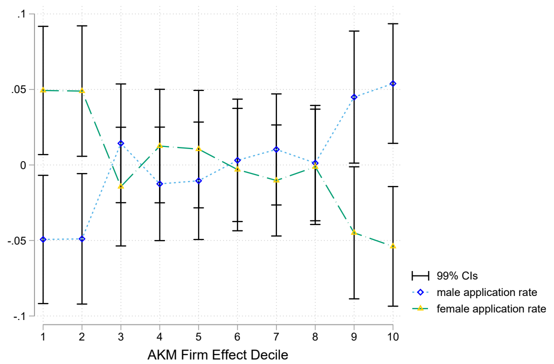
Note: Full-time jobs only. The variables are defined as follows. a) and b) male selection rate=1/number of all appl. if hired, and in this case, the female selection rate equals zero. Additionally, the female selection rate=1/number of all appl. if hired; in this case, male selection rate equals zero. c) and d) male selection rate=1/number of male suitable appl. if a man is hired; in this case, the female selection rate equals zero, and the female selection rate=1/number of female suitable applicants if a woman is hired. In this case, the male selection rate equals zero. e) and f) male selection rate = 1/invited male applicants if hired; in this case, the female selection rate equals zero, and female selection rate = 1/invited female applicants if hired. In this case, the male selection rate equals zero. g) and h) male selection rate=number of male suitable appl./number of male appl. if hired. In this case, the female selection rate equals zero, and the female selection rate=number female suitable appl./number of female appl. if 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.

C.6 Application and Selection Behavior within Task Complexities

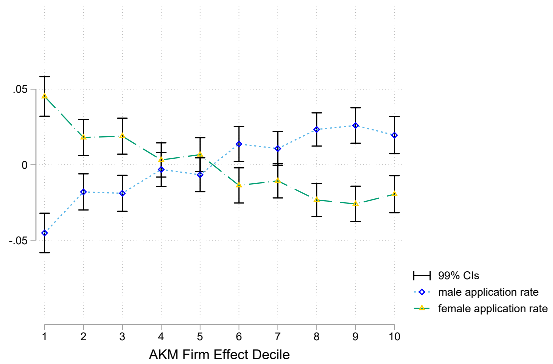
Figures C.7 and C.8 show the gender-specific residualized application and selection rates within different task complexity groups (unskilled, trained, expert, and specialist), which are defined based on the fifth digit of the occupational code (KldB2010).

Figure C.7: Residualized share of male applicants across the grid of AKM firm effect deciles by task complexity

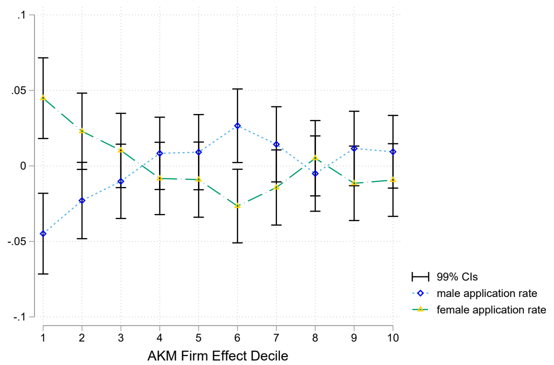
(a) Helper



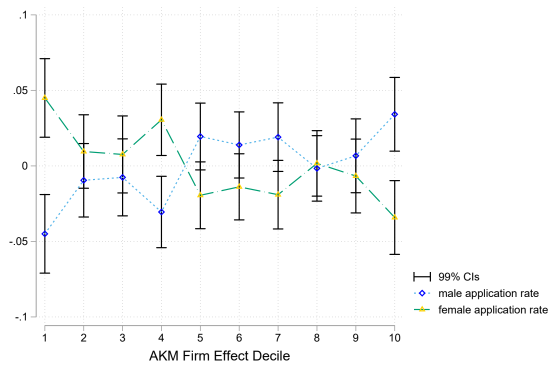
(b) Trained



(c) Specialist



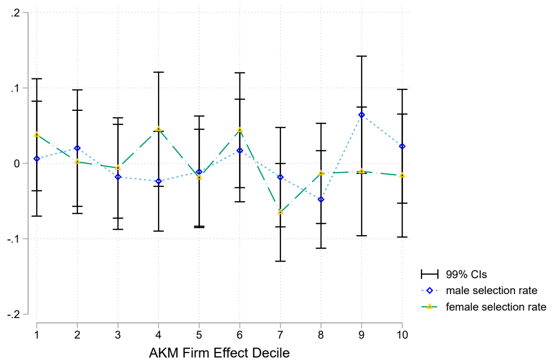
(d) Expert



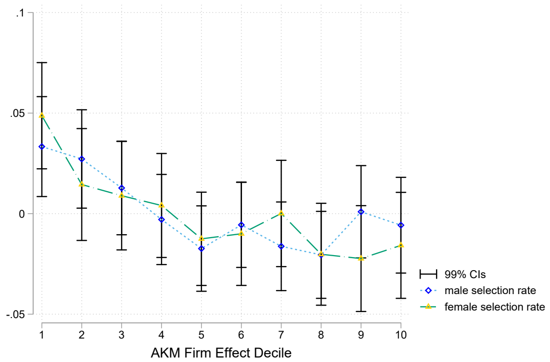
Note: Full-time jobs only. The variables are defined as follows: a)–d) share of male appl.=number of male appl./number of all appl. and share of female appl.=number of female appl./number of all appl. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories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

Figure C.8: Residualized selection rates across the grid of AKM firm effect deciles by job level

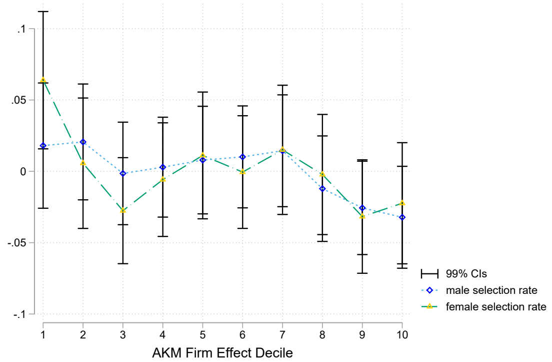
(a) Helper



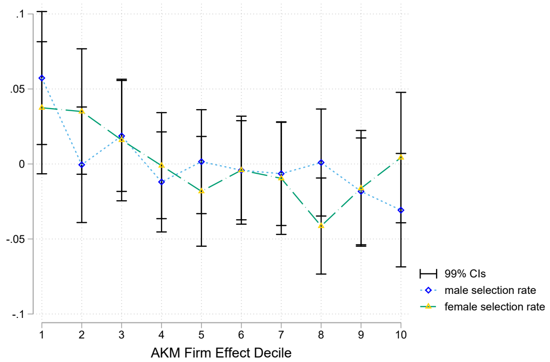
(b) Trained



(c) Specialist



(d) Expert



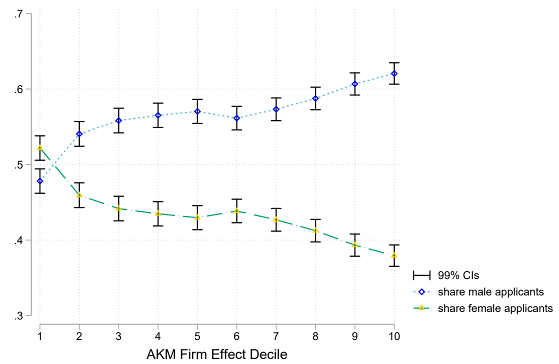
Note: Full-time jobs only. The variables are defined as follows: a)–d) male selection rate=1/number of male appl. if hired, and in this case, the female selection rate equals zero, and female selection rate=1/number of female appl. if hired, and in this case, male selection rate equals zero. Control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

C.7 Application and Selection Behavior with Alternative Firm Fixed Effects

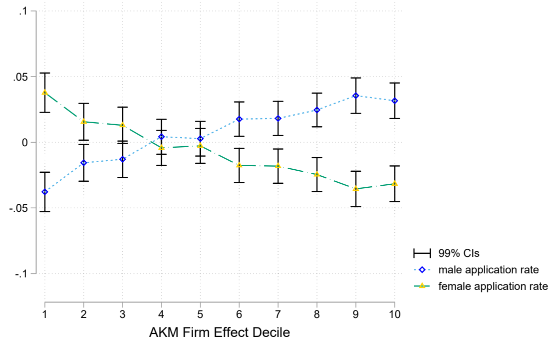
Figures C.9 and C.10 show the patterns in the data with differently estimated firm fixed effects. In this case, the firm fixed effects are gender specific; that is, they are estimated separately for men and women (i.e., each firm has two types of wage premia: one for men and one for women).

Figure C.9: Application and selection rates by gender and AKM firm effect deciles (estimated for men only)

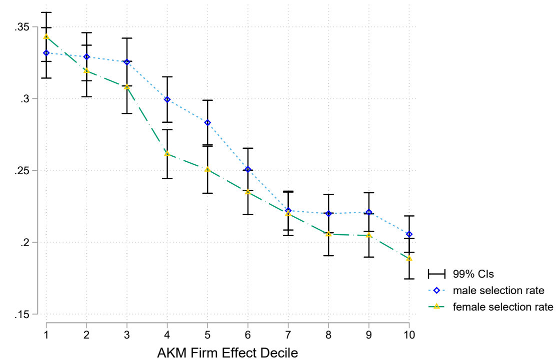
(a) Share of female/male applications



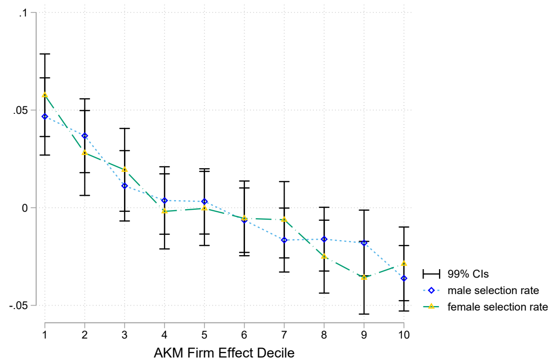
(b) Residualized share of female/male applications



(c) Female/male selection rate



(d) Residualized female/male selection rate

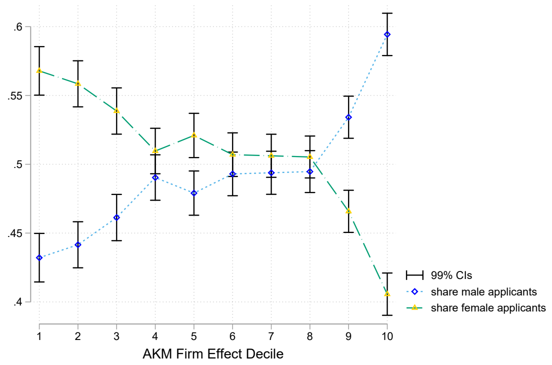


Note: Full-time jobs only. Firm effects estimate for men only. The variables are defined as follows: a) and b) share of male appl.=number of male appl./number of all appl. and share of female appl.=number of female appl./number of all appl. c) and d) male selection rate=1/number of male appl. if hired, and in this case, the female selection rate equals zero, and female selection rate=1/number of female appl. if hired, and 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.

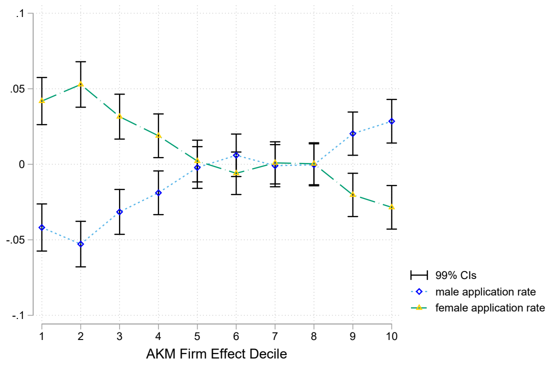
Note that the comparison of these separately estimated rankings with the ranking based on gender-pooled firm fixed effects itself is informative in terms of our model predictions. An AKM firm effect ranking based only on men should show discrimination-free wages. However, if discrimination plays a role,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

Figure C.10: Application and selection rates by gender and AKM firm effect deciles (estimated for women only)

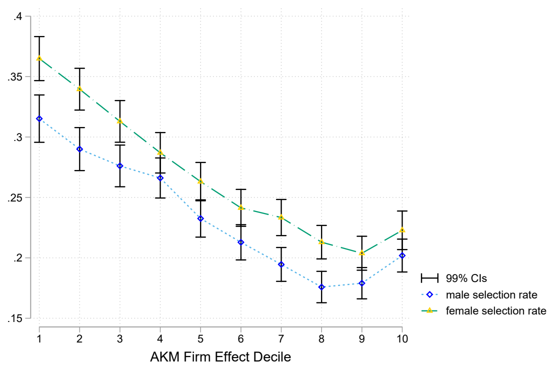
(a) Share of female/male applications



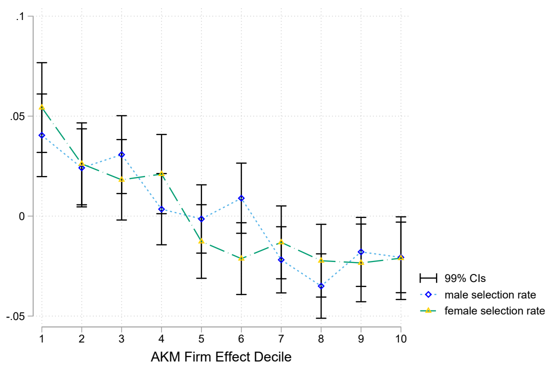
(b) Residualized share of female/male applications



(c) Female/male selection rate



(d) Residualized female/male selection rate



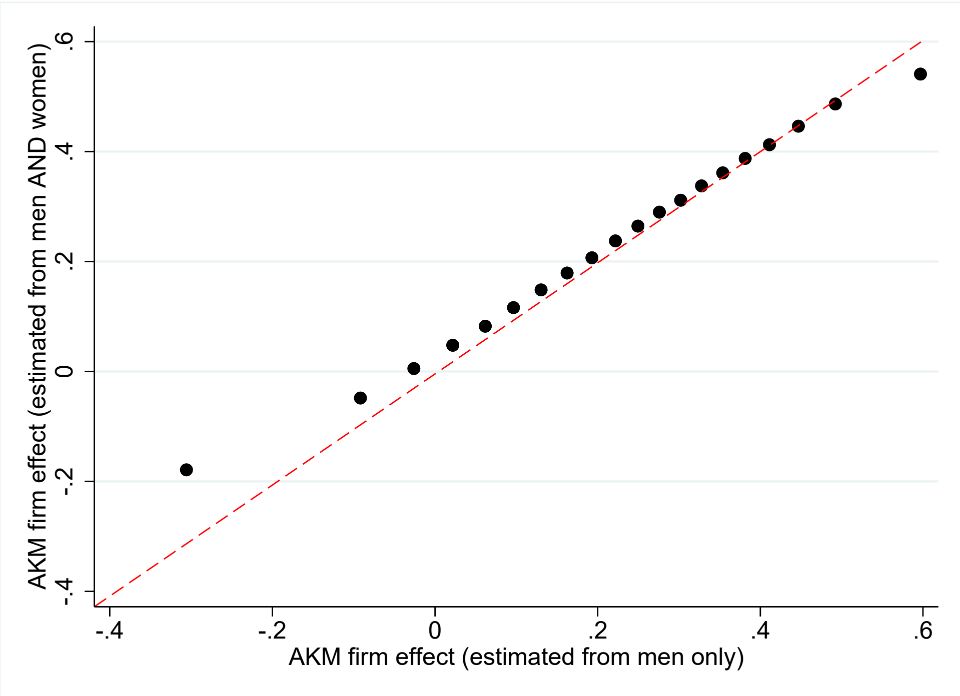
Note: Full-time jobs only. Firm effects estimate for women only. The variables are defined as follows: a) and b) share of male appl.=number of male appl./number of all appl. and share of female appl.=number of female appl./number of all appl. c) and d) male selection rate=1/number of male appl. if hired, and in this case, the female selection rate equals zero, and female selection rate=1/number of female appl. if hired, and 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.

those in nondiscriminating firms. Hence, discriminating firms should have a lower rank than should nondiscriminating firms.

In the model scenario with nonlinear production functions, men are more likely to apply for jobs that require more flexibility. However, conditional on hiring women, wages should be the same; hence, we should not observe any difference in the rankings of firms.

Figure C.11 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 C.11: AKM ranking comparison



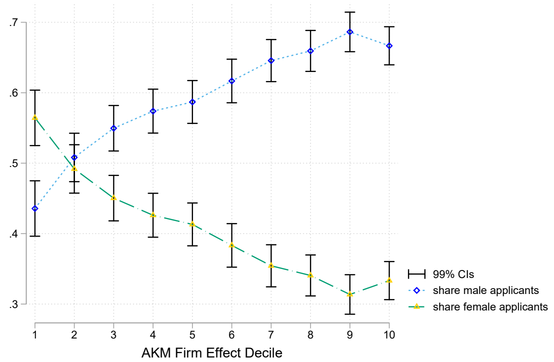
Note: This figure shows a binscatter that compares the AKM firm effects estimated from a sample with men only with the AKM firm effects estimated from a sample with men and women (as in the remaining paper). Source: IEB, JVS.

C.8 Application and Selection Behavior and Bargaining

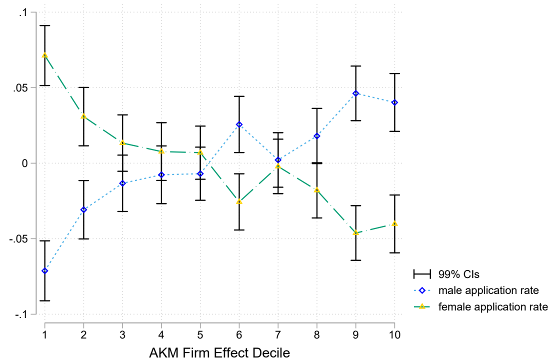
Figures C.12 and C.13 show the application and selection behavior across AKM firm effect deciles separately for firms that are subject to a collective or firm-level bargaining agreement (denoted by organized bargaining) and those that are not, respectively. Although the application rates differ somewhat in the raw data, once we include our full set of controls, the quantitative results are very similar to those from our baseline sample.

Figure C.12: Application and selection rate by gender and AKM firm effect deciles, with organized bargaining

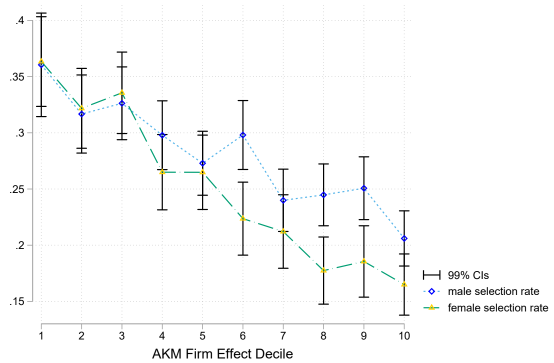
(a) Share of female/male applications



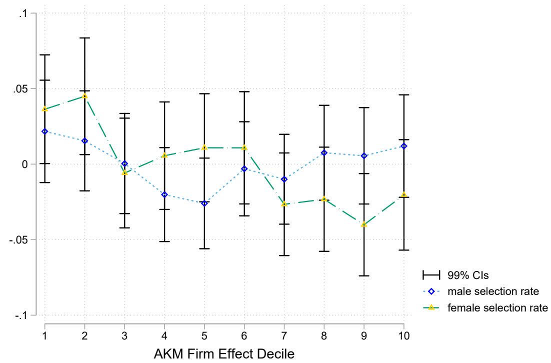
(b) Residualized share of female/male applications



(c) Female/male selection rate



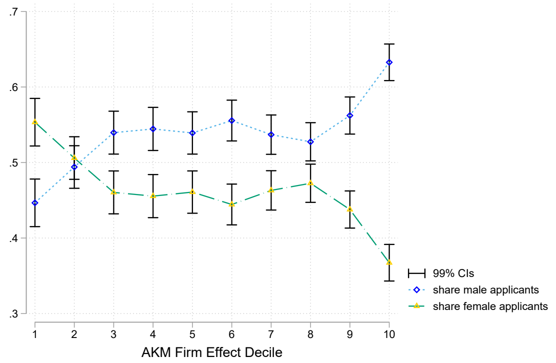
(d) Residualized female/male selection rate



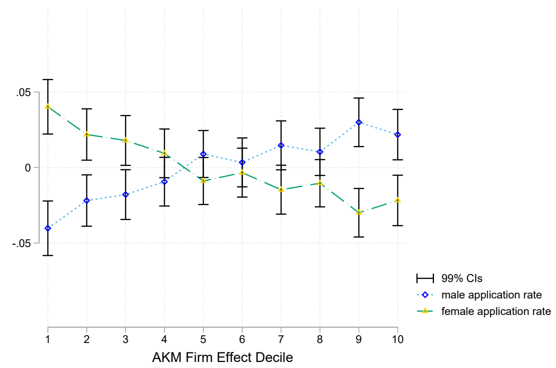
Note: Full-time jobs with organized bargaining only. Firm effects estimate for women only. The variables are defined as follows: a) and b) share of male appl.=number of male appl./number of all appl. and share of female appl.=number of female appl./number of all appl. c) and d) male selection rate=1/number of male appl. if hired, and in this case, the female selection rate equals zero, and female selection rate=1/number of female appl. if hired, and 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.

Figure C.13: Application and selection rate by gender and AKM firm effect deciles, without organized bargaining

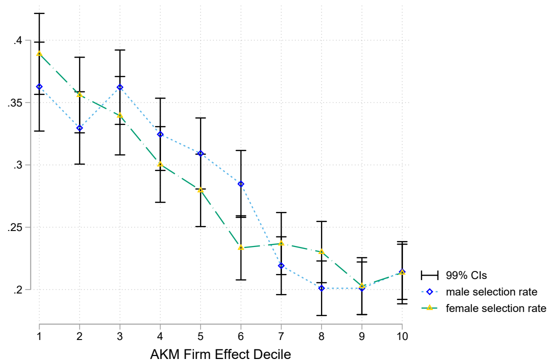
(a) Share of female/male applications



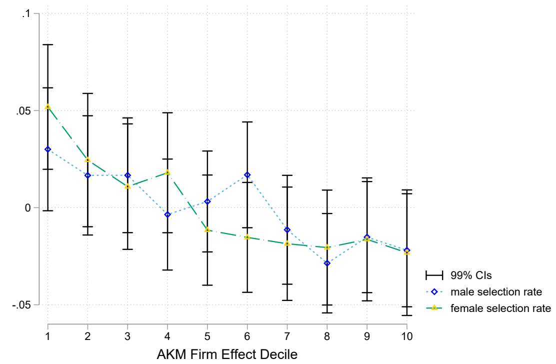
(b) Residualized share of female/male applications



(c) Female/male selection rate



(d) Residualized female/male selection rate



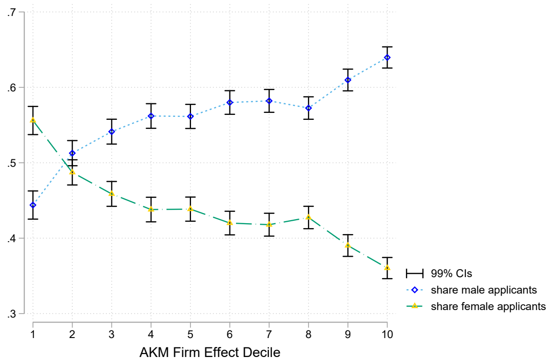
Note: Full-time jobs without organized bargaining only. Firm effects estimate for women only. The variables are defined as follows: a) and b) share of male appl.=number of male appl./number of all appl. and share of female appl.=number of female appl./number of all appl. c) and d) male selection rate=1/number of male appl. if hired, and in this case, the female selection rate equals zero, and female selection rate=1/number of female appl. if hired, and 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.

D Alternative Sample Restriction

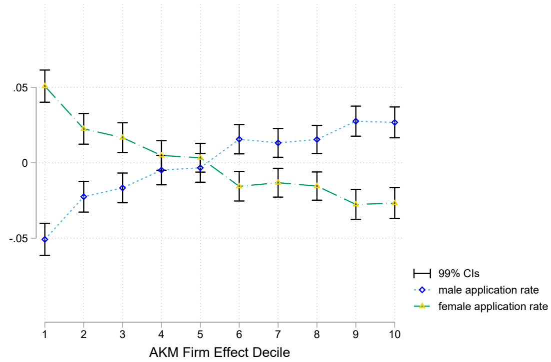
This appendix replicates all the main results without imposing the full-time restriction (i.e., confining the sample to only workers with more than 25 hours of working time). All our key insights are unaffected by the chosen sample restrictions, although the quantitative numbers differ somewhat.

Figure D.1: Application and selection rate by gender and AKM firm effect deciles

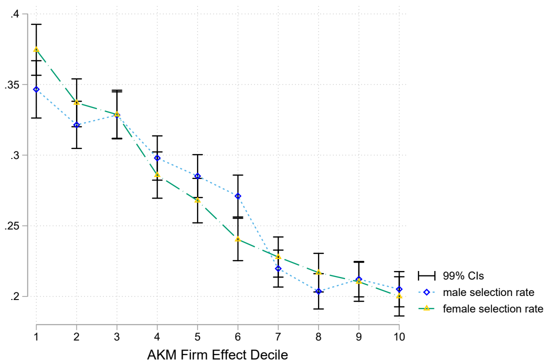
(a) Share of female/male applications



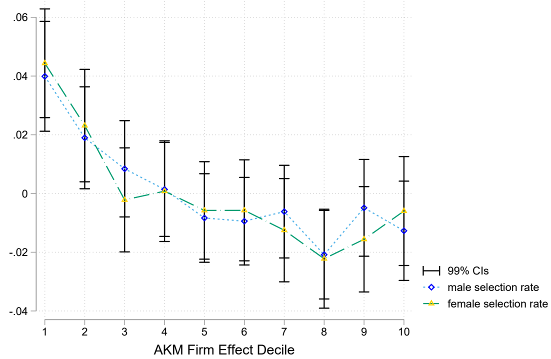
(b) Residualized share of female/male applications



(c) Female/male selection rate

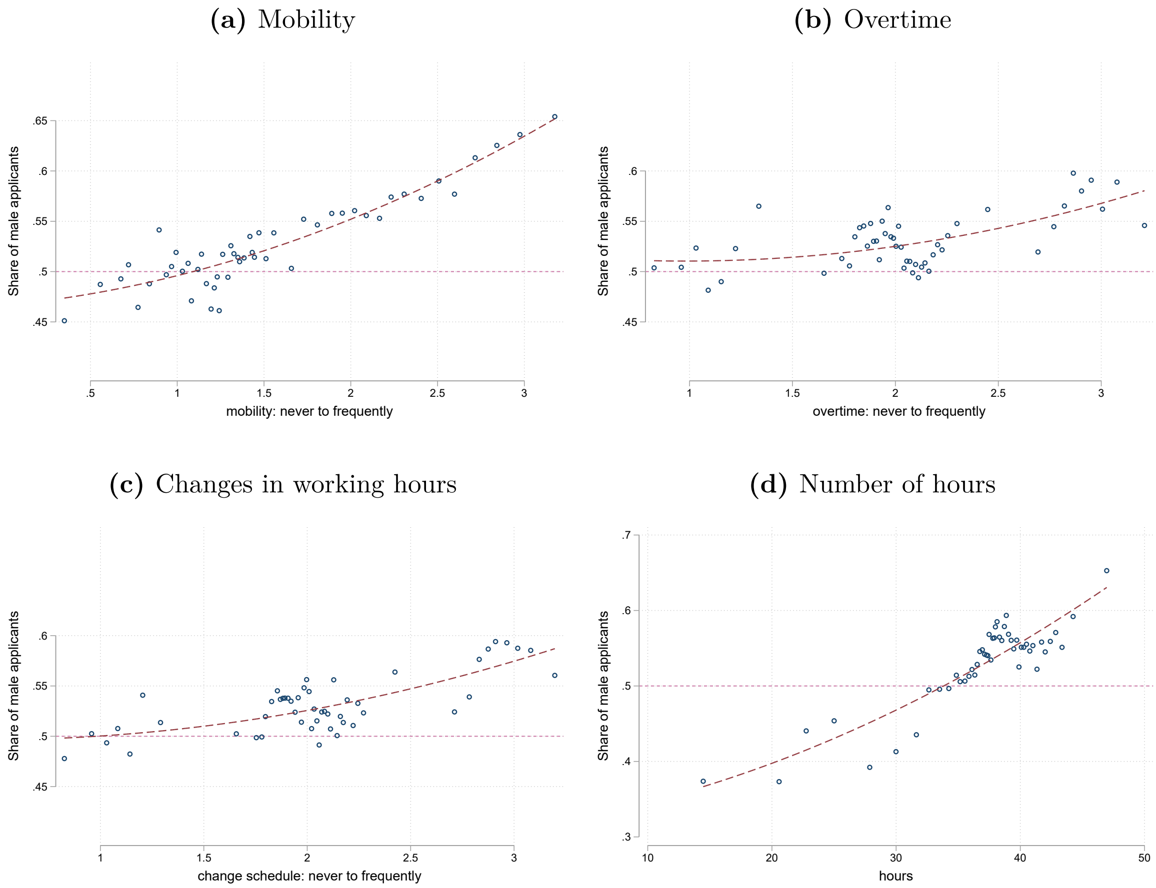


(d) Residualized female/male selection rate



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 rate=1/number of male appl. if hired, and in this case, the female selection rate equals zero, and female selection rate=1/number of female appl. if hired, and 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.

Figure D.2: Share of male applicants and flexibility requirements



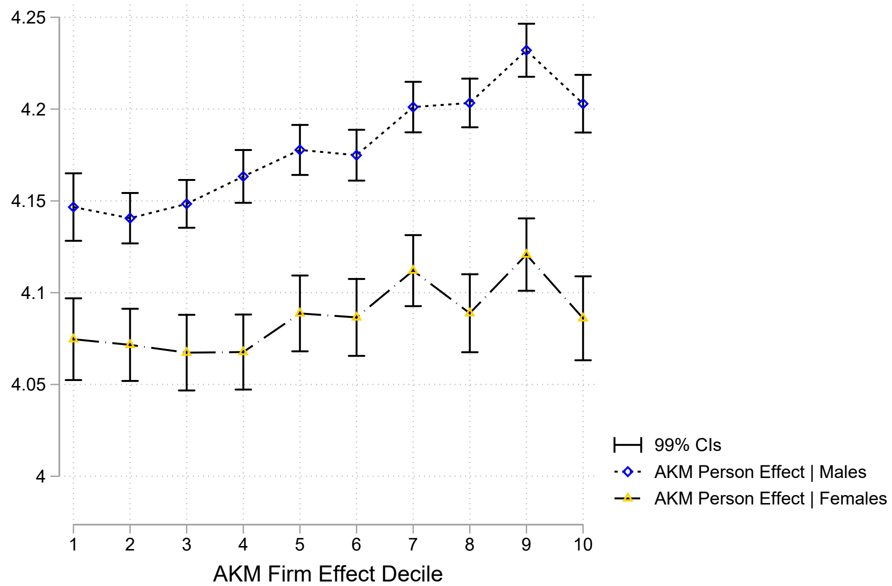
Note: These figures show binscatters with 50 bins and quadratic fit lines. To residualize the x and y variables, we regress each variable on the controls, generate the residuals, and add the sample mean of each variable back to its residual. We then group the x-axis variable into equal-sized bins, compute 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 D.1: Gender hiring earnings gap

		Coef.	Std. Error	Reduction	R^2	Obs.
	Initial residual earnings gap	-0.203	0.008		0.552	14,292
+	Working hours	-0.141	0.007	-30.6%	0.642	14,292
+	Job mobility, overtime, change schedule	-0.129	0.009	-36.8%	0.651	14,292
+	Distance residence-workplace	-0.123	0.006	-39.7%	0.694	14,292
+	Flexibility requirement index	-0.153	0.008	-24.6%	0.597	14,292
+	Distance residence-workplace	-0.143	0.008	-29.6%	0.635	14,292
	Initial residual earnings gap	-0.206	0.008		0.557	13,024
+	Share of male applicants	-0.097	0.010	-52.7%	0.566	13,024

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 and part-time workers. Source: IEB, JVS.

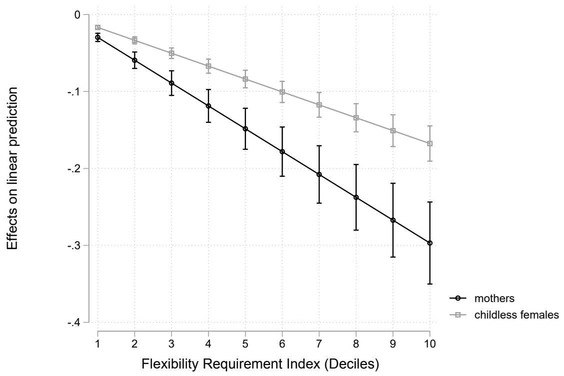
Figure D.3: Worker and firm fixed effects



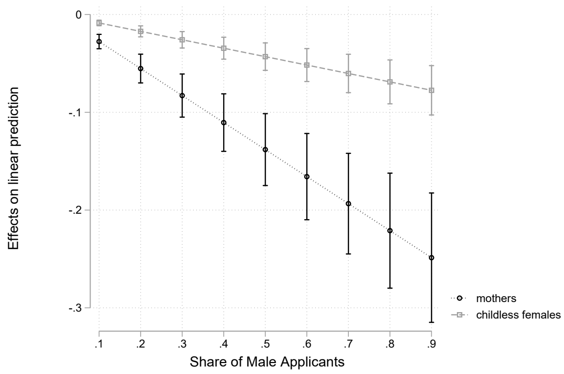
Note: This figure shows the residualized average worker fixed effects for matches within different firm fixed effect deciles. The AKM person fixed effect is estimated as explained in Section 5.1. Full-time and part-time jobs. Control variables: industry categories (Nace Rev 2), firm size categories, and occupation categories (5 digits). Source: IEB, JVS.

Figure D.4: Mothers and women without children

(a) Flexibility requirement index



(b) Share of Male Applicants



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 labor market status (nonemployed, unemployed, or employed), working hours of the new contract, dummies for formal job requirements, year dummies, industry categories, occupation categories, and establishment size deciles; full-time and part-time jobs. Source: IEB, JVS.