Gendered Job Search and Labor Market Outcomes: Evidence from Brazil

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Abstract

Despite women surpassing men in educational attainment in Brazil, large gender wage gaps persist. We use a unique linked dataset matching job applications from an online platform to administrative employer-employee records to examine whether gender disparities emerge at the application stage. We document significant gender gaps in application behavior: women are less likely to apply to managerial positions and apply to roles requiring fewer skills, and these gaps are pervasive across education levels, experience levels, seniority groups, and motherhood status. Despite these application gaps, outcome gaps are substantially more muted: women are no less likely than men to hold managerial positions after applying, a pattern consistent with conservative applications as an effective search strategy. The gender application gap remains largely unexplained after controlling for education, amenity preferences, and past labor market trajectories, pointing toward differences in beliefs or expectations about employer responses as a likely residual driver.

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1 Introduction

Globally, women are paid on average 20 percent less than men (UN, 2022). Despite increasing educational attainment among women, female workers tend to be concentrated in lower-paying, lower-skilled jobs, and wide gender gaps in earnings remain for high-skilled workers (Blau and Kahn, 2017). Brazil presents a relevant context, as the gender gap in education has not only closed but reversed. Enrollment in secondary education is higher for girls than for boys (OECD, 2021), and nearly two-thirds of graduates from tertiary institutions are women (Gukovas et al., 2016). Despite the educational advantage, women in Brazil continue to face persistent large and persistent wage gaps, especially in top-paid professions (World Bank Group, 2012).

What explains the persistent gender wage gap despite rising educational attainment of women? Existing literature highlights factors such as promotion inequities within the firm (Bronson and Thoursie, 2021; Cullen and Perez-Truglia, 2023) and discrimination at hiring (Goldin and Rouse, 2000; Reuben et al., 2014). One explanation that is relatively less explored is whether gender disparities emerge as early as the application stage, when job seekers self-select into roles based on gendered perceptions of their own skills, pay and negotiation expectations, and preferences for job amenities. Empirical evidence in this area remains scant, largely due to the scarcity of datasets that simultaneously capture application patterns and actual job outcomes.

In this paper, we examine gender gaps in application behaviors using a unique linked dataset of Brazilian workers: we match Brazilian workers who apply through an online platform to administrative employer-employee records. This enables us to construct a dataset that captures each individual's application record, as well as their complete employment history both before and after their application.

First, we document that there are significant gender differences in applications. We find that women are less likely to apply to positions that are classified as managers and also apply to positions with fewer required skills listed. However, when we compare the application gaps

to actual outcome gaps, we find that the outcome gaps are more muted. Women are only slightly less likely to be found in manager jobs after application. We also examine women's skill mobility patterns, and find that women are more likely to apply to jobs that match their existing skill profile, making fewer stretch applications into roles that require skills they do not have and fewer underutilizing applications by applying to roles that don't use their skill set. The application gap is pervasive across educational levels, experience levels, seniority levels, and motherhood.

To understand what drives these application gaps, we examine the role of qualifications, amenity preferences, and past labor market experience. Education and preferences for non-wage amenities explains little of the gap. Conditioning on actual past labor market trajectories, including prior occupation, industry, skills, wages, and seniority, meaningfully narrows the gap, though substantial unexplained gaps remain. Oaxaca-Blinder decompositions confirm that observable characteristics explain less than half of most application gaps, pointing toward differences in beliefs or expectations about employer responses as a likely residual driver.

Finally, we ask whether women's more conservative search strategies ultimately hurt their labor market outcomes. The evidence suggests that the outcomes are muted. In the short run, women's application gaps do not translate proportionally into outcome gaps: despite being 7 percentage points less likely to apply to managerial positions, women are only 3 percentage points less likely to hold such positions after searching. This pattern is consistent with conservative applications constituting an effective search strategy.

Using an event study design that traces longer-run labor market trajectories, we find that both male and female applicants turn to the online platform during periods of stagnating earnings, but neither group experiences improved outcomes. Five years after first application, both genders remain below expected earnings conditional on age and education. Despite women's more conservative application behavior, their post-application trajectories closely mirror men's: gender gaps in earnings and seniority widen temporarily immediately

following application but close within two years, suggesting small and temporary penalty from conservative search strategies.

A closely related paper to ours is Fluchtmann et al. (2024) which studies gender gaps in job applications among Danish unemployment insurance recipients. They find that women apply to jobs with lower typical wages than those applied to by men, and this gender application gap explains a significant portion of the gender wage gap. Similar to Fluchtmann et al. (2024), we find a gender application gap among a sample of Brazilian workers applying through an online job platform. However, we also find meaningful differences that application gaps translate less into outcome gaps in our Brazilian data. Moreover, we were able to extend the analysis of Fluchtmann et al. (2024) in doing a formal decomposition of the gender application gap as our unique job platform data enable us to construct detailed measures of worker qualifications, job amenities, and labor market experience.

2 Data, Sample and Summary Statistics

In this section, we discuss how we construct our study sample and key variables for analysis, and discuss its representativeness.

2.1 Platform data: vacancies, applications, and applicant self-reported labor market histories

This study utilizes data from BuscoJobs, a job portal originating in Uruguay with coverage across multiple Latin American countries, including Brazil. The dataset includes all content uploaded between 2010 and 2023, capturing labor demand through firm-posted vacancies and labor supply via applicant profiles and detailed employment biographies. For the Brazilian labor market, the data contain 29,640,298 job vacancies and 1,826,748 applicant profiles. Furthermore, it records direct platform engagement, identifying 136,932 applicants who actively submitted applications through the BuscoJobs system.

On the BuscoJobs platform, individuals can create free accounts to register detailed profiles encompassing personal demographics, such as age, gender, and geographic region, alongside comprehensive labor market biographies that detail past employment, tenure, and salaries. Registered applicants can browse and apply to job vacancies either posted directly by firms or aggregated by the platform from other online sources. The system tracks these interactions, capturing applications submitted directly through the internal portal, via uploaded documents, or through redirection to external application URLs. Consequently, this dataset encompasses both the supply and demand sides of the labor market, enabling the precise observation of individual job search and application behaviors. [1]

To systematically analyze the unstructured text within job advertisements and applicant histories, this research applies an established taxonomy of skills and amenities (Escudero et al., 2024; Adamczyk et al., 2025b,a). This methodological framework categorizes labor attributes into cognitive, socioemotional, and manual domains, which are further subdivided into 15 specific skill subcategories.[2] Concurrently, 16 distinct amenity categories are extracted directly from keywords present in the job postings.[3]

2.2 Administrative data

Our analysis relies on administrative data from the Relação Anual de Informações Sociais (RAIS) job spells database, accessed through the Instituto de Pesquisa Econômica Aplicada (IPEA). RAIS is a comprehensive, matched employer-employee administrative registry main-

[1] Details regarding platform functionality were obtained directly from BuscoJobs data documentation and correspondence with platform employees.

[2] Skills include cognitive skills (core cognitive skills, sophisticated cognitive skills, general computer skills, software skills and technical support, machine learning and AI, financial skills, writing skills, and project and process management), socio-emotional skills (character skills, social skills, people management skills, and customer service skills), and manual skills (finger-dexterity skills, hand-foot-eye coordination skills, and physical skills).

[3] Amenities include variable earnings (bonuses and commissions, hourly work and overtime), fringe benefits (paid time-off, health insurance, retirement contributions, food and services subsidies, and other employee discounts), job attributes (office space and other office amenities, location and commuting, work equipment and allowances), working conditions (work schedule flexibility, workplace safety, job security), and working characteristics (work environment and impact on society, physical effort and pace of work, working in teams, human capital development).

tained by the Brazilian federal government, functioning as an annual census of the formal labor market. The dataset provides detailed information identified at the individual level, allowing for the tracking of employment trajectories, worker demographics, and firm characteristics over time (Adamczyk et al., 2024; Dix-Carneiro, 2014; Dix-Carneiro and Kovak, 2017).

To construct our analytical sample, we utilize RAIS datasets covering the entire country from 2006 to 2021. The sample is restricted to individuals of Brazilian nationality born between 1971 and 1990, who were between the ages of 18 and 65 at the time of observation. We focus exclusively on full-time workers, defined as having 40 or more contractual hours per week, with positive salary values. Furthermore, we drop workers employed in the agricultural sector, which is mostly informal and not adequately covered by RAIS, as well as any individuals who have ever held public sector employment during their observed labor market history, given the distinctive career progression and stability characteristic of public sector jobs.

Drawing from this refined sample, we utilize several key variables including occupation, industry, city of employment, educational attainment, and work experience. Occupation variables are constructed using the Brazilian Classification of Occupations (CBO), which is the standard used to classify occupations in RAIS. This classification is based on the International Standard Classification of Occupations (ISCO) and features a highly fine-grained structure, ranging from 10 one-digit categories down to 2,694 six-digit categories.

For our wage measure, we utilize the average monthly salary, deflated using the annual Brazilian official Extended National Consumer Price Index (IPCA). Hourly wages are calculated by dividing this real monthly salary by four times the weekly contractual hours, followed by a logarithmic transformation to obtain log wages. Additionally, we leverage the raw administrative records to construct specific variables central to our research design, namely measures for seniority, an indicator for motherhood, and the previously established taxonomy of skills.

2.3 Matching procedure and sample construction

To integrate the Brazilian BuscoJobs applicant profiles with the RAIS administrative records, we employ a matching methodology utilizing Natural Language Processing (NLP) techniques applied to individual identifiers. Since there are no common identifiers, such as tax identifiers, to directly link the databases, we resort to names and birth dates. The names from both datasets undergo extensive text normalization: strings are converted to uppercase, accents and non-alphabetic characters are stripped using regular expressions, and Portuguese stop-words (such as "de", "da", and "dos") are systematically eliminated. This NLP-driven cleaning process generates a standardized full name variable that, alongside a harmonized date of birth, forms the primary linkage key.

The integration relies on a record linkage methodology designed to efficiently handle the computational complexity of comparing 37,280,651 unique RAIS individuals against 1,880,162 unique BuscoJobs applicants. To optimize the matching, the algorithm employs a dual-level blocking strategy, iteratively evaluating records for each unique date-of-birth partitions. Within each specific birthdate block, candidate pairs are established by strictly matching the extracted first two names. Then, a Jaro-Winkler string distance algorithm is computed to evaluate the similarity between the standardized full names from both datasets. Jaro-Winkler allows for detecting typographical errors, transpositions, and spelling variations in names. This process ensures that names misspelled or with different formats in either database can be retrieved correctly. Name changes are also common, especially for women who take their husband's surname after marriage, making it important to account for such name changes when matching the databases.

Candidate links are formally accepted as valid matches if their calculated Jaro-Winkler similarity score meets the threshold of 0.85. This threshold ensures confidence in the integration of the two datasets while accommodating minor character variations and string truncations. The application of this probabilistic linkage framework yields a total of 10,396,350 matched observations for 673,802 unique individuals, which were later subject to visual in-

spection.

2.4 Summary statistics

Table 1 describes our main analysis sample, which consists of 23,789 workers who have at least one RAIS record before application and at least one RAIS record after application year. Appendix Table A1 shows the complete sample construction process and the number of observations at each step. The average applicant in the analysis sample was born in 1982. 47% of the applicants are female. 98.2% of the applicants have a high school degree and 64.4% have a college degree.

Given that our analysis sample is highly educated, we compare them to a sample of unmatched formal sector workers who have a high school degree and a sample of unmatched formal sector workers who have a college degree. Comparison with the full administrative data sample and the entire population of platform applicants are shown in Appendix Table A3. The unmatched sample is constructed by first selecting a random 100,000 sample from all unmatched RAIS workers, and then restricting to those with a high school degree and those with a college degree.

We find that the analysis sample's past average hourly wage is 18 BRL, which is 43% higher than the average high school worker and 34% lower than that of the average college-educated worker. Our analysis sample is highly attached to the labor market, with an average of 14 years observed in RAIS, which is nearly double the number of years observed for the average high school worker and more than double that of the average college-educated worker. The vast majority work full-time, with 90% of observed years in full-time employment, comparable to the high school sample (90.7%) and slightly higher than the college sample (84.5%). In terms of career progression, 24.2% of the analysis sample has ever held a senior position, similar to college graduates and nearly three times the rate of high school workers (9%). Finally, 14.2% has ever taken parental leave, above both the high school (11.6%) and college (13.1%) benchmarks.

Appendix Table A2 presents summary statistics for the analysis sample by gender. Women and men are similar in age, seniority, and labor market experience. Women are somewhat more educated: 99% hold a high school degree and 68.8% hold a college degree, compared to 97.5% and 60.4% among men.The most notable gender differences concern work intensity and family. Women have slightly lower average contractual hours (41.8 vs. 42.6) and spend a smaller share of their observed years in full-time employment (86.5% vs. 92.9%). Parental leave is almost exclusively taken by women: 29.7% of female applicants have ever taken parental leave, compared to just 0.3% of men.

Moreover, the analysis sample has high rates of mobility. This is in part mechanical: by construction, our sample consists of workers who actively sought new employment on an online platform, and is therefore likely to skew toward more mobile workers relative to the broader formal sector. On average, a worker in the analysis sample changes firms every 2.8 years, changes occupations every 3.5 years, changes industries every 3.3 years, and changes cities every 5.5 years. The mobility rate is more than twice that of the average college-educated worker. Consistent with this, the analysis sample worker has worked in an average of 2.7 distinct occupations and 4.6 distinct industries over their career. Women and men show broadly similar mobility rates, with the exception that women are slightly more likely to change firms and less likely to change cities.

3 Gender Application Gap: Do Men and Women Apply to the Same Jobs?

In this section, we document whether men and women apply to different jobs on the platform, how their application behavior relates to their past labor market experiences, and how these patterns vary across subgroups.

Table 1: Summary Statistics

	Analysis sample	RAIS (HS)	RAIS (College)
Demographics			
Female	0.473	0.462**	0.542***
	(0.499)	(0.499)	(0.498)
Year of birth	1982.397	1981.917***	1982.275*
	(4.929)	(5.400)	(5.217)
High school degree	0.982	1.000***	1.000***
	(0.133)	(0.000)	(0.000)
College degree	0.644	0.228***	1.000***
	(0.479)	(0.419)	(0.000)
Labor market			
Hourly wage (Jan 2018 BRL)	18.814	13.134***	28.365***
	(20.494)	(21.761)	(48.695)
Weekly contractual hours	42.241	42.502***	40.588***
	(2.926)	(3.918)	(6.612)
Share of years full-time	0.899	0.907***	0.845***
	(0.194)	(0.230)	(0.321)
Ever senior	0.242	0.090***	0.234
	(0.428)	(0.287)	(0.424)
Max labor market experience (years)	13.580	9.828***	11.480***
	(4.311)	(5.845)	(5.778)
Ever parental leave	0.142	0.116***	0.131***
	(0.349)	(0.320)	(0.337)
Years observed in RAIS	13.556	7.994***	6.119***
	(3.612)	(5.231)	(4.805)
Mobility			
Firm changes	0.357	0.220***	0.135***
	(0.170)	(0.203)	(0.173)
Occupation changes	0.287	0.178***	0.115***
	(0.158)	(0.183)	(0.159)
Industry changes	0.307	0.203***	0.133***
	(0.150)	(0.181)	(0.160)
City changes	0.181	0.105***	0.067***
	(0.157)	(0.158)	(0.128)
Number of occupations	2.700	1.789***	1.514***
	(1.053)	(0.914)	(0.758)
Number of industries	4.561	2.605***	1.957***
	(1.765)	(1.493)	(1.155)
Observations	23,789	83,335	18,959

Standard deviations in parentheses. Stars indicate significance of two-sample t-test vs. analysis sample: * p<0.05, ** p<0.01, *** p<0.001. Analysis sample includes individuals with both prior and future RAIS records who made at least one application on BuscoJobs. RAIS (HS) includes formal sector workers with high school degree. RAIS (College) includes formal sector workers with college degree. Hourly wage is in January 2018 BRL (IPCA index = 4930.72). Mobility measures are normalized by years observed in RAIS.

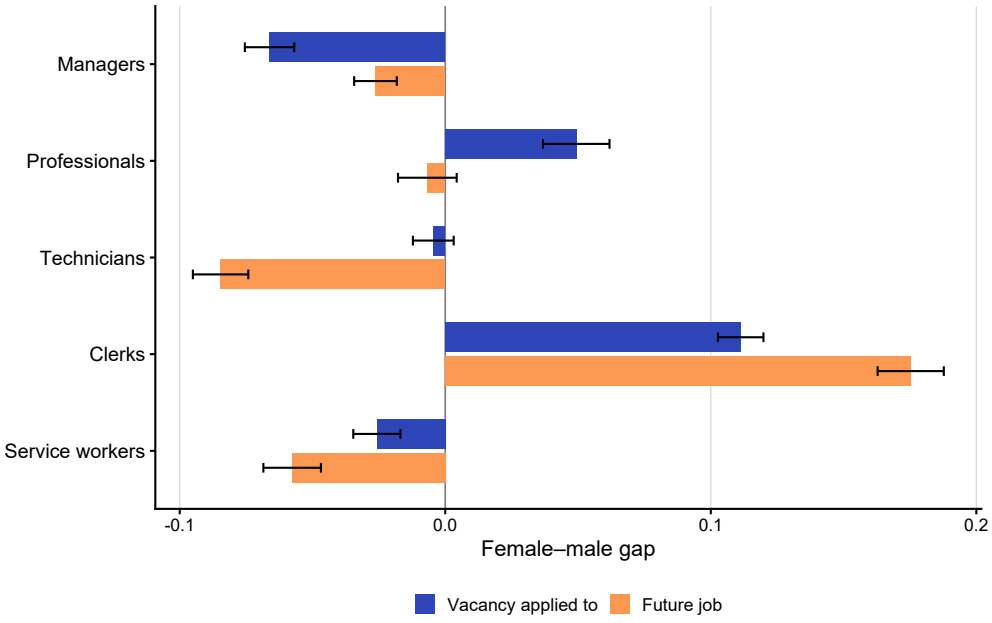
3.1 Gender differences in application and labor market outcomes

First, we describe raw gender differences in application behavior and labor market outcomes, where outcomes are defined as the first RAIS observation following a platform application. Our main descriptive results are presented in Figures 1 and 2 and Table 2.

We begin by asking whether formal sector participation changes differently for men and women after application, since subsequent labor market outcomes are only observed for applicants who are employed in the formal sector. We find that women are 2 percentage points more likely to be found in the formal sector (Table 2).

Restricting to applicants observed in the formal sector both before and after application, we examine gender differences in applications and outcomes by occupation, defined using the first digit of the occupation code (Figure 1). Professional jobs were the most common application destination for both men and women, attracting 43% of women's applications and 38% of men's. The remaining applications were distributed across occupations, including managers (13% of women, 20% of men), clerks (18% of women, 7% of men), service workers (13% of women, 16% of men), and technicians (10% for both).

Figure 1: Gender Application and Outcome Gap: Occupation



In terms of gender differences in application, women are significantly less likely to apply to jobs classified as managers and service workers, and significantly more likely to apply to jobs classified as professionals and clerks. The largest gap is in managers: 13% of women and 20% of men applied to manager positions, a gender application gap of -7 percentage points, or 34%, significant at the 1% level. In addition, women are 11 percentage points (154%) more likely to apply to clerk positions, 5 percentage points (13%) more likely to apply to professional positions, and 3 percentage points (17%) less likely to apply to service worker positions.

Gender differences in occupation outcomes are measured using the occupation of the first formal sector jobs after applying. For women, clerk jobs are the most common outcome (40%), followed by professional jobs (20%), service workers (17%), technicians (14%), and managers (8%). For men, clerk jobs are also the most common outcome (22.9%), followed by service workers (22.7%), technicians (22.4%), professionals (21%), and managers (11%).

Taken together, women are both less likely to apply to and less likely to hold manager and service worker jobs, and more likely to apply to and more likely to hold clerk jobs. For manager jobs, the gender application gap (-7 percentage points) is larger in magnitude than the gender outcomes gap (-3 percentage points), while the gender outcomes gap is larger than application gap for clerks and service workers. For professionals, women are more likely to apply but not more likely to hold these jobs, and for technicians, women are similarly likely to apply but are much less likely to hold these positions after application.

We next examine gender differences in applications and labor market outcomes in terms of skills (Figure 2). For applications, we define skills required based on the job description. For outcomes, we define skills required based on the description of the six-digit occupation code that the applicants work in. We find that women both apply to positions that require fewer skills and end up in positions that require fewer skills.

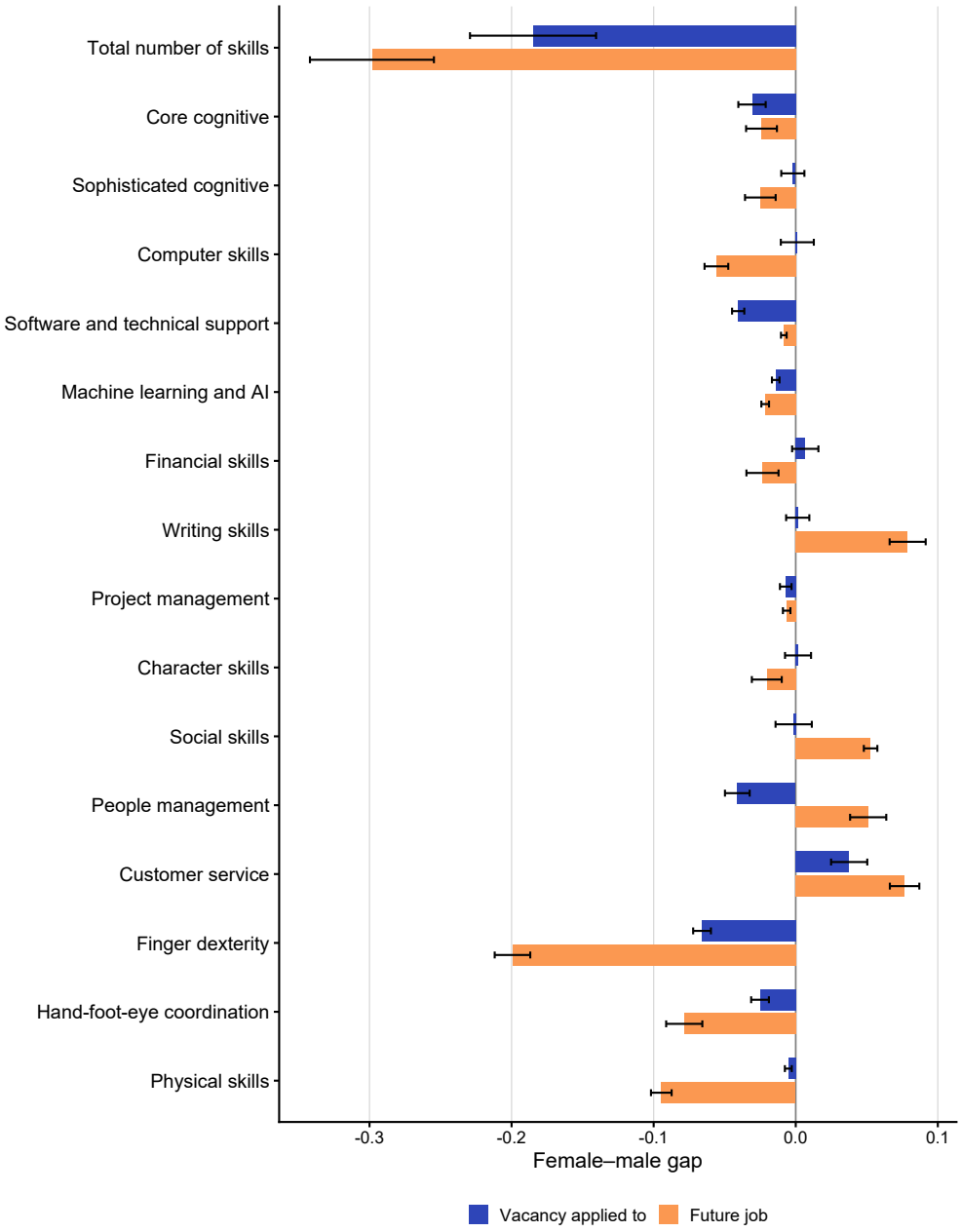
The gender application gap for skills is mostly negative, suggesting that women apply to jobs with lower skill requirements than men across a broad range of skill categories. The

largest negative gaps are for finger dexterity (-6.6 percentage points, 65%), people management (-4.1 percentage points, 26%), software and technical support (-4.1 percentage points, 78%), core cognitive skills (-3.1 percentage points, 16%), hand-foot-eye coordination (-2.5 percentage points, 32%), and machine learning and AI (-1.4 percentage points, 75%). Smaller but statistically significant negative gaps are found for project management (-0.7 percentage points, 23%) and physical skills (-0.5 percentage points, 44%). Six skills have application gaps that are not statistically significant: sophisticated cognitive skills, computer skills, writing skills, social skills, character skills, and financial skills. Only customer service skill has a positive and statistically significant application gap, where women are 3.8 percentage points (8%) more likely to apply to jobs that require this skill.

Comparing the application gaps to the realized outcome gaps, the negative realized gap even exceeds the negative application gap in magnitude for sophisticated cognitive skills, computer skills, machine learning and AI, finger dexterity, and physical skills. For other skills, however, the patterns are different. For writing and social skills, the application gap is statistically insignificant while the realized gap is positive and significant; women are 7.9 percentage points more likely than men to end up in jobs that require writing skills. For financial skills, the application gap statistically insignificant while the outcome gap is negative and significant. Most strikingly, for people management the application gap is negative but the realized gap is positive: women are 4.1 percentage points less likely than men to apply to roles that require people management, yet are 5.1 percentage points more likely to end up in roles that require it.

The occupational and skill gaps documented above coincide with meaningful wage and seniority penalties: female applicants earn approximately 16% lower wages and are 1.1 percentage points less likely to hold a senior position after application, both statistically significant at the 5% level. Women are also less likely to hold full-time positions: 88% of the female applicants hold full-time positions while 93% of the male applicants hold full-time positions, and the average weekly contractual hours is slightly lower for women (-0.7 hours, or 1.5%).

Figure 2: Gender Application and Outcome Gaps: Skills



Senior positions are defined across all occupations as whether the job title contains words associated with senior roles such as "manager" or "director", distinct from the managerial occupation category which is based on first-digit occupation codes. Occupational segregation is moderate, with a 1-digit Duncan index of 0.133 at the application stage rising to 0.175 in realized jobs. Industry segregation in realized jobs is similarly moderate, with a Duncan index of 0.144 at the 7-category level and 0.233 at the 2-digit level. These results are shown in Table 2.

Importantly, the application and realized outcome gaps do not simply reflect a general aversion to job transitions among women. As shown in Table 2, women are 7.5 percentage points less likely to change city, yet 4 percentage points more likely to have changed firm, and are equally likely to have changed occupation and industry. Women are thus not broadly averse to job transitions but appear to be making systematically different kinds of transitions than men, which we explore further in sections 4 and 5.

3.2 Skill mobility

Beyond raw application gaps, we examine whether men and women differ in their tendency to apply upward or downward in the job ladder.

We compare each applicant's skill profile to the skill requirements of the jobs they apply to. Our first measure uses self-reported past job responsibilities from the platform, which are available for 69% of the sample and allow us to construct skill profiles at the individual level. Our second measure uses the average skill requirements constructed using each applicant's prior six-digit occupation, which extends coverage to the full sample. For each skill dimension, we classify an application as a *match*, a *stretch* (applying upward to a job that requires a skill the applicant does not have), or an *underutilization* (applying downward to a job that does not require a skill the applicant has).

The two measures differ in how they assign skill endowments to applicants. The platform measure assigns skills at the individual level using applicants' own descriptions of their past

Table 2: Gender Gaps in Applications and Future Jobs

	Vacancy applied to	Future job
Formal sector participation		
In RAIS		0.020***
		(0.005)
Wage and hours		
Log wage		-0.175***
		(0.009)
Hours worked		-0.619***
		(0.062)
Full-time ($\geq$ 40 hours)		-0.051***
		(0.004)
Seniority		-0.011***
		(0.003)
Occupational segregation (Duncan index)		
1-digit	0.133	0.175
	(0.006)	(0.006)
2-digit	0.304	0.330
	(0.006)	(0.006)
Industry segregation (Duncan index)		
7 categories		0.144
		(0.006)
2-digit		0.233
		(0.006)
Job transitions		
Changed firm		0.040***
		(0.005)
Changed occupation		0.011
		(0.006)
Changed industry		0.002
		(0.005)
Changed city		-0.075***
		(0.006)

$N = 23,789$ for all outcomes except shows up in RAIS (sample includes all matched applicants who have RAIS records before and after application); $N = 32,007$ for shows up in RAIS (sample includes all matched applicants who have RAIS records prior to application). Standard errors in parentheses. Duncan index bootstrap SEs based on 2000 replications. Vacancy side uses ISCO classification; future job side uses CBO classification. Future job is first observed job within 5 years after application year. Job transitions compare last pre-application job to first post-application job (non-missing per variable). * p<0.05, ** p<0.01, *** p<0.001.

job responsibilities, allowing two workers in the same six-digit occupation to have different skill profiles. The administrative measure assigns skills at the occupation level, using the average skill requirements of each applicant's prior six-digit occupation, and assumes that all workers in the same six-digit occupation share the same skill endowments. We use both measures to assess whether gender gaps in stretch and underutilization reflect a core pattern that is robust across measurement approaches.

Women are less likely than men to both stretch and underutilize across most skill categories, suggesting that they are more likely to apply to jobs that match their existing skill sets. This pattern holds across both platform-based and administrative skill measures, suggesting that the pattern is robust across self-reported and administrative measures. These results are presented in Figure 3.

For stretch gaps, one clear exception is computer skills, where women are more likely to stretch than men, also consistent for both measures. Women also stretch more in financial skills using the administrative measure, though this is not evident in the platform measure.

For underutilization gaps, both measures indicate that women underutilize writing skills and customer service skills. Platform data also suggests that women underutilize sophisticated cognitive skills, while administrative data suggests that women underutilize people management skills.

The broad consistency across measures supports the conclusion that women apply to jobs that are better matches for their existing skill sets. The differences across measures may reflect either gendered task assignments within occupations, which occupation-level skill measures do not capture, or gendered differences in how applicants describe their past responsibilities on the platform. We discuss this further in section 4.1.

3.3 Heterogeneity

We examine heterogeneity in the gender application and labor market outcome gaps across four dimensions: education, labor market experience, seniority, and motherhood.

Figure 3: Gender Skill Mobility Gap (Platform Measure)

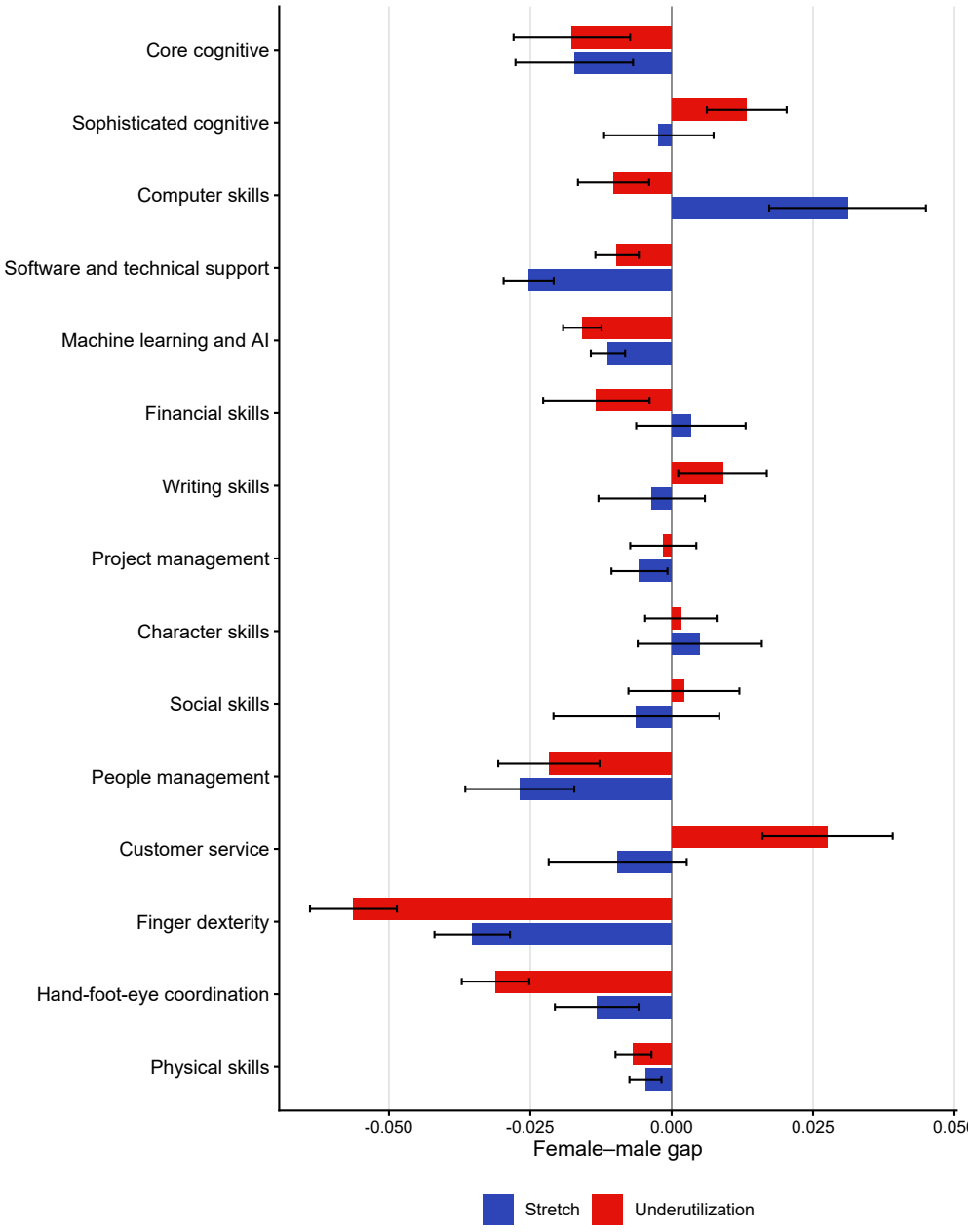
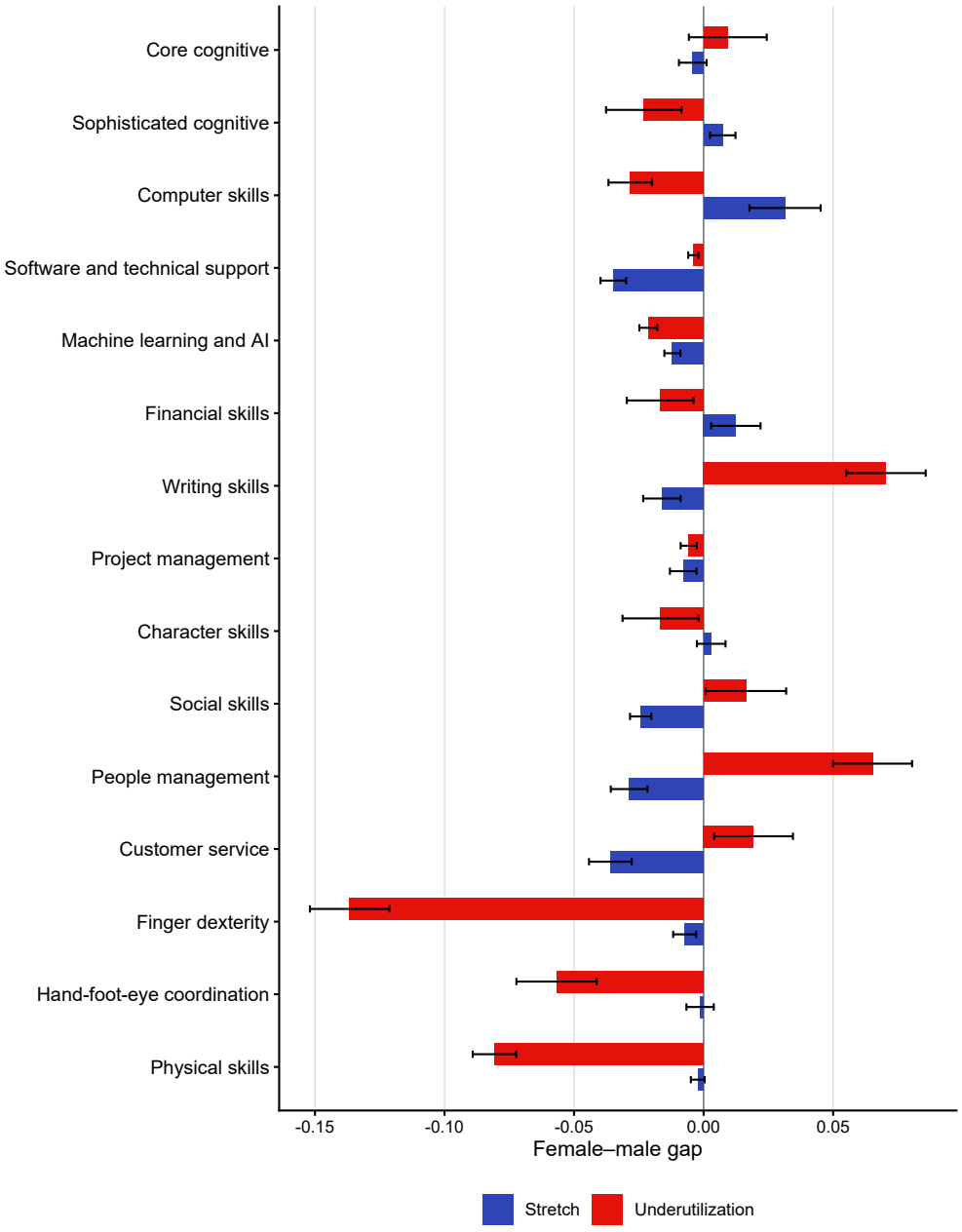


Figure 4: Gender Skill Mobility Gap (Administrative Measure)



For each dimension of heterogeneity, we partition the sample in two groups and examine the in-group gendered differences. For education, we examine gendered differences for those with a college degree and those without. For labor market experience, we divide the sample by having less than five years of formal sector experience or more. For seniority, we divide the sample by ever having had a senior job in the formal sector or not. Lastly, the partition for motherhood is different than the other dimensions. We define parenthood as having ever taken parental leave while working in the formal sector prior to the application year. Since maternity leave is much more common than paternity leave, we were able to identify a group of mothers, but not a group of fathers with enough sample size. Therefore, for this dimension of heterogeneity, we examine the differences between identified mothers and all men, and other women (some of whom may be mothers as well) and all men.

The complete figures with application and labor market outcome gaps for all subgroups are presented in Appendix Figures A1 to A4. Figure 5 below summarizes the results, showing gaps for manager occupations and total number of skills only.

Our heterogeneity analysis reveals four main patterns. First, the gender application gap is pervasive rather than concentrated among a particular subgroup of women. Both subgroups in every split show application gaps in the same direction, and very few differ statistically at the 5% level. Across all subgroups, women apply to fewer manager positions and to roles requiring fewer skills than their male counterparts, and in every subgroup the outcome gap for manager positions is smaller in magnitude than the application gap, consistent with the aggregate result. Women also apply to roles requiring fewer total skills than men across all subgroups, and end up in jobs requiring fewer total skills.

Second, higher qualifications and labor market experience do not dampen the application gap. If anything, women with college degrees, more than five years of experience, or prior senior positions exhibit larger application gaps than their less-educated, less-experienced, and non-senior counterparts, though these differences are not statistically significant. This suggests that application gaps are not solely driven by a lack of qualifications or experience.

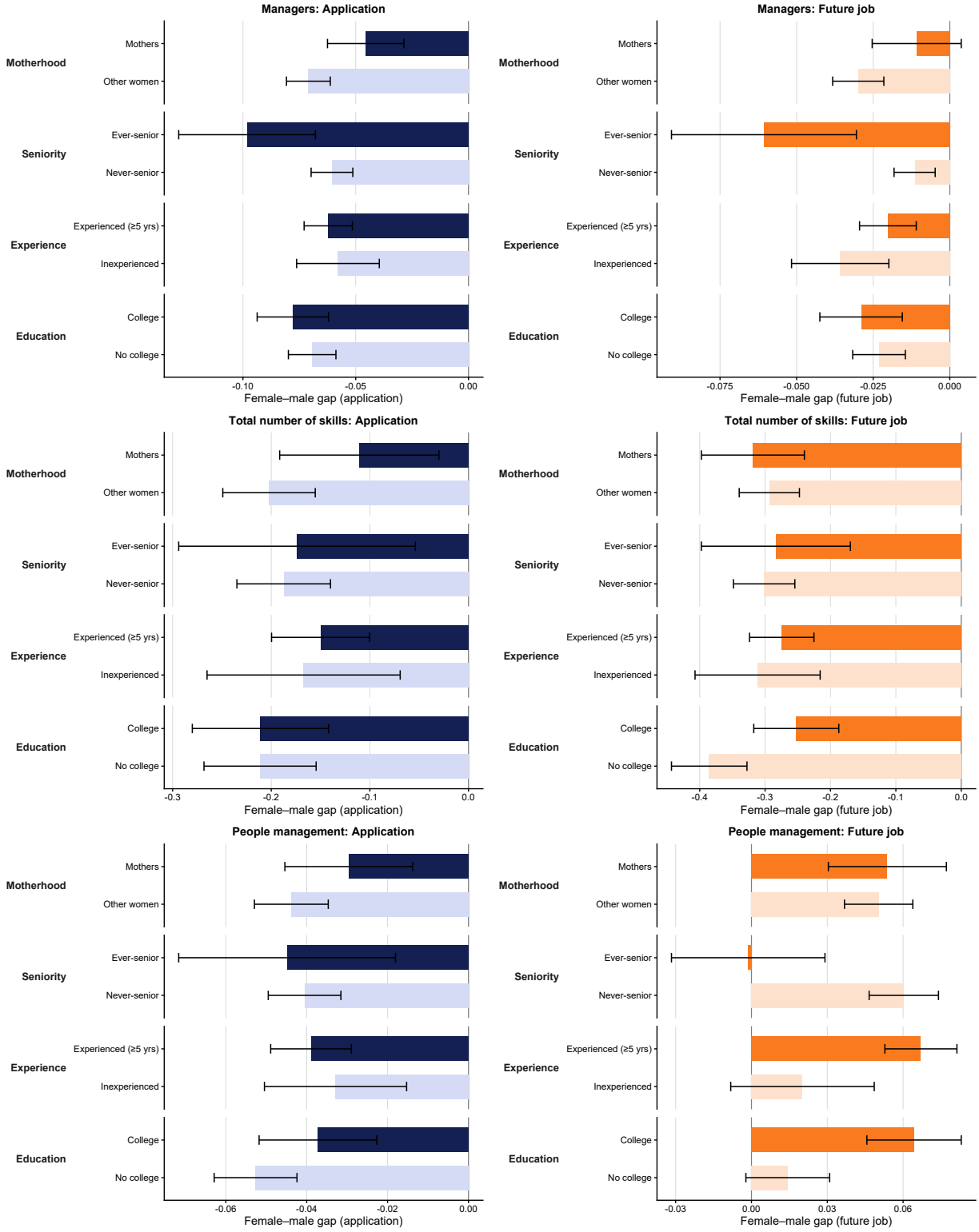
Third, in section 3.1, we noted that most outcome gaps mirror application gaps except for people management, where women are less likely to apply for jobs requiring people management but more likely to end up in jobs that require them. We find that this pattern is driven by college-educated women. College-educated women are 3.7 percentage points less likely than men to apply to roles requiring people management skills, yet are 6.4 percentage points more likely to end up in jobs that require them.

Finally, there is no strong evidence that application gaps are driven by motherhood. With the caveat that we can only identify mothers through past maternity leave records, and therefore the comparison group of other women likely includes some mothers as well, identified mothers do not show systematically larger application or skill gaps. Identified mothers apply to fewer manager roles than men, and while this gap is statistically significant, it is smaller in magnitude than the application gap for other women. In terms of realized outcomes, identified mothers are actually slightly more likely than men to work in manager occupations while other women are slightly less likely, though the difference between the two gaps is not statistically significant. This suggests that for formal sector workers in Brazil, motherhood and maternity leave are not associated with an additional penalty in application or realized outcomes. However, we cannot rule out selection as an explanation: women who were formally employed, took maternity leave, and subsequently returned to actively search for new jobs may be a positively selected group relative to all mothers.

4 Mechanisms: What Explains the Gender Application Gap?

In this section, we explore what drives the gender application gap documented above. We begin by characterizing gender differences in the observable characteristics that may shape job search behavior, including educational attainment, preferences for non-wage amenities, and past labor market experience. We then examine the extent to which these differences

Figure 5: Heterogeneity in Gender Application and Outcome Gaps



can account for the application gaps, using both OLS regressions and Oaxaca-Blinder decompositions.

4.1 Gender differences in qualifications, preferences and labor market experience

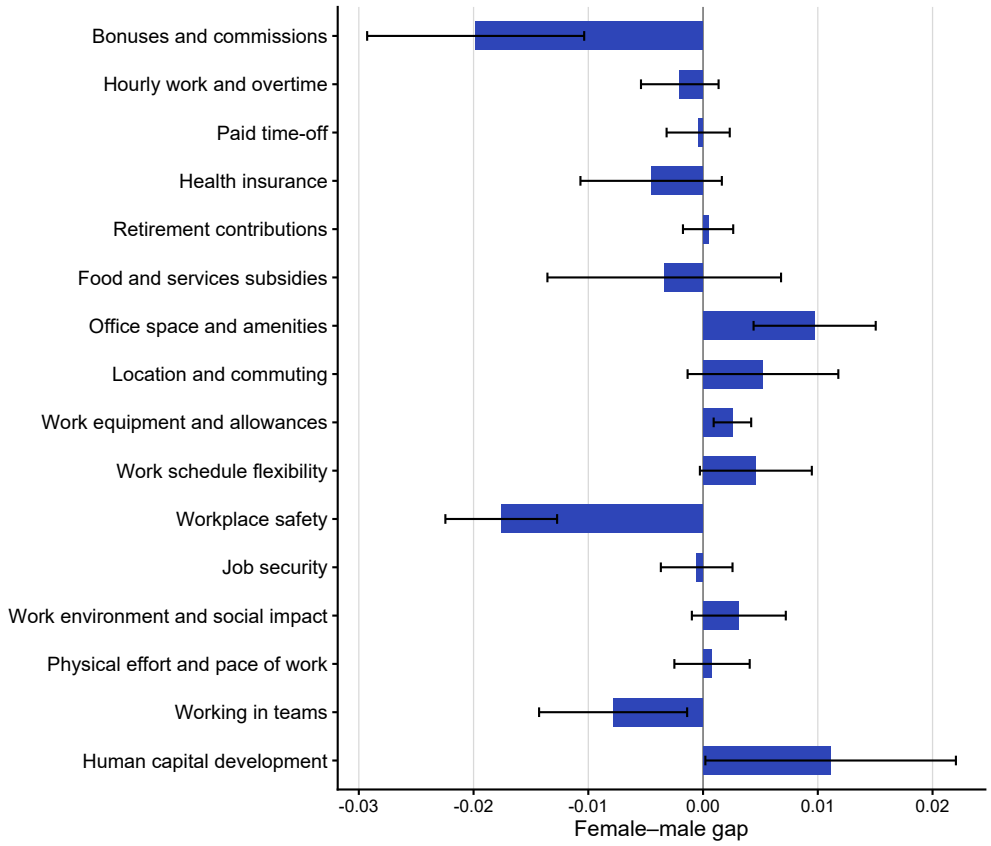
First, we document gender differences in the characteristics that may shape job search behavior: educational attainment, preferences for non-wage amenities, self-reported past labor market experience and inferred skills, and actual past labor market experience and inferred skills drawn from administrative records. These differences motivate the decomposition exercise that follows, which examines the extent to which gender application gaps can be explained by differences in qualifications, preferences, and prior labor market trajectories.

Women in our sample are more highly educated than men on average. They are 5.2 percentage points (6%) more likely to have graduated from high school and 6.8 percentage points (18%) more likely to have a college degree. This pattern mirrors broader trends in Brazil's formal labor market, where women have outpaced men in educational attainment in recent decades, yet continue to face disadvantages in labor market outcomes.

Motivated by recent literature suggesting that a higher valuation of non-wage job characteristics may drive gender differences in applications, we examine whether women and men apply to jobs with different non-wage amenities in our sample. As shown in Figure 6, women are more likely to apply to jobs with office space amenities and those with work equipment and allowances, but less likely to apply to jobs with bonuses and commissions, workplace safety, and working in teams. However, most application gaps for amenities are statistically indistinguishable from zero. Overall, we do not find evidence that women systematically apply to jobs with higher non-wage amenities relative to men.

Beyond education and amenity preferences, we examine whether women have systematically different past labor market experiences. Past labor market experiences may shape application behavior through two channels: employers may treat applicants with different

Figure 6: Gender Application Gap in Amenities



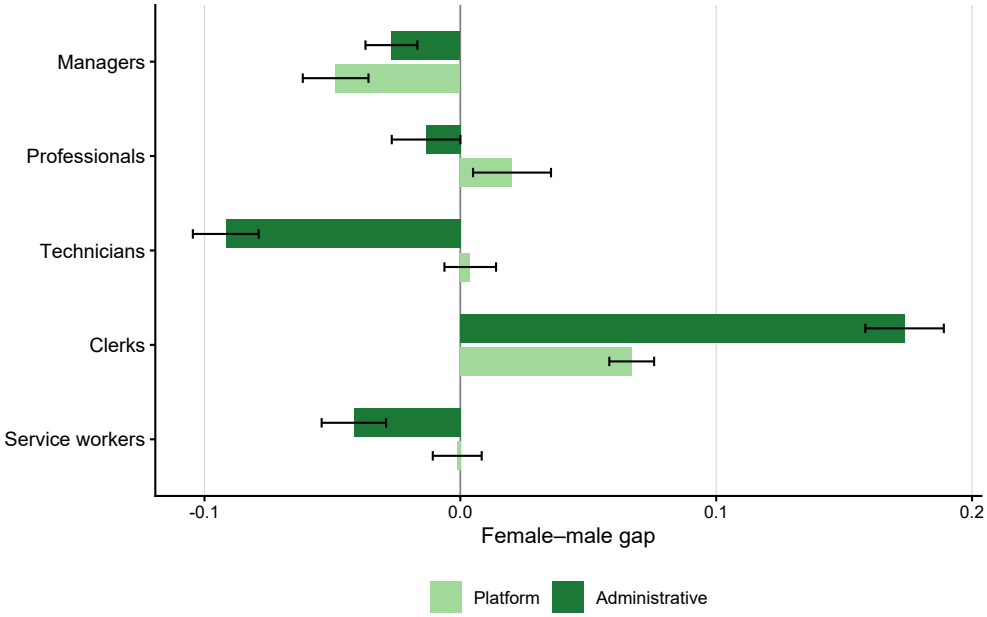
histories differently, or applicants may internalize their past experiences in ways that shape their expectations and beliefs about where to apply, reflecting path dependence. We examine both channels using two complementary sources of information: self-reported occupations and skills from the platform, which capture how applicants present their histories to employers, and administrative records from RAIS, which capture actual past labor market trajectories.

Looking at their last jobs prior to application in the administrative data, we find that women's hourly wages were 19 log points lower, and they are 5 percentage points (5.3%) less likely to be full time workers. However, we find no statstical difference in whether they held a senior position prior to application.

In terms of occupations, we find that women are less likely to have been managers and more likely to have been clerks. The gap in manager positions is -2.6 percentage points for

administrative data and -4.9 percentage points for platform data. The gap in clerk positions is 17 percentage points for admnistrative data and 6.7 percentage points for platform data. The administrative data also shows that women are 9.2 percentage points less likely to have been technicians and 4.2 percentage points less likely to have been service workers, while the platform data shows no statistically significant differences in these occupations. The platform data shows that women are 2 percentage points more likely to have been professionals while the administrative data shows no such difference. This divergence between administrative and self-reported occupational histories suggests that either women are assigned different tasks within the same administrative-data-coded occupation, or that women and men present their past experience differently when describing themselves on a job application platform.

Figure 7: Gender Differences in Past Occupation



In addition, there are gender differences in skills inferred from the last job prior to application. Across both measures, women have fewer core cognitive skills, computer skills, software and technical support skills, machine learning and AI skills, finger dexterity skills, hand-foot-eye coordination skills, and physical skills, and more writing skills, social skills, and customer service skills. However, the two measures diverge in interesting ways. Women

have fewer sophisticated cognitive skills according to their administrative occupation history, but report job responsibilities consistent with more sophisticated cognitive skills on the platform. Conversely, women's administrative records imply more people management skills than men's, yet women report fewer job responsibilities associated with people management. Similar to occupations, these divergences are both consistent with gender differences in task assignment within occupations and with systematic differences in how women and men present their labor market histories to prospective employers.

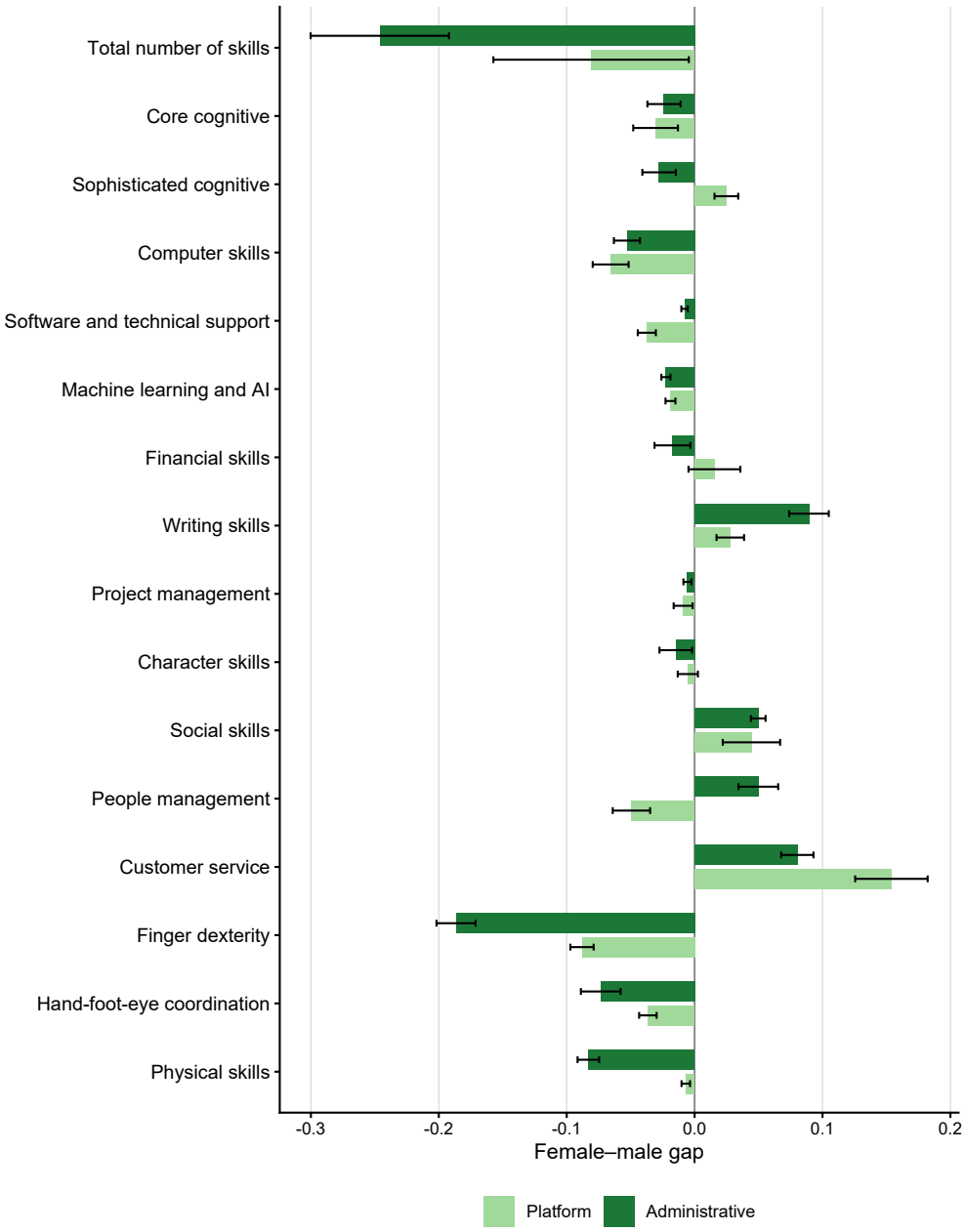
4.2 Controlling for qualifications, preferences and labor market experience

In this section, we use observable applicant characteristics to examine what explains the gender application gap. Table 4 presents our main results. The sample is restricted to applicants who have both prior and future formal sector records and self-reported labor market histories on the platform. Each coefficient comes from a separate regression of a vacancy characteristic on a female indicator and controls; we report the coefficient and standard error on the female indicator. Columns differ in which controls are included.

Column (1) presents the raw gender application gaps conditional only on year fixed effects. Column (2) adds education attainment controls. Column (3) further adds amenity controls for the applied-to vacancy. Column (4) adds self-reported past occupations and skills from the platform, capturing how applicants describe their own labor market histories. Column (5) adds controls for actual past labor market experience including past occupation, industry, and implied skills from administrative records. Column (6) further adds past wages and seniority.

We find a consistent pattern across outcomes. Controlling for education explains little of the application gap. In many cases it widens it, consistent with women being more highly educated than men in our sample. Controlling for amenities also explains little, suggesting that differential preferences over workplace characteristics are not the primary driver of the

Figure 8: Gender Differences in Past Skills



gap. Adding controls for self-reported occupations and skills has similarly little effect, indicating that the gap is not driven by differences in how women present themselves relative to men. In contrast, controlling for actual past labor market experiences including occupation, industry, skills, wages, and seniority does narrow the gap meaningfully, suggesting that prior labor market trajectories shape job search behavior beyond what education, preferences, and

self-presentation can account for. Nevertheless, substantial gender application gaps remain unexplained even after conditioning on this rich set of controls. One potential explanation of the residual gap is gender differences in beliefs. Women may believe that they will be seen differently by employers even if they apply to the same job as similarly qualified men. This is consistent with our results that women are more likely to apply to jobs that match their skill set rather than reach beyond or fall below their skill set.

As an illustration, the manager raw application gap is -6.8 percentage points. It widens to -7.6 percentage points after controlling for education, consistent with women being more highly educated than men. After additionally controlling for amenities and self-reported characteristics, the gap narrows to -7.0 percentage points, still above the raw gap. Controlling for past industry, occupation and implied skills narrows the gap to -5.8 percentage points, and controlling for past wages and seniority further narrows it to -5.0 percentage points. Taken together, past labor market histories explain approximately 26 percent of the raw application gap to managerial vacancies, with 74 percent remaining unexplained.

While application gaps in occupation remain largely unexplained by observables, observable characteristics account for a meaningful share of the application gaps across skill requirements. Taking machine learning and AI as an example, the raw application gap is -1.3 percentage points. It remains largely unchanged after controlling for education, amenities, and self-reported characteristics. Controlling for past industry, occupation and implied skills narrows the gap to -0.6 percentage points, and controlling for past wages and seniority leaves it at -0.6 percentage points. Taken together, past labor market histories explain approximately 54 percent of the raw application gap for machine learning and AI vacancies, with 46 percent remaining unexplained.

Most skill application gaps are negative, meaning that women are less likely to apply to positions requiring the skill. Customer service and financial skills are the sole outliers where women are more likely than men to apply to positions requiring customer service and financial skills. For customer service skills, once we control for self-reported past occupations

and skills, the gap becomes statistically indistinguishable from zero, suggesting that the raw positive gap is entirely explained by differences in how women and men describe their prior experience. For financial skills, the gap becomes statistically insignificant after controlling for education, suggesting that the raw positive gap is entirely explained by gender differences in education attainment.

4.3 Decomposing the gender application gap

Table 5 presents Oaxaca-Blinder decompositions of the gender application gaps, separating each raw gap into the share explained by observable characteristics and the share that remains unexplained. For each outcome, the decomposition includes the full set of observable characteristics: education, job amenities, and platform-reported labor market history including self-reported occupations and skills inferred from self-reported job responsibilities, as well as administrative records of past occupations, industries, and skills inferred from past wages and seniority. Appendix Table A4 presents additionally shares explained by each set of observable characteristics.

The decompositions reveal that the application gaps in occupation are largely unexplained by observable characteristics, with explained shares below 50 percent. For occupational gaps, observables explain roughly 27 percent of the managerial gap, 15.5 percent of the professional gap, and 37 percent of the clerical gap, leaving the majority of each gap unexplained.

Observables explain 24 percent of the gap in total number of skills and 25.5 percent of the gap in people management skills. For core cognitive skills, software and technical support, machine learning and AI, finger dexterity, hand-foot-eye coordination, and physical skills, observables explain 44-58% of the gap. For financial skills and customer service skills, the only two skills that exhibit a positive application gap, observables explain more than 100% of the gap, suggesting that women are not applying for jobs with these skills any more than their education, preference for amenities, and past experiences and skills would predict.

Taken together, the Oaxaca-Blinder decomposition corroborates the mechanisms section

that while past labor market trajectories shape where women and men apply, a large share of gender application gaps reflects factors beyond observable characteristics, pointing toward differences in beliefs or expectations about employer responses as a likely residual driver.

5 Outcomes: The Muted Consequences of Gendered Job Search

A central puzzle in our findings is that gender application gaps do not translate proportionally into outcome gaps. The manager result is the most striking: women are 6.6 percentage points less likely to apply to manager positions, yet are only 2.6 percentage point less likely to hold one in their first formal job after searching, a gap less than half the size of the application gap.

Why doesn't applying to worse jobs lead to worse outcomes? We consider two candidate explanations. The first is offer selectivity: women may reject worse offers and hold out for better ones, trading off longer search duration for better offers. The second is that women's conservative applications were an intentional strategy, that applying more conservatively meant they were more likely to obtain offers that were well-matched to them. We examine which explanation is more consistent with the data in section 5.1.

But even if the immediate outcome gap is muted, it is possible that women's different search strategies result in penalties over time, leading to growing gaps in wages, hours, or seniority in subsequent years. We discuss the long-term consequences of women's job search in section 5.2.

5.1 Do women's conservative search strategies pay off?

We examine whether the muted outcome gaps reflect offer selectivity or an intentionally conservative search strategy by examining heterogeneity by formal sector status during the year of job search. We hypothesize that formal sector employees are more likely to be able

to afford to reject offers and extend their search compared to their informal and unemployed counterparts, since they likely have higher income and job security. If offer selectivity is the only explanation that drives the small outcome gaps, we would expect it to operate most strongly for this group, and the outcome gaps to widen for those searching while informal or unemployed, who may face greater pressure to accept any offer they receive.

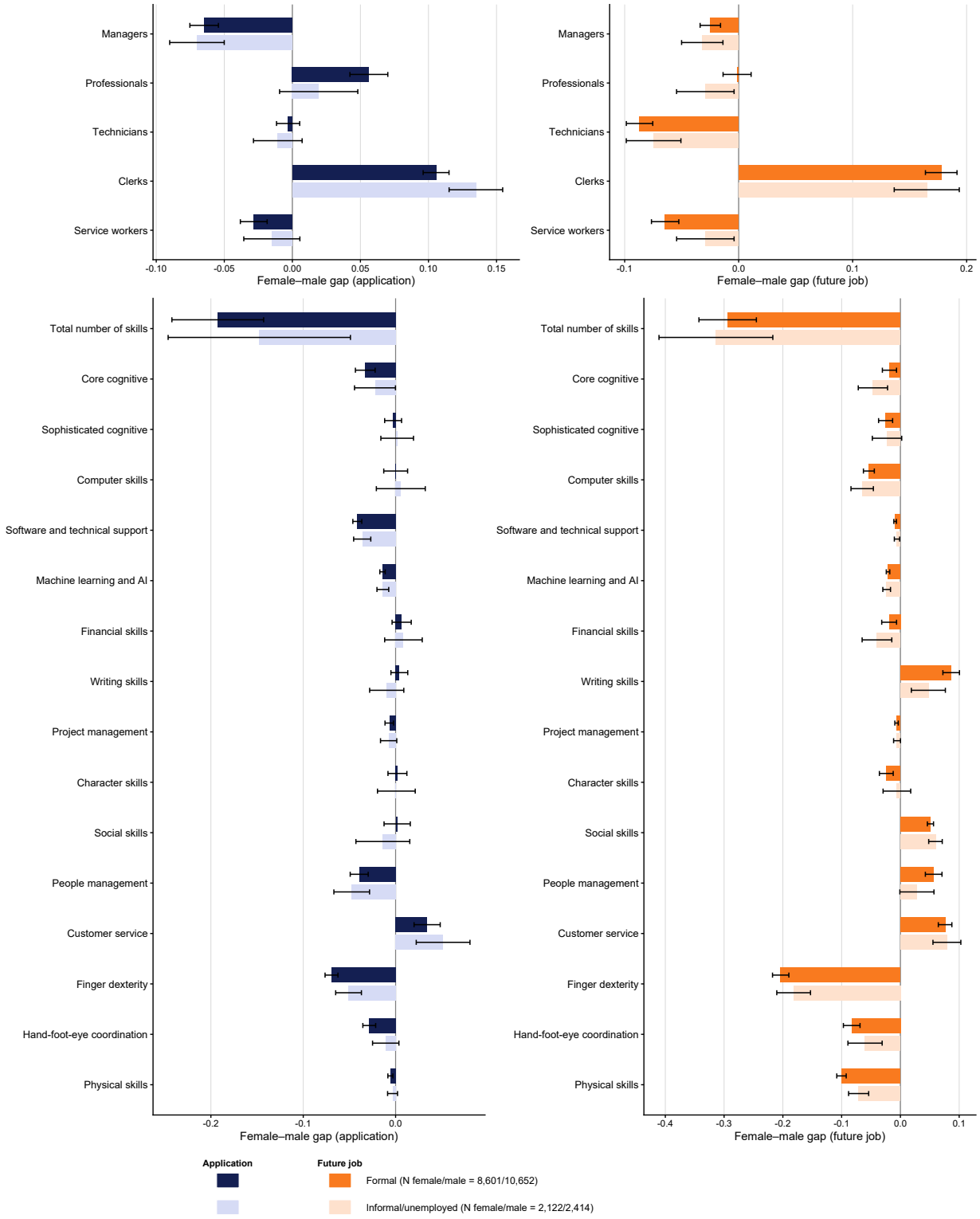
Figure 9 presents application and outcome gaps separately for workers who are present in RAIS in the year they apply (whom we term on-the-job searchers) and those who are either unemployed or working in the informal sector at the time of application. The results are not consistent with the offer selectivity explanation. Among on-the-job searchers, the manager application gap is -6.5 percentage points, while the manager outcome gap is considerably smaller at -2.5 percentage points. The same pattern holds for workers searching from outside the formal sector: despite a -7.0 percentage point application gap for manager positions, the outcome gap is just -3.2 percentage points. In both cases, the outcome gap is substantially smaller than the application gap, consistent with women's conservative application behavior constituting an effective search strategy. Even though women apply more conservatively than men, employers do not appear to select against them at a rate commensurate with the application gap.

Our results stand in strong contrast with Fluchtmann et al. (2024), who find that gender differences in applications can explain more than 70 percent of the residual gender wage gap among Danish unemployment insurance recipients. This suggests that while gender application gaps may persist across different contexts, their policy implications differ depending on institutions, norms, and labor market structures. Understanding what drives this heterogeneity would be an important avenue of future research.

5.2 Do women's conservative search strategies hurt them later?

To assess whether women's more conservative application patterns translate into worse labor market outcomes, we estimate an event study specification that traces how wages, earn-

Figure 9: Heterogeneity: Formal Sector vs. Informal or Unemployed



ings, hours, and job seniority evolve around the time of first platform application. For each applicant, we index all years relative to their first platform application ($t = 0$), normalizing outcomes to the year immediately prior to application ($t = -1$).

First, we estimate separate regressions for male and female applicants, controlling for age, age squared, educational attainment (high school and college completion), and year fixed effects.

$$Y_{it}^{g} = \sum_{j=-10}^{5} \rho_j^g \mathbb{I}(t = j) + \gamma^g \mathbf{X}_{it} + \epsilon_{it}^g \tag{1}$$

Then, we pool across genders to estimate the evolution of the gender gap. For the gender gap specification, we control for the same set of variables and the interaction of gender and all control variables. The identifying assumption is that, absent the application event, outcomes for male and female applicants would have followed parallel trends.

$$\begin{aligned} Y_{it} = \gamma_1 Female_i + \sum_{j=-10}^{5} \rho_j \mathbb{I}(t = j) + \sum_{j=-10}^{5} b_j Female_i \times \mathbb{I}(t = j) \\ + \gamma \mathbf{X}_{it} + + \zeta Female_i \times \mathbf{X}_{it} + \epsilon_{it} \end{aligned} \tag{2}$$

Figures 10 present the event study results for log monthly earnings, seniority, and weekly contractual hours. First, we examine the time trends in the pre-application period, and find that applicants of both genders exhibit declining conditional earnings in the years leading up to their first application. Conditional on covariates, their seniority also slightly decrease, while their hours slightly increase. Importantly, these trends are similar for male and female applicants, and we find that the gender gap in outcomes remains stable throughout the pre-application window: none of the gender gap coefficients from $t = -5$ to $t = -2$ are statistically significant for any outcome. This pattern supports the parallel trends assumption underlying our identification strategy, suggesting that the evolution of the gender gap in the post-application period can be interpreted as the causal effect of differential search and hiring outcomes.

The post-application trajectories reveal that online job search disrupts labor market outcomes for both genders. At $t = 0$, both men and women experience immediate declines in conditional monthly earnings (9.9% for men, 12.2% for women) relative to the year before application. While by five years after first application, average monthly earnings for male applicants are essentially unchanged (0.7% below pre-application levels) and women's average earnings have risen 3.3% above their pre-application baseline, we find that their earnings trajectories remain depressed relative to what we would predict based on their age and education: controlling for observables, men's earnings remain 5.1% below t=-1 levels, while women's earnings remain 5.9% below.

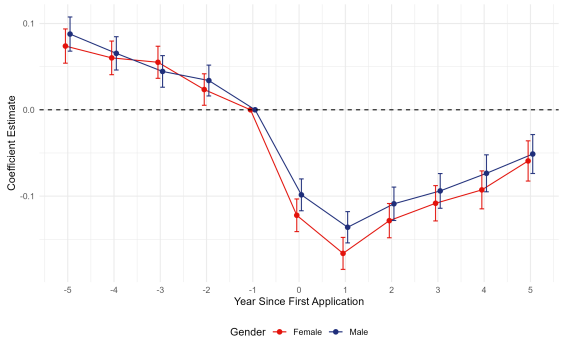
Women experience slightly larger initial setbacks than men in earnings and job seniority, though these differences are temporary. One year after first application, women's earnings remain 16.6% below their pre-application baseline while men's have recovered to 13.6% below baseline, widening the gender gap in monthly earnings by 3.0 percentage points. Similarly, the gender gap in job seniority widens by 1.2 percentage points at t=1. These patterns suggest that the application event temporarily amplifies existing gender gaps, with women landing in slightly worse positions initially. However, both the earnings and seniority gaps close within one to two years and remain statistically indistinguishable from zero thereafter. In other words, women's more conservative application strategies lead to initially worse outcomes, but the long-term consequences for earnings and seniority are muted.

The one persistent gender gap emerges in weekly contractual hours. The hours gap widens starting two years after application and remains significant through year five. While statistically significant, the magnitude is modest, ranging from 0.26 to 0.38 hours per week (less than 1% of baseline hours). Unlike the transient widening in gender gaps of earnings and seniority, this hours gap does not close over time.

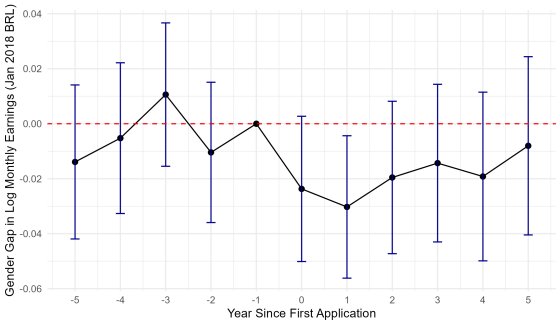
Taken together, the event study results suggest that both male and female applicants turn to the online platform in response to stagnating earnings trajectories, but their new positions do not place them on improved career paths. Despite women's more conservative application

strategies, their long-term labor market trajectories closely mirror men's: both experience similar persistent earnings penalties, and the gender gaps in wages and advancement that widen immediately after application close within two years. The one durable difference is a modest reduction in hours worked for women.

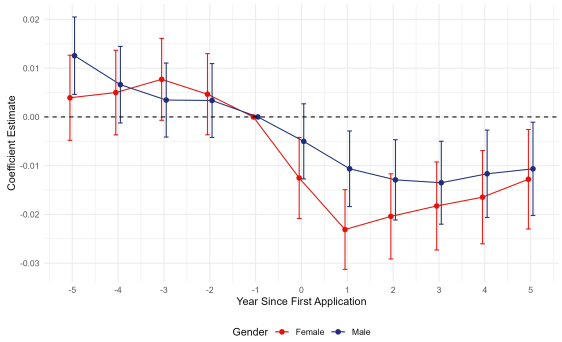
Figure 10: Effect of Application on Earnings, Seniority and Contractual Hours



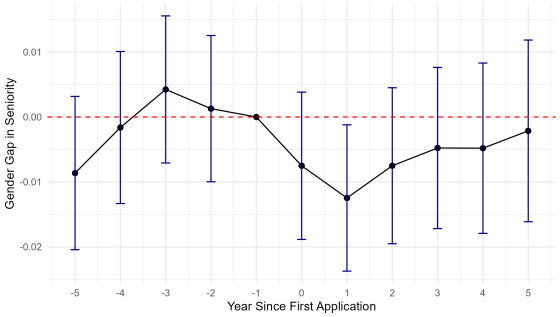
(a) Effect of application on log monthly earnings, by gender and time



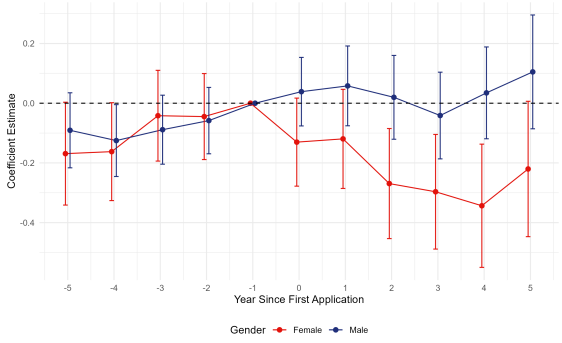
(d) Effect of application on gender gap in log monthly earnings



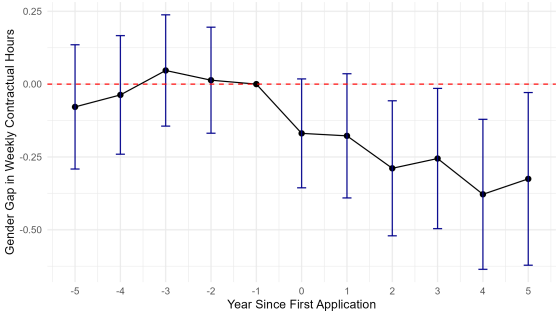
(b) Effect of application on seniority, by gender and time



(e) Effect of application on gender gap in seniority



(c) Effect of application on weekly contractual hours, by gender and time



(f) Effect of application on gender gap in weekly contractual hours

6 Conclusion

This paper examines gender gaps in job application behavior using a unique linked dataset that matches Brazilian workers who apply through an online job platform to administrative employer-employee records. We document that women are significantly less likely to apply to managerial positions and apply to roles requiring fewer skills, and that these gaps are pervasive across education levels, experience levels, seniority groups, and motherhood status. Despite these application gaps, outcome gaps are substantially more muted.

Our results suggest that women make conservative applications, but these likely reflect a search strategy is similarly effective as men. We corroborate this with evidence that women are more likely to apply to jobs that match their skill sets and less likely to make stretch applications into roles that require skills they do not have. The gender application gap remains largely unexplained after controlling for education, preferences, and past labor market experiences. This suggests that differences in beliefs or expectations about employer responses are a likely driver: women may have concluded that applying to stretch roles carries higher costs and lower returns, and these expectations appear to be shaped by factors beyond what observable characteristics can capture.

Event study analysis of labor market trajectories shows that both male and female applicants turn to the platform when their earnings trajectories stagnate, but neither group experiences improved long-term outcomes: five years after first application, both remain below expected earnings conditional on age and education. Despite women's more conservative application behavior, their trajectories closely mirror men's, with gender gaps in earnings and seniority widening only temporarily before closing within two years. Understanding why frequent job search and transitions do not lead to better outcomes for either gender remains an important direction for future research.

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Table 3: Gender Differences in Labor Market Experiences

	Administrative	Platform
Education		
High school degree	0.052***	
	(0.004)	
College degree	0.068***	
	(0.008)	
Wages and Hours		
Log wage	-0.188***	
	(0.012)	
Hours worked	-0.609***	
	(0.067)	
Full-time (≥40h)	-0.050***	
	(0.004)	
Seniority	-0.007	
	(0.004)	
Occupational segregation (Duncan index)		
1-digit	0.174	0.071
	(0.008)	(0.006)
Industry segregation (Duncan index)		
7 categories	0.103	
	(0.006)	
2-digit	0.225	
	(0.007)	

$N = 16,041$. Sample: applicants with prior and future RAIS records and non-missing platform occupation and skills (mirrors Table 2 sample). Standard errors in parentheses. Duncan index bootstrap SEs based on 2000 replications. Administrative column uses RAIS records; platform column uses BuscoJobs application data. Education, wages, seniority, and industry are from RAIS only (not observed on platform). Occupational segregation compares RAIS occupation (1-digit CBO) to BuscoJobs applied-to vacancy occupation (1-digit ISCO). * p<0.05, ** p<0.01, *** p<0.001.

Table 4: Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)
Occupation of vacancy						
Managers	-0.068***	-0.076***	-0.070***	-0.071***	-0.058***	-0.050***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Professionals	0.056***	0.046***	0.037***	0.055***	0.047***	0.043***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Technicians	-0.004	-0.002	0.001	0.001	-0.005	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Clerks	0.102***	0.108***	0.105***	0.090***	0.068***	0.066***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Service workers	-0.030***	-0.025***	-0.021***	-0.039***	-0.036***	-0.037***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Skill of vacancy						
Total number of skills	-0.150***	-0.172***	-0.165***	-0.168***	-0.133***	-0.119***
	(0.027)	(0.027)	(0.025)	(0.026)	(0.029)	(0.029)
Core cognitive	-0.037***	-0.042***	-0.039***	-0.031***	-0.021**	-0.017*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Sophisticated cognitive	0.004	0.001	-0.001	0.003	-0.000	0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Computer skills	0.010	0.008	0.005	0.011	0.008	0.008
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Software and technical support	-0.039***	-0.040***	-0.042***	-0.028***	-0.022***	-0.022***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Machine learning and AI	-0.013***	-0.014***	-0.014***	-0.009***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Financial skills	0.014*	0.009	0.009	0.002	-0.007	-0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Writing skills	0.002	0.001	0.001	-0.006	-0.009	-0.008
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Project management	-0.007**	-0.008**	-0.007**	-0.009**	-0.009**	-0.007*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Character skills	0.003	0.002	0.002	-0.001	0.004	0.004
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Social skills	0.011	0.011	0.013	0.005	0.007	0.008
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
People management	-0.043***	-0.047***	-0.042***	-0.040***	-0.036***	-0.032***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Customer service	0.024**	0.026**	0.027***	-0.004	-0.007	-0.007
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Finger dexterity	-0.058***	-0.057***	-0.056***	-0.040***	-0.025***	-0.024***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Hand-foot-eye coordination	-0.018***	-0.016***	-0.016***	-0.014***	-0.008	-0.008
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Physical skills	-0.005**	-0.005**	-0.005**	-0.004**	-0.003	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Education controls	No	Yes	Yes	Yes	Yes	Yes
Amenity controls	No	No	Yes	Yes	Yes	Yes
BJ skills controls	No	No	No	Yes	Yes	Yes
BJ occupation FE	No	No	No	Yes	Yes	Yes
RAIS skills controls	No	No	No	No	Yes	Yes
RAIS occupation FE	No	No	No	No	Yes	Yes
RAIS industry FE	No	No	No	No	Yes	Yes
Past wages & hours	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,041	16,041	16,041	16,039	16,027	16,027

Experienced workers with non-missing BJ self-reported occupation (`isco_two.x`) and skills (S00–S14 from last self-reported job spell). Sample is fixed across all columns. Outcome variables are characteristics of the vacancy applied to. Observation is at the applicant level using each applicant's first application. The coefficient of interest is on the female indicator. Education controls: high school and college degree indicators from RAIS. Amenity controls: 16 amenity indicators of the applied-to vacancy (A01–A16). RAIS skills/occupation/industry controls: same as Table 1. BJ skills controls: S00–S14 from last self-reported job spell. BJ occupation FE: 2-digit ISCO fixed effects from last self-reported job. Past seniority and wages: senior1 and log wage from last RAIS job spell. Heteroskedasticity-robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Table 5: Oaxaca-Blinder Decomposition of Gender Application Gaps

	Raw gap	Total expl.	Unexplained
Occupation of vacancy			
Managers	-0.069***	27.0%	73.0%
Professionals	0.051***	15.5%	84.5%
Technicians	-0.004	-22.1%	122.1%
Clerks	0.104***	37.3%	62.7%
Service workers	-0.028***	-31.3%	131.3%
Skill of vacancy			
Total number of skills	-0.158***	23.8%	76.2%
Core cognitive	-0.037***	51.8%	48.2%
Sophisticated cognitive	0.003	64.1%	35.9%
Computer skills	0.007	-16.4%	116.4%
Software and technical support	-0.039***	43.8%	56.2%
Machine learning and AI	-0.013***	51.3%	48.7%
Financial skills	0.012*	138.6%	-38.6%
Writing skills	0.003	365.7%	-265.7%
Project management	-0.008**	2.4%	97.6%
Character skills	0.005	15.1%	84.9%
Social skills	0.009	20.3%	79.7%
People management	-0.044***	25.5%	74.5%
Customer service	0.025**	126.4%	-26.4%
Finger dexterity	-0.057***	58.1%	41.9%
Hand-foot-eye coordination	-0.018***	54.1%	45.9%
Physical skills	-0.005**	46.3%	53.7%
Observations		16,041	

Experienced workers with non-missing platform occupation and skills. Raw gap is the coefficient on the female indicator from a regression with year fixed effects only; stars from heteroskedasticity-robust standard errors. Total explained + unexplained = 100%. Decomposition uses pooled regression coefficients (with group indicator) as the reference wage structure (Jann, 2008; Fortin, Lemieux and Firpo, 2011). * p<0.05, ** p<0.01, *** p<0.001.

Table A1: Sample Construction

Restriction	All	Prior	Both	Platform
Raw applicant level	81,965	81,965	81,965	81,965
Non-missing gender, vacancy characteristics	79,972	79,972	79,972	79,972
Has prior RAIS record	79,972	32,133	32,133	32,133
Non-missing RAIS controls (occupation, industry, skills, wage, seniority)	79,972	32,007	32,007	32,007
Has future RAIS record	79,972	32,007	23,909	23,909
Non-missing future outcomes (occupation, industry, skills, wage, seniority)	79,972	32,007	23,789	23,789
Has self-reported job history (NumMilestones > 0)	79,972	32,007	23,789	18,813
Non-missing platform occupation, skills	79,972	32,007	23,789	16,041

Sample sizes after each sample selection criteria. *All*: all applicants who applied through BuscoJobs (no RAIS requirement). *Prior*: applicants with at least one RAIS record before application year. *Both*: applicants with RAIS records both before and after application year. *Platform*: subset of *Both* with complete self-reported job history on BuscoJobs.

Table A2: Summary Statistics by Gender

	Female	Male
Demographics		
Year of birth	1982.960	1981.891***
	(4.825)	(4.967)
High school degree	0.990	0.975***
	(0.101)	(0.156)
College degree	0.688	0.604***
	(0.463)	(0.489)
Labor market		
Hourly wage (Jan 2018 BRL)	16.872	20.558***
	(21.730)	(19.150)
Weekly contractual hours	41.843	42.599***
	(3.186)	(2.619)
Share of years full-time	0.865	0.929***
	(0.223)	(0.159)
Ever senior	0.241	0.242
	(0.428)	(0.429)
Max labor market experience (years)	13.116	13.998***
	(4.266)	(4.309)
Ever parental leave	0.297	0.003***
	(0.457)	(0.050)
Years observed in RAIS	13.329	13.760***
	(3.678)	(3.539)
Mobility		
Firm changes	0.363	0.352***
	(0.167)	(0.173)
Occupation changes	0.286	0.287
	(0.156)	(0.160)
Industry changes	0.308	0.306
	(0.148)	(0.152)
City changes	0.163	0.197***
	(0.151)	(0.160)
Number of occupations	2.600	2.790***
	(1.000)	(1.091)
Number of industries	4.529	4.589**
	(1.750)	(1.778)
Platform engagement		
Share with 1 application	0.678	0.645***
	(0.467)	(0.478)
Share with 2 applications	0.149	0.162**
	(0.356)	(0.369)
Share with 3+ applications	0.174	0.192***
	(0.379)	(0.394)
First application year	2016.430	2016.485
	(2.471)	(2.366)
Observations	11,259	12,530

Standard deviations in parentheses. Stars indicate significance of two-sample t-test: * p<0.05, ** p<0.01, *** p<0.001. Sample includes individuals with both prior and future RAIS records who made at least one application on BuscoJobs. Hourly wage is in January 2018 BRL (IPCA index = 4930.72). Mobility measures are normalized by years observed in RAIS.

Table A3: Summary Statistics: RAIS full sample, all Platform Users

	Analysis sample	RAIS (all)	Platform
Demographics			
Female	0.473	0.450***	
	(0.499)	(0.497)	
Year of birth	1982.397	1981.535***	1987.302***
	(4.929)	(5.511)	(8.259)
High school degree	0.982	0.833***	
	(0.133)	(0.373)	
College degree	0.644	0.190***	
	(0.479)	(0.392)	
Labor market			
Hourly wage (Jan 2018 BRL)	18.814	12.103***	
	(20.494)	(19.548)	
Weekly contractual hours	42.350	42.731***	
	(3.009)	(3.708)	
Ever senior	0.242	0.082***	
	(0.428)	(0.274)	
Max labor market experience (years)	13.580	9.717***	
	(4.311)	(5.917)	
Years observed in RAIS	13.556	9.692***	
	(3.612)	(5.280)	
Mobility			
Firm changes per year	0.357	0.259***	
	(0.170)	(0.208)	
Occupation changes per year	0.287	0.205***	
	(0.158)	(0.184)	
Industry changes per year	0.307	0.227***	
	(0.150)	(0.180)	
City changes per year	0.181	0.128***	
	(0.157)	(0.168)	
Number of occupations (ever)	2.700	1.951***	
	(1.053)	(0.970)	
Number of industries (ever)	4.561	3.031***	
	(1.765)	(1.659)	
Platform engagement			
Number of applications (mean)	2.329		2.041***
	(5.134)		(5.496)
Number of applications (median)	1.000		1.000
First application year	2016.459		2018.164***
	(2.417)		(3.335)
Observations	23,789	100,000	79,972

Standard deviations in parentheses. Stars indicate significance of two-sample t-test vs. analysis sample: * p<0.05, ** p<0.01, *** p<0.001. Analysis sample includes individuals with both prior and future RAIS records who made at least one application on BuscoJobs. RAIS (all) includes all formal sector workers not matched to BuscoJobs. Platform includes all individuals who made at least one application on BuscoJobs. Hourly wage is in January 2018 BRL (IPCA index = 4930.72). Mobility measures are normalized by years observed in RAIS.

Figure A1: Heterogeneity in Gender Application and Outcome Gaps: Motherhood

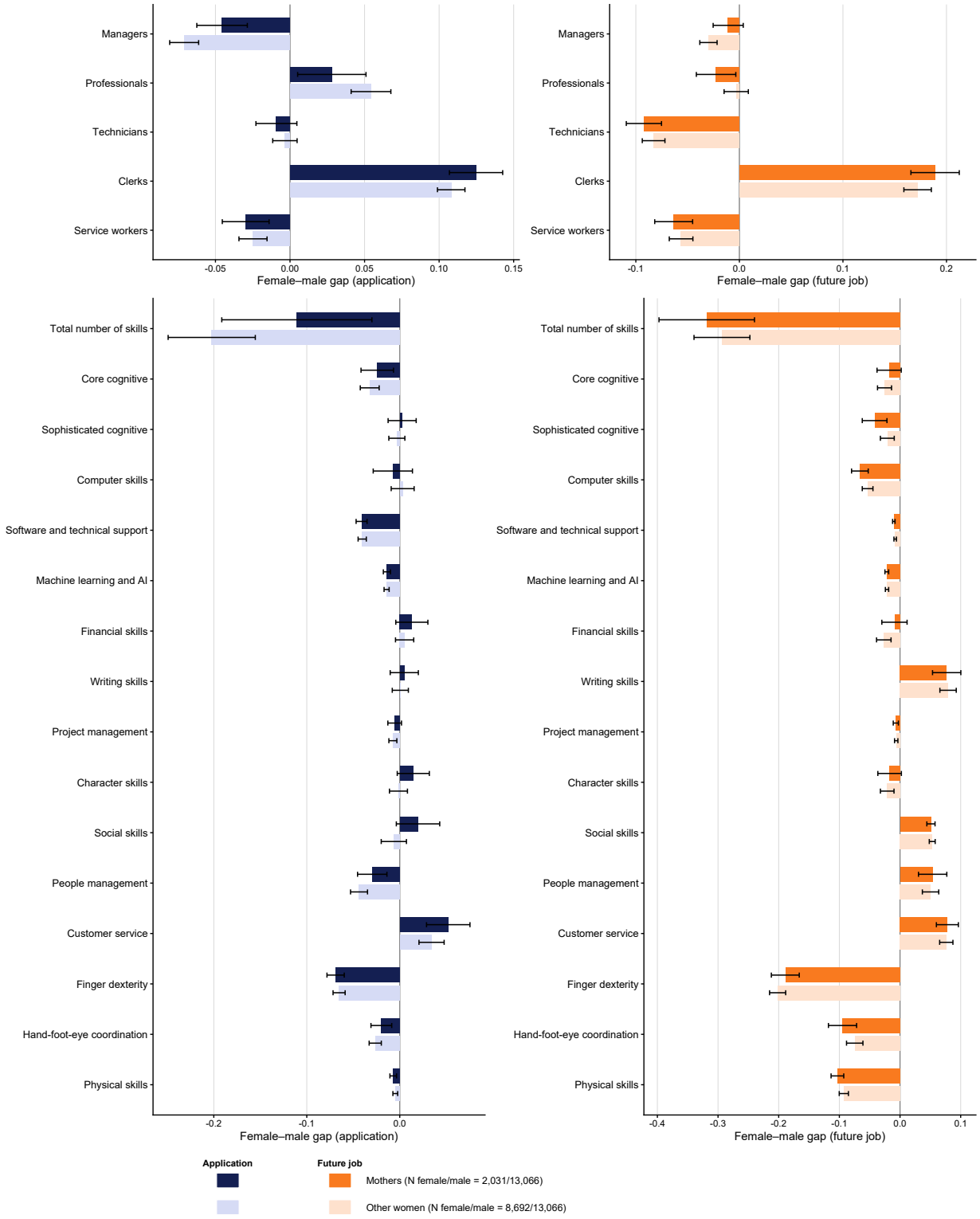


Figure A2: Heterogeneity in Gender Application and Outcome Gaps: Seniority

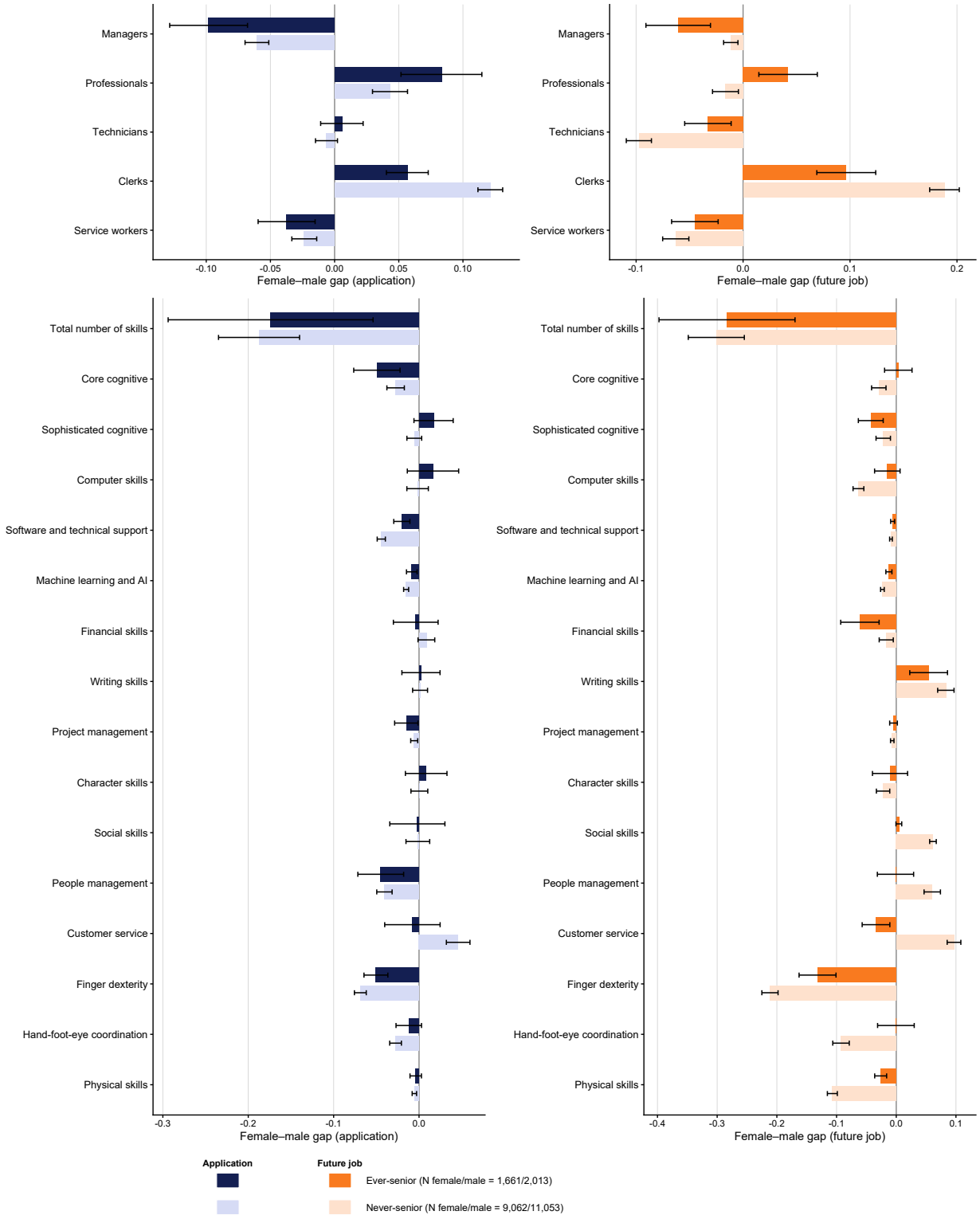


Figure A3: Heterogeneity in Gender Application and Outcome Gaps: Experience

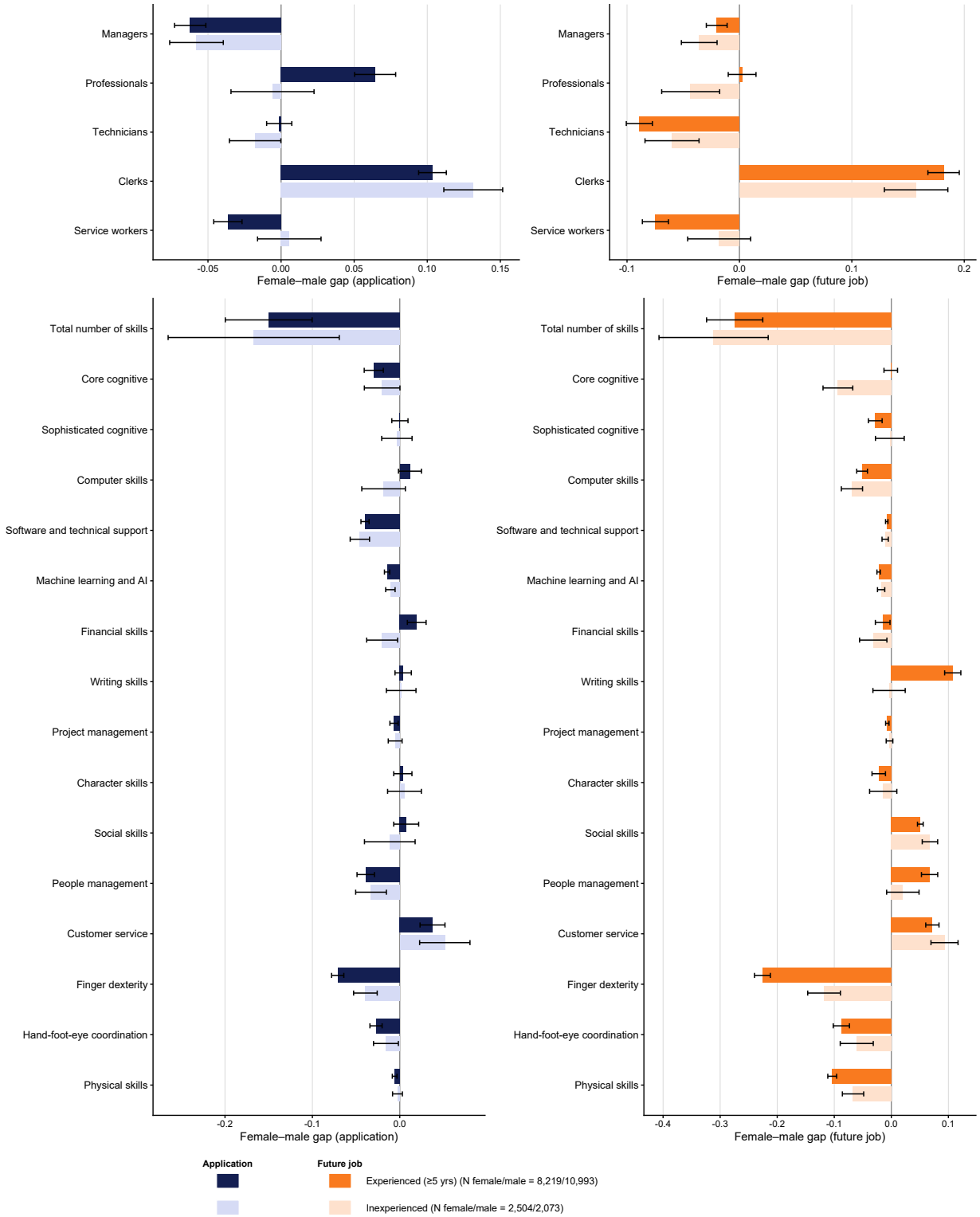


Figure A4: Heterogeneity in Gender Application and Outcome Gaps: Education

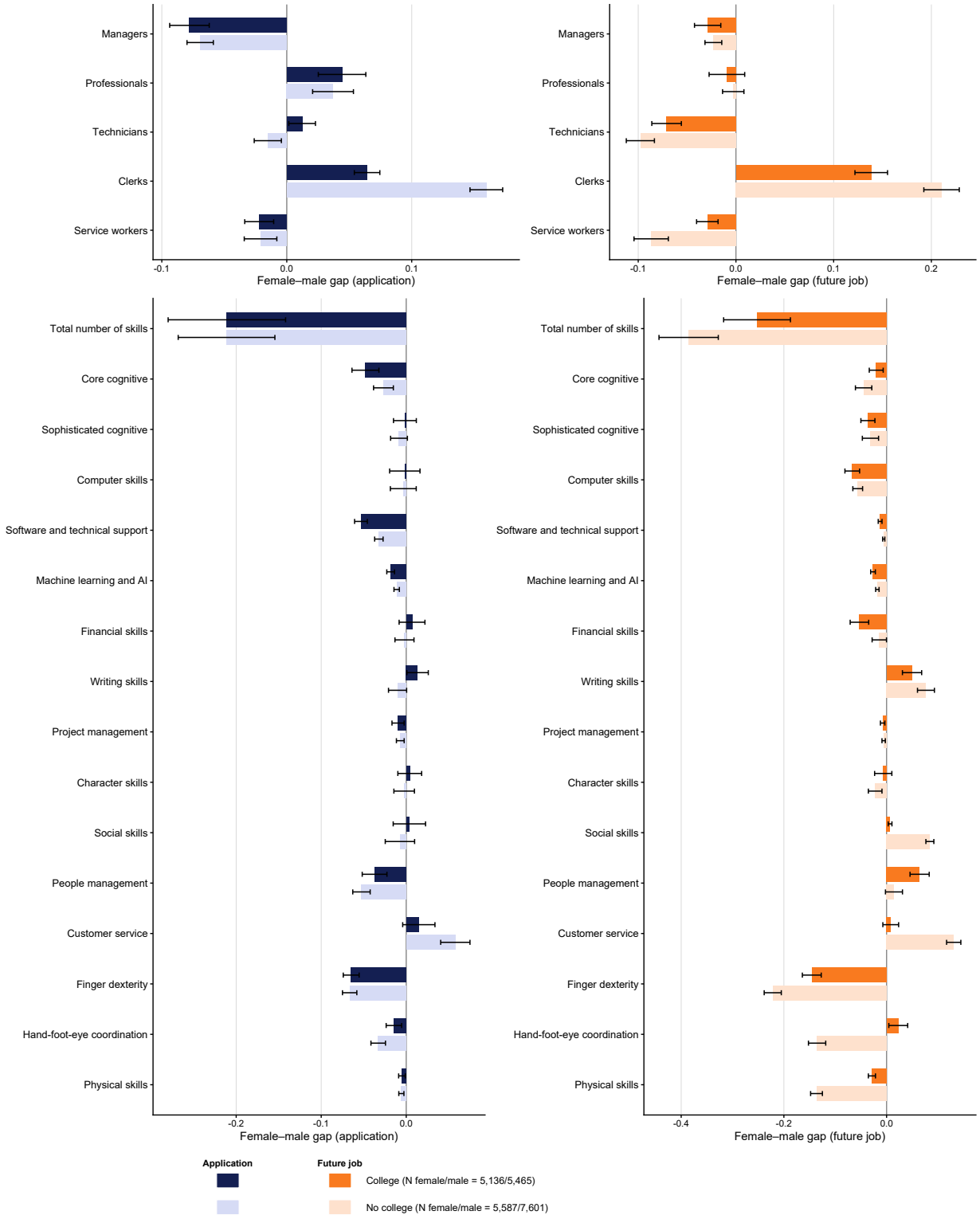


Table A4: Oaxaca-Blinder Decomposition of Gender Application Gaps

	Raw gap	Education	Amenities	Platform occ & skills	RAIS occ & skills	RAIS hours & wages	Total expl.	Unexplained
Occupation of vacancy								
Managers	-0.069***	-2.4%	7.6%	-3.5%	8.9%	17.9%	27.0%	73.0%
Professionals	0.051***	6.5%	15.8%	-27.2%	16.1%	11.4%	15.5%	84.5%
Technicians	-0.004	28.6%	72.5%	5.3%	-99.3%	-21.7%	-22.1%	122.1%
Clerks	0.104***	-2.1%	2.9%	9.8%	21.0%	4.6%	37.3%	62.7%
Service workers	-0.028***	4.5%	15.0%	-46.8%	1.4%	-3.7%	-31.3%	131.3%
Skill of vacancy								
Total number of skills	-0.158***	-5.7%	7.5%	-4.8%	14.0%	13.3%	23.8%	76.2%
Core cognitive	-0.037***	-4.1%	5.8%	10.3%	26.6%	13.5%	51.8%	48.2%
Sophisticated cognitive	0.003	39.9%	29.0%	-121.2%	190.1%	-82.5%	64.1%	35.9%
Computer skills	0.007	1.2%	17.9%	-73.6%	60.0%	8.9%	-16.4%	116.4%
Software and technical support	-0.039***	0.5%	-2.5%	23.8%	21.7%	0.6%	43.8%	56.2%
Machine learning and AI	-0.013***	-0.6%	-1.2%	26.2%	27.3%	0.2%	51.3%	48.7%
Financial skills	0.012*	6.7%	4.2%	50.3%	112.4%	-30.6%	138.6%	-38.6%
Writing skills	0.003	28.1%	5.9%	159.4%	177.9%	-41.9%	365.7%	-265.7%
Project management	-0.008**	-10.8%	13.6%	-13.0%	-20.0%	26.2%	2.4%	97.6%
Character skills	0.005	12.6%	-1.9%	92.3%	-118.2%	-11.9%	15.1%	84.9%
Social skills	0.009	5.2%	-23.8%	60.1%	2.5%	-10.7%	20.3%	79.7%
People management	-0.044***	-3.4%	11.5%	2.4%	4.4%	10.7%	25.5%	74.5%
Customer service	0.025**	2.0%	-7.7%	93.8%	35.0%	0.7%	126.4%	-26.4%
Finger dexterity	-0.057***	-1.1%	3.2%	20.4%	34.4%	2.3%	58.1%	41.9%
Hand-foot-eye coordination	-0.018***	-0.2%	7.0%	0.8%	52.2%	-5.1%	54.1%	45.9%
Physical skills	-0.005**	-3.6%	1.4%	-2.8%	38.4%	14.7%	46.3%	53.7%
Observations					16,041			

Raw gap is the coefficient on the female indicator from a regression with year fixed effects only; stars from heteroskedasticity-robust standard errors. Remaining columns report the percentage of the raw gap explained by each group of characteristics, from a Blinder-Oaxaca decomposition using pooled regression coefficients (with group indicator) as the reference wage structure (Jann, 2008; Fortin, Lemieux and Firpo, 2011). Total explained + unexplained = 100%. * p<0.05, ** p<0.01, *** p<0.001.