

Macroeconomic Consequences of Gender Differences in Job Search

Corinne Stephenson*

Current version: March 25, 2025

First version: November 1, 2024

[*Link to most recent version*](#)

Abstract

This paper examines how gender differences in job search behavior and preferences contribute to the gender wage gap. Using data from the Survey of Consumer Expectations, I document that women search for jobs more frequently and intensively than men but receive a similar number of job offers, implying lower offer yields. Women's best job offers feature lower wages, shorter hours, and fewer fringe benefits. They are more sensitive to nonwage job attributes—such as commute time, hours, and location—and are more likely to search exclusively for part-time work or to have recent nonemployment spells. Motivated by these patterns, I develop an on-the-job search model with endogenous effort, allowing jobs to differ in wages and amenity values. The model incorporates parental leave and the arrival of children as key mechanisms influencing search behavior and job preferences by gender. Through calibrated counterfactuals, I show that gender differences in amenity valuation alone explain nearly 20 percent of the overall gender wage gap.

Keywords: Job search, on-the-job search, amenities, gender pay gap

JEL Codes: J13, J16, J22, J31, J32

*Department of Economics, Boston University. Email: corinnes@bu.edu. I am extremely grateful to Pascual Restrepo, Kevin Lang, and Tarek Hassan for invaluable advice and encouragement. For helpful comments, I also thank Joaquín Blaum, Patricia Cortés, Eric Donald, Thorsten Drautzberg, Masao Fukui, Chris Foote, Santiago Franco, Adam Guren, Robert King, Nils Lehr, Franco Maldonado, Shraddha Mandi, Ryan Michaels, Chris Moser, Daniele Paserman, Dhiren Patki, Johannes Schmieder, Bryan Stuart, and seminar participants at Boston University, Bentley University, the Federal Reserve Bank of Boston, and the Federal Reserve Bank of Philadelphia, and conference participants at the Midwest Economics Association, and Northeast Universities Gender Conference.

1 Introduction

Gender disparities in labor market outcomes are well documented. However, much less is known about gender differences in the job search process and how these differences might affect outcomes. This paper addresses that gap by investigating whether and how men and women differ in their job search behavior and job preferences, and what the implications are for aggregate labor market outcomes, in particular, for the gender wage gap.

The central question of the paper is: Do differences in how men and women search for jobs and the types of jobs they seek lead to different employment outcomes, and can these differences help explain the persistent wage gap between genders? To answer this question, I combine empirical analysis of job search data with an equilibrium model of on-the-job search. In doing so, I present new evidence on gendered job search patterns and quantify the extent to which these patterns contribute to wage differentials between men and women.

Using the Job Search Supplement (JSS) of the Survey of Consumer Expectations (SCE), I document several striking gender differences in job search outcomes and strategies. First, women engage in job search more actively than men: they are significantly more likely to be searching for a job at any given time and devote more effort when they search (for example, sending more applications and spending more hours on search). Despite this higher search intensity, women do not receive more job offers. Men and women obtain a similar number of offers on average, which means women's search efforts yield fewer offers per search input (application or hour). According to my estimates, women are on average 23% less effective in generating job offers from their search efforts than men.

Second, the best job that women are offered tend to have different characteristics than those offered to men. The wage of the best job offered to women is roughly 15% lower and entails 7% fewer hours on average, after controlling for a rich set of worker and job offer attributes. The lower wages offered to women are not offset by greater nonwage compensation in the form of fringe benefits. If anything, the opposite is true: women's offers are significantly less likely to include fringe benefits, such as health insurance or retirement plans. These patterns indicate that women, relative to men, tend to have jobs that are lower paying, less time-intensive, and more likely to lack benefits.

Additionally, women appear to navigate the job search process differently: they obtain more offers through referrals, whereas men more frequently receive unsolicited offers. Women are also less likely to have an idea of the wage before being extended an offer and are less likely to negotiate their starting salaries. Taken together, these facts paint a

consistent picture in which women's greater search activity does not translate into equally improved job outcomes in quantity or quality of offers.

Third, I find evidence that women prioritize nonwage job amenities more than men do, which in turn influences their search behavior and outcomes. A key indicator comes from examining how one's current wage relates to search intensity. According to standard job ladder models, workers in lower-paying jobs search harder for new jobs compared to those in well-paying jobs, since the potential gains from switching are bigger. Consistent with the theory, I estimate a significant negative elasticity of search intensity with respect to the current wage for both genders, but this elasticity is much larger in magnitude for men than for women. In particular, a 1% increase in the current wage of men is associated with about a 0.78% decrease in his search effort, while for women the decrease is only around 0.39%. In other words, men sharply reduce their job-search effort once they have a better-paying job, but women continue to search fairly actively even when they are relatively well paid. This finding suggests that women are often looking for something beyond higher wages.

In fact, additional evidence shows that women will turn down job opportunities that pay their reservation wage if those jobs lack certain amenities much more than men. In a hypothetical choice scenario, women are significantly less likely than men to accept a job offer at their own stated reservation wage if the job requires longer hours, doubling their commute or relocating. This greater reluctance to sacrifice flexibility for pay implies that many women place substantial weight on job attributes like schedule flexibility, even if it means accepting lower wages. Such preferences can lead to women searching broadly to find jobs that meet these criteria yet ending up with offers that trade off some salary for non-wage benefits that are not captured by fringe benefits, contributing to the observed wage gap. Consistent with this interpretation, when asked why they are searching, women more often than men cite reasons related to flexibility – for instance, dissatisfaction with inflexible work arrangements or a desire to reduce commuting time. These self-reported motivations align with the idea that nonwage amenities play a bigger role in women's job decisions.

Furthermore, an important source of heterogeneity in these patterns is the family composition. I find that the presence of children in the household largely drives the gender gap in amenity preferences. Women without children behave much more like men in their job search: Their search effort elasticity with respect to the current wage is similar to that of men (around -0.72 , nearly as high in magnitude as the male elasticity). In contrast, for women with children, the elasticity is essentially zero (about -0.02), which means that women with children in the household exhibit almost no decline in search

effort as their current wage increases.

In other words, a woman with household children will continue to search for a potentially better fit job regardless of how much she currently earns, presumably because wage is not the only factor in what she considers a 'better' job. Consequently, women with household children search more intensively on both extensive and intensive margins than women without children, and they are more likely to be searching specifically for part-time work or roles with greater flexibility. For example, among those who limit their search to part-time jobs, child care considerations are the most commonly cited reason for women. These findings highlight that family responsibilities and the need for flexibility significantly influence many women's job search behavior. This emphasis on amenities and flexibility among women is consistent with a growing literature showing that women value job flexibility and related amenities more highly than men do, and that this can lead to earnings differentials even in the absence of discrimination (Goldin, 2024).

Building on the empirical evidence above, the second part of the paper develops a structural model to quantify the macroeconomic impacts of these gender differences in job search behavior and preferences. I extend a standard on-the-job search framework following Faberman et al., 2022 in three key ways to capture gender dimensions. First, I allow jobs in the model to vary along two dimensions, wage and nonwage amenity value, to reflect the trade-offs between pay and amenities. Second, I allow search technology to differ by gender and by employment status. Third, I incorporate a choice for child fertility, which temporarily interrupts careers and permanently changes the evaluation of the job amenities of the worker. These features ensure that the model replicates the empirical patterns: women search more intensively than men, value amenities more, and women with household children differ from those without children in their search behavior.

I calibrate the model to the observed data and then perform counterfactual exercises to isolate the role of gender-specific factors. In particular, I simulate what the labor market outcomes would look like if men and women were identical in all respects except for one factor at a time – for instance, making women have the same preference for amenities as men, or the same level of job attachment as men (no career interruptions), holding everything else equal. Comparing these scenarios quantifies how much each factor contributes to the overall gender wage gap. The model reveals that differences in amenity valuation between men and women can account for nearly 20% of the gender wage gap on their own. In other words, women's stronger preferences for flexible or otherwise amenity-rich jobs (and the corresponding wage trade-offs) explain a sizable share of why women, on average, earn less than men. Other factors, such as gender gaps in search effectiveness or job continuity, also play roles, but the amenity preference gap is

a major contributor. This is an important insight because it suggests that a non-negligible portion of the wage disparity arises from choice and preference-driven job sorting rather than direct discrimination or differences in skills.

In general, the contributions of this paper are twofold. First, it provides new empirical evidence on how gender differences in job search behavior and priorities can lead to different job outcomes. Second, it offers a quantitative assessment of how these differences matter for the gender wage gap, embedding them in an equilibrium search model. The findings bridge related literature threads: one on gender differences in labor market behavior showing how job search and amenity preferences differ by gender, and one on the role of nonwage amenities in job markets. By clearly identifying and then quantifying the impact of gendered job search patterns, the paper adds to our understanding of why the gender wage gap persists and how much of it might be attributable to differing preferences and constraints faced by women in the labor market.

1.1 Related Literature

This paper contributes to several strands of the literature. First, it relates to the extensive work on the gender wage gap, especially research emphasizing the role of motherhood and flexibility. Recent work by [Goldin \(2024\)](#) argues that the final chapter of gender convergence hinges on flexibility in the workplace. Models of time constraints and job inflexibility also explain persistent wage gaps among highly skilled workers ([Cortés and Pan, 2019](#); [Goldin and Katz, 2011](#); [Goldin and Katz, 2016](#); [Bertrand et al., 2010](#)). This paper complements that work by showing how preferences for flexibility and nonwage job features shape women’s job search behavior, particularly among mothers.

Second, the paper contributes to the growing literature on gender differences in the valuation of nonwage amenities. Empirical studies find that women are more likely to trade off wages for better amenities such as remote work, flexible hours, or shorter commutes ([Chen et al., 2024](#); [Le Barbanchon et al., 2021](#); [Mas and Pallais, 2019](#); [Wiswall and Zafar, 2018](#); [Goldin, 2014](#)). This paper builds on those findings by linking amenity preferences not only to job acceptance decisions, but also to job search intensity and outcomes, and by quantifying how these preferences affect the gender wage gap through structural estimation.

Third, this paper contributes to a broader literature on the role of nonwage amenities in labor markets. Nonwage job characteristics are a significant source of compensation and vary widely across jobs ([Maestas et al., 2023](#); [Sockin, 2024](#)). [Hall and Mueller \(2018\)](#) show that amenities are more dispersed than wages, implying greater search frictions.

I extend this insight by modeling how amenity dispersion, coupled with heterogeneous preferences across genders, alters search behavior and labor market outcomes.

Finally, this paper adds to models of job search with endogenous effort ([Christensen et al., 2005](#); [Hornstein et al., 2011](#); [Bagger and Lentz, 2019](#); [Faberman et al., 2022](#)). These frameworks typically abstract from gender. I extend them to allow for gender- and child-status-specific search costs, offer arrival rates, and preferences over wages versus amenities. In doing so, the paper highlights a new mechanism, namely the gendered valuation of non-wage amenities, as a quantitatively important contributor to wage inequality.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 describes empirical patterns in job search behavior. Section 4 presents the results of the job search process and the characteristics of the job offer. Section 5 presents evidence on the valuation of non-wage amenities. Section 6 introduces the job search model. Section ?? presents the quantitative results, including counterfactual analyses, and discusses the contributions of various factors to the gender wage gap. Section 8 concludes with implications and potential avenues for future research.

2 Data

This paper uses data from the Job Search Supplement (JSS) of the Survey of Consumer Expectations (SCE). The SCE is a nationally representative survey conducted by the Federal Reserve Bank of New York. It is fielded monthly and surveys approximately 1,300 household heads on their expectations of future macroeconomic and personal economic conditions. The JSS is a supplement to the SCE and is fielded annually in October. It provides detailed cross-sectional data on job search behavior and outcomes. The sampling frame of the JSS is the same as the SCE (for additional details see [Armantier et al. \(2017\)](#)). While the SCE is a rotating panel with respondents surveyed up to 12 months, the JSS is a repeated cross-section. The results in this paper pool data from all publicly available years, which spans 2013–2021. The JSS was designed by the authors of [Faberman et al. \(2022\)](#).

Table 1 shows summary statistics of the JSS, in comparison to the Current Population Survey (CPS). Since this paper focuses on gender differences, the summary statistics include all respondents as well as broken down by gender. Although respondents in both datasets are similar in the percent who are of prime working age, respondents in the JSS tend to be more White, married, and homeowners compared to the CPS. Given these differences, throughout the paper I present results without any controls as well as results reflecting various sets of controls. All results are weighted using given survey weights.

Table 1: Summary statistics: JSS and CPS

	JSS	CPS	JSS		CPS	
	All	All	Men	Women	Men	Women
<i>Demographics (percent)</i>						
Male	49.6	51.1				
Aged 25-54	70.4	68.4	68.4	72.4	68.6	68.2
White non-Hispanic	72.6	63.2	76.4	68.8	65.1	61.3
Education: high school	33.4	34.3	32.3	34.6	36.2	32.4
Education: some college	30.8	29.2	29.2	32.3	27.5	30.9
Education: college or more	35.8	36.5	38.5	33.1	36.4	36.7
Married	65.1	50.5	71.1	59.2	55.9	44.9
Children under 6	15.7	13.1	15.1	16.2	12.3	13.9
Homeowner	68.0	59.7	73.8	62.3	62.7	56.6
Renter	30.2	39.0	24.6	35.7	36.0	42.2
<i>Labor Force Statistics</i>						
Labor force participation rate	80.8	79.0	83.5	78.1	84.6	73.2
Employment to population ratio	77.6	75.7	81.0	74.2	81.4	69.7
Unemployment rate	4.0	4.2	3.0	5.0	3.5	4.1
<i>Observations</i>	7,769	333,331	3,913	3,856	168,291	165,040

In terms of labor force statistics, the JSS and CPS are very similar when considering all respondents (first two columns). However when broken down by gender, the labor force statistics vary more for women than for men. For example, the unemployment rate in the JSS is 0.9 percentage points higher for women and 0.5 percentage points lower for men. The labor force participation rate in the JSS is about five percentage points higher for women, and roughly one percentage point lower for men. When calculating the unemployment rate and labor force participation rate, I follow the definition used in the CPS to have as close of a comparison as possible. Below I discuss the slightly broader definition of unemployment that I use in the rest of the paper following [Faberman et al. \(2022\)](#).

Labor force status in the JSS is defined consistently with the CPS. Respondents are classified as in the labor force if they (i) are currently working for pay; (ii) are not working but have actively searched for a job in the past four weeks and are available to work; or (iii) are on temporary layoff. The definition of “active search” follows the Bureau of Labor Statistics (BLS) and includes engaging in any of the standard BLS job search activities or submitting an application ([BLS, 2024](#)).

However, the JSS adopts a slightly broader definition of unemployment than the CPS. In the CPS, only respondents who first indicate they “want work” are asked about job

search activity. In contrast, the JSS asks all respondents—regardless of whether they express a desire to work—about their recent job search behavior. This distinction results in a more inclusive measure of active search and unemployment.

2.1 Data on job search behavior

Most labor market surveys collect job search information only from unemployed individuals or those out of the labor force. In contrast, the JSS asks all respondents—regardless of labor force or employment status—about their job search behavior and outcomes. This feature is critical for the analysis, as it enables estimation of search effort elasticity with respect to current wages among the employed—a key input for the structural model. Estimating this elasticity by gender provides a target for calibrating the weight placed on nonwage amenities in job preferences.

The JSS collects rich information from employed respondents on the characteristics of their current job, including hours, earnings, fringe benefits, industry, occupation, firm size, tenure, and unionization. It also includes retrospective questions on how the current job was obtained, such as the search method, number of applications and offers, wage setting process, and starting pay. For non-employed respondents, the survey captures both the nature and duration of nonemployment spells and the characteristics of the most recent job, where applicable.

Respondents who report searching for work or being open to a new job are asked detailed questions on job preferences and search behavior. These include whether they prefer full-time or part-time work and why, reasons for searching, methods used to search, whether they are seeking a new job or additional work, the number of applications sent, and time spent searching in the past week.

2.2 Data on job search outcomes

The JSS collects detailed information on job search outcomes, including the number of offers and interviews received in the past four weeks, as well as characteristics of respondents’ “best” job offer. These include industry, occupation, wage, hours, and fringe benefits, and are comparable to the attributes reported for respondents’ current job (if employed) or most recent job (if not employed).

The survey also captures the method by which the best offer was obtained (e.g., referral, unsolicited offer, online application), whether the respondent accepted or plans to accept the offer, and the factors influencing that decision (such as pay, benefits, location, or hours). Additional questions probe the wage-setting process, including whether the respondent

knew the wage in advance, whether bargaining occurred, and whether the employer made a counter-offer. To assess search frictions and offer censoring, the survey further asks whether employers were willing to extend an offer that the respondent declined to pursue.

2.3 Data on nonwage amenities pertaining to flexibility

I use three complementary approaches to measure gender differences in the valuation of nonwage amenities.

First, I estimate the elasticity of job search effort with respect to current wages among employed workers. A lower (in absolute value) elasticity indicates that search behavior is guided less by wages and more by nonwage factors. Comparing elasticities by gender provides a revealed-preference measure of the relative importance placed on wages versus amenities.

Second, I exploit a series of hypothetical choice experiments in the survey. Respondents who searched in the last four weeks—or reported openness to a new job—are asked their reservation wage and hours. They are then presented with hypothetical job offers at their reservation wage, altered to include one of several disamenities: a 10% increase in working hours, a doubled daily commute, relocation to another city, or the absence of health insurance.

Sensitivity to these disamenities is captured on both the extensive and intensive margins. The extensive margin measures whether respondents would accept the offer at their reservation wage; the intensive margin measures how much their wage would need to increase for them to accept. In this paper, I focus on the three disamenities most directly tied to flexibility—hours, commute time, and relocation.

Third, the survey asks respondents to report their satisfaction with “other aspects of the job, such as benefits, maternity/paternity leave, flexibility in work hours, etc.” Paired with reported satisfaction with their current wage, these responses allow me to trace out indifference curves between wage and amenity satisfaction.

3 Job Search Behavior

This section documents three empirical patterns that characterize gender differences in job search behavior and outcomes. These facts motivate the structural model that follows.

First, women are more likely than men to engage in job search activities and do so with greater intensity. They submit more applications and devote more time to search, both on

extensive and intensive margins. Women are also more likely to receive their best job offer through referrals, while men are more likely to receive unsolicited offers. In addition, women are less likely to negotiate pay or have clear information on compensation prior to accepting an offer.

Second, despite their greater search effort, women and men receive a similar number of job offers. This implies a lower offer yield for women—defined as job offers per search input. Conditional on observable characteristics, women’s best offers include wages that are approximately 12% lower than men’s and are less likely to include fringe benefits such as health insurance or life insurance.

Third, women’s job acceptance decisions are more sensitive to nonwage job attributes, especially those related to flexibility. They are significantly less likely to accept hypothetical job offers that involve longer hours, longer commutes, or relocation. Consistent with this, the elasticity of search effort with respect to current wage is substantially smaller for women, suggesting that they place relatively greater weight on nonwage amenities in guiding their search behavior.

I also examine heterogeneity by parental status. Women with household children search more intensively than those without household children, and their search effort appears nearly unresponsive to current wages. In contrast, women without children behave more similarly to men. This heterogeneity helps explain broader gender differences in labor force attachment and job preferences: women with children are more likely to seek part-time work, to report having been out of work in the past five years, and to cite family obligations or childcare as key reasons for reduced labor force attachment.

Together, these results provide a detailed empirical foundation for analyzing gender-specific preferences and constraints in job search, which I incorporate into the model presented in Section 6.

3.1 Job Search Efforts

This section examines gender differences in job search motivations and effort. Using data from the JSS, I find that women are more likely than men to engage in job search along both the extensive margin (whether they search at all) and the intensive margin (how much effort they devote to search). Moreover, women’s search behavior appears to be shaped by household and demographic factors in ways that differ from men’s.

When asked why they are searching for a new job, men and women largely agree on the top two reasons (Appendix Table 25). These are (i) dissatisfaction with pay or benefits and (ii) dissatisfaction with job duties. However, beyond these top reasons, motivations

diverge by gender. Men are more likely to cite under-utilization of skills or a desire for change in role. Women are more likely to cite a long commute or a low quality of work life as drivers of their job search.

These gender gaps in search motivation are especially pronounced for parents. Among respondents with children, women much more frequently cite long commutes and poor work-life quality, whereas men emphasize skill mismatch and wanting a change. In contrast, among childless respondents, gender differences in stated reasons are smaller, suggesting that household constraints (such as childcare or family obligations) help explain the divergence in job search motives.

3.1.1 Extensive margin of search

On the extensive margin, women are significantly more likely to be active job seekers than men across all reference periods. As shown in Table 2, the probability of active search exceeds men's by roughly 8 percentage points during the last week, last month, and last year. For example, 24.7% of women report actively searching in the last 7 days, compared to 17.0% of men, a gap of 7.7 percentage points (significant at the 1% level). These gaps remain statistically significant even after controlling for a rich set of worker characteristics (including recent wage, age, education, race, marital status, presence of young children), as well as employment status and state and year fixed effects. In the fully controlled specification, the gender gap in 7-day search incidence narrows to about 3.5 percentage points, but remains highly significant. Appendix Table 26 confirms that these extensive margin differences are robust across various model specifications (following the control strategy of Blau and Kahn 2017), so both unadjusted and adjusted estimates are reported given potential endogeneity of certain covariates.

Table 3 breaks down the extensive margin of search by demographic group, revealing several notable patterns. Younger workers have the highest search rates. For instance, among 25–34 year-olds, roughly 28% of women and 25% of men report active search (last 4 weeks). Gender differences in search emerge around age 30 and persist until mid-career: in the 35–44 age group, 25.8% of women searched vs 17.6% of men (a 8.2 pp gap, $p < 0.01$). These patterns by age are illustrated in Appendix Figure 2. The incidence of searches increases with education for men but varies little by education for women. College-educated men are more likely to search than men with less education, while women's search rates are similar across education levels. As a result, gender gaps are largest at lower education levels (approximately 9 pp for high school or less) and smallest among college graduates (4–5 pp). Black respondents — especially Black women — have the highest search rates of any racial group. For example, 47.4% of Black women actively

Table 2: Extensive margin of job search

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
<i>Percent who:</i>				
Actively searched, last 7 days	17.0	24.7	7.7*** (1.3)	3.5*** (1.2)
Actively searched, last 4 weeks	20.3	28.8	8.6*** (1.4)	2.7** (1.3)
Actively searched, last 12 months	33.6	45.5	11.9*** (1.6)	5.6*** (1.5)
Sent application(s), last 4 weeks	16.9	25.6	8.7*** (1.4)	2.9** (1.2)
Observations	3,291	3,132	6,423	6,423
Worker controls			no	yes
State and year fixed effects			no	yes

Notes: The sample includes individuals aged 25-64 who are currently in the labor force and do not have missing data on the following controls. Worker controls include log recent wage (current wage if employed and most recent wage if unemployed), age, age-squared, employment status, three education categories, four race categories, marital status, and presence of children under six. Regressions are weighted using survey weights. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* Estimates calculated using the October 2013–2021 waves of the SCE Job Search Supplement.

searched in the last year, versus 24.7% of Black men (a 16.3 pp difference). In contrast, white respondents have lower search rates and much smaller gender gaps (around 2 pp). Married individuals of both genders are less likely to search than those who are not married. Among singles, 28.6% of women vs. 21.1% of men are active searchers (7.5 pp gap). Among married respondents, 19.9% of women vs. 15.9% of men searched (4.0 pp gap). Although there is a gender gap for both groups, the overall incidence of search is suppressed by marriage for men and women alike.

Industry and occupation also shape search activity. The incidence of search is highest in the health care, hospitality and information services industries, and the most search-intensive occupations are administrative support and sales roles (Appendix Table 27). Finally, the gender gap in search is concentrated among the employed: virtually all unemployed respondents report recent search by definition, and with small samples of unemployed men and women, any gender differences in that group are not statistically significant (Appendix Table 28). In sum, women's higher propensity to search is pervasive across various subpopulations, though its magnitude can vary with demographic and job characteristics.

Table 3: Extensive margin of job search by demographic group

	Actively searched (%)			Sent application (%)		
	Men	Women	Difference	Men	Women	Difference
<i>Panel A. Age groups</i>						
25-34	24.7	27.7	2.9 (1.0)	21.8	24.5	2.8 (1.0)
35-44	17.6	25.8	8.2*** (3.3)	14.4	22.6	8.2*** (3.6)
45-54	17.9	23.7	5.8** (2.5)	14.6	21.4	6.8*** (3.0)
55-64	12.2	17.6	5.4*** (2.7)	10.4	14.9	4.5** (2.4)
<i>Panel B. Education</i>						
High school or less	15.6	24.5	8.9*** (3.1)	12.8	21.9	9.0*** (3.2)
Some college	16.6	22.0	5.4*** (3.2)	14.2	20.1	5.9*** (3.7)
College or more	19.5	23.9	4.4*** (3.5)	16.5	20.0	3.5*** (2.9)
<i>Panel C. Race</i>						
White	18.9	23.2	2.2* (1.7)	15.3	19.6	2.3* (1.9)
Black	24.7	47.4	16.3*** (3.5)	20.0	45.4	18.6*** (4.1)
Hispanic	25.1	38.2	12.2*** (2.7)	24.3	37.0	11.7*** (2.6)
<i>Panel D. Marital status</i>						
Not married	21.1	28.6	4.1*** (2.9)	18.1	25.4	4.2*** (3.2)
Married	15.9	19.9	7.5*** (3.3)	13.2	17.4	7.3*** (3.3)

3.1.2 Intensive margin of search

Turning to the intensive margin of job search effort, women also exhibit greater search intensity than men. Table 4 shows that women, on average, send more applications and spend more time searching than their male counterparts. In the past four weeks, women submitted approximately 1.73 applications versus 1.03 applications for men. Similarly, in the past 7 days, women spent about 1.69 hours on job search compared to 1.07 hours for men. These raw gaps – roughly 0.7 additional applications and 0.6 additional hours by women – are highly significant ($p < 0.01$). Even after controlling for worker characteristics and fixed effects, women still devote more effort than men: the women-men difference remains about 0.32 applications ($p < 0.10$) and 0.24 hours ($p < 0.10$) in the regressions with full controls. Thus, women's greater search effort is not explained solely by observable factors; it persists after accounting for differences in wages, demographics, and job attributes.

Table 4: Intensive margin of job search

	Men	Women	Coefficient on women indicator from separate OLS regressions	
			Difference	Difference
<i>Number of:</i>				
Hours spent searching, past 7 days	1.07	1.69	0.62*** (0.12)	0.24* (0.13)
Applications sent, past 4 weeks	1.03	1.73	0.69*** (0.16)	0.32* (0.17)
Applications for new job, past 4 weeks	0.83	1.40	0.57*** (0.13)	0.28** (0.13)
Observations	3,291	3,132	6,423	6,423
Worker controls			no	yes
State and year fixed effects			no	yes

Notes: Notes: The sample includes individuals aged 25-64 who are currently in the labor force and do not have missing data on the following controls. Worker controls include log recent wage (current wage if employed and most recent wage if unemployed), age, age-squared, employment status, three education categories, four race categories, marital status, presence of children under six. Regressions are weighted using survey weights. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* Estimates calculated using the October 2013–2021 waves of the SCE Job Search Supplement.

These patterns of higher search intensity for women are consistent in most demographic subgroups. Among men, search effort (hours and applications) is highest for the young, the college-educated, and the unmarried. Among women, it is highest for the young, Black, and unmarried – with little variation by education level. In fact, women with a college degree search just as intensively as college-educated men, essentially eliminating the gender gap in the top education group. Overall, the evidence indicates that women tend to put forth greater job-search effort than men across both margins. This gender difference in search behavior is robust and appears only partly attributable to differences in personal characteristics or employment situations.

Table 5: Intensive margin of job search by demographic group

	Hours searching			Applications sent		
	Men	Women	Difference	Men	Women	Difference
<i>Panel A. Age groups</i>						
25-34	1.3	1.8	0.5 (1.4)	1.1	1.4	0.3 (0.9)
35-44	0.8	1.7	0.9*** (3.1)	1.0	1.5	0.6** (2.2)
45-54	1.1	1.3	0.2 (0.6)	1.1	1.5	0.4 (1.1)
55-64	0.5	0.8	0.3* (1.9)	0.7	1.0	0.3* (1.9)
<i>Panel B. Education</i>						
High school or less	0.6	1.4	0.8*** (3.2)	0.8	1.5	0.7* (1.8)
Some college	0.9	1.6	0.7*** (2.9)	1.0	1.5	0.5** (2.5)
College or more	1.2	1.2	0.0 (-0.1)	1.1	1.2	0.1 (0.7)
<i>Panel C. Race</i>						
White	0.8	0.9	0.1 (0.9)	0.9	0.9	0.0 (0.0)
Black	1.1	3.1	2.0*** (3.9)	1.5	3.1	1.6** (2.1)
Hispanic	1.1	2.2	1.1** (2.2)	1.2	2.0	0.8* (1.7)
<i>Panel D. Marital status</i>						
Not married	1.0	1.8	0.8*** (3.5)	1.3	1.8	0.5 (1.5)
Married	0.9	1.1	0.2 (1.4)	0.8	1.1	0.2* (1.9)

3.2 Job search methods and wage setting protocols

Men and women also differ in how they receive job offers. Table 6 shows that more than 90 percent of job offers to both groups arrive through four main channels: referrals, unsolicited contacts, online searches, and employers' websites. However, women are significantly more likely than men to obtain their best job offer through a referral, and less likely to receive an unsolicited offer. For example, referrals account for 40.4 percent of women's best offers versus 33.0 percent for men—a 7.4 percentage point gender gap that remains around 7.2 points after controlling for worker characteristics and fixed effects (see Table 6). Conversely, unsolicited offers make up only 16.5 percent of women's best offers compared to 27.7 percent for men, an 11.2 percentage point gap (about 7.6 points with controls).

The prominence of referrals for women is somewhat surprising in light of prior evidence that women face disadvantages in network-based job search. For example, Mengel (2020) finds that male professional networks exhibit strong same-gender bias, and Zeltzer (2020) shows that physicians tend to refer colleagues of their own gender. Such patterns would disadvantage female job seekers. Yet in the SCE data, women are more likely than men to secure referrals from former colleagues, whereas men more often rely on referrals

Table 6: Search method for best offer

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
<i>Method of best offer (percent):</i>				
Referral	33.0	40.4	7.4*** (2.8)	7.2** (3.6)
Unsolicited	27.7	16.5	−11.2*** (2.9)	−7.6*** (2.9)
Online search	17.7	17.8	0.2 (2.7)	−2.8 (2.7)
Employer’s website	16.2	16.3	0.2 (1.9)	−1.7 (2.0)
Enquired with employer directly	8.3	7.5	−0.9 (2.0)	−1.2 (1.9)
Previously worked for employer	7.8	9.9	2.1 (2.6)	2.6 (2.2)
Employment agency	5.5	4.9	−0.6 (1.7)	−1.4 (1.6)
Union	0.9	0.5	−0.5 (0.4)	0.2 (0.5)
Other means	2.9	4.1	1.2 (1.5)	1.0 (1.7)
Observations	582	640	1,222	1,222
Workers controls			no	yes
State and year fixed effects			no	yes

from friends or current coworkers.

By contrast, the gender gap in unsolicited offers aligns with expectations from earlier studies. Résumé audit experiments find that women receive fewer callbacks than men for jobs in male-dominated or high-skill fields (Neumark et al., 1996; Petit, 2007; Booth and Leigh, 2010; see review in Bertrand and Duflo, 2017). Consistent with this literature, women in my sample are about 9 percentage points less likely than men to receive an unsolicited job offer, even after controlling for occupation and industry.

Beyond how offers are obtained, men and women also differ in the wage-setting stage of the hiring process. Table 7 shows that although a majority of both groups had a good idea of the wage before accepting their best offer, women were significantly less likely than men to have this prior wage knowledge. Only 55.7 percent of women knew their prospective wage upfront, compared to 67.3 percent of men—a gap of 11.6 percentage points (10.5 points with controls). Women were also less likely to engage in wage bargaining: 34.0 percent of women versus 42.7 percent of men reported that bargaining took place, an 8.8 percentage point difference (7.5 points with controls). In contrast, other aspects of the wage-setting process show no significant gender differences: the incidence of counter-offers is similar (roughly 13 percent for both), as is the share of cases where the employer knew the applicant’s prior salary (about one-third for both).

Table 7: Wage setting characteristics of best job offer

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
<i>Wage setting of best offer (percent):</i>				
Applicant had good idea of pay	67.3	55.7	−11.6*** (3.6)	−10.5*** (3.7)
Bargaining involved	42.7	34.0	−8.8** (3.6)	−7.5** (3.6)
Counter-offer involved	13.6	12.3	−1.4 (2.5)	−0.7 (2.5)
Employer knew applicant’s recent salary	34.4	35.7	1.4 (3.5)	2.5 (3.6)
Observations	582	640	1,222	1,222
Workers controls			no	yes
State and year fixed effects			no	yes

The lower propensity of women to negotiate salary is consistent with prior research showing that men are more inclined to initiate wage negotiations. Studies by [Babcock et al. \(2003\)](#), [Leibbrandt and List \(2015\)](#), and [Biasi and Sarsons \(2022\)](#) all document that men are more likely to negotiate starting pay. Thus, the gender differences in wage-setting observed in the SCE data mirror broader patterns identified in the literature, potentially contributing to gender disparities in earnings outcomes.

4 Job search outcomes

Having documented empirical facts about the job search process in terms of search efforts, search methods, and wage setting mechanisms, the next section turns to the outcome of the search process in terms of the quantity and quality of offers, as reflected in various characteristics.

4.1 Number of job offers

This section examines gender differences in the immediate outcomes of job search, focusing first on the number of job offers received. To ensure comparability, I consider outcomes for respondents seeking a new primary job (excluding offers of additional work or side jobs). Table 8 presents key statistics. Women and men receive a similar number of job offers. On average, women received 0.16 offers in the last four weeks, compared to 0.13 offers for men, a gap that is small and not statistically significant after controlling for worker characteristics. In terms of having any offers, women are more likely than men to

report at least one formal job offer in the last month (9.1% of women vs. 6.7% of men), but this difference is fully explained by observable characteristics and is not statistically significant in adjusted regressions. Men have a slightly higher incidence of unsolicited offers (offers received without applying, 2.4% for men vs. 2.1% for women), but this gap is not statistically significant. These patterns indicate that despite women’s greater search effort, their offer rates are roughly on par with men’s once accounting for differences in demographics and job history. Results are similar when including the possibility of additional work. Appendix Table 32 shows that even when counting offers for extra or secondary jobs, women and men exhibit statistically indistinguishable outcomes. The same holds for broader outcome measures such as the number of offers over a six-month horizon or the number of interviews in the past four weeks—by these measures as well, gender differences in outcomes are negligible.

Table 8: Job search outcomes for a new job

	Men	Women	Coefficient on women indicator from separate OLS regressions	
			Difference	Difference
<i>Number of:</i>				
Offers for new job, last 4 weeks	0.13	0.16	0.03 (0.03)	−0.01 (0.03)
<i>Percent with:</i>				
Formal offer for new job	6.68	9.06	2.38*** (0.67)	0.69 (0.90)
Unsolicited offer for new job	2.42	2.10	−0.32 (0.37)	−0.18 (0.52)
Observations	3,291	3,132	6,423	6,423
Worker controls			no	yes
State and year fixed effects			no	yes

Notes: The sample includes individuals aged 25–64 who are currently in the labor force and do not have missing data on the following controls. Worker controls include log recent wage (current wage if employed and most recent wage if unemployed), age, age-squared, employment status, three education categories, four race categories, marital status, and presence of children under six. Regressions are weighted using survey weights. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* Estimates calculated using the October 2013–2021 waves of the SCE Job Search Supplement.

While women and men receive about the same number of offers, women appear to expend more effort per offer. Table 9 quantifies the efficiency of search effort by gender. I define an offer yield as the number of job offers (or the probability of having at least one offer) per unit of search input. The table considers two output measures—(i) the number of offers and (ii) an indicator for at least one offer—and two input measures—(i) the number of applications submitted and (ii) hours spent searching. Formally, for input i and output j :

$$\text{Offer Yield}(i, j) = \frac{\text{Output } j}{\text{Input } i},$$

where the inputs are either total applications or search hours, and outputs are either total offers or a dummy for any offer. Across all four input-output combinations, women have a lower offer yield than men. For example, each hour of search yields 0.28 offers for the average man but only 0.21 offers for the average woman; similarly, per hour of search, 13% of men (0.13 probability) secure at least one offer compared to 11% of women. In other words, women’s offer yield is about 75–85% of men’s, depending on the measure.

The gender gap in efficiency is larger on the intensive margin of offers (when using the number of offers as the outcome) and somewhat smaller on the extensive margin (using the probability of any offer). A woman is just as likely as a man to receive an offer (extensive margin), but tends to receive fewer total offers given the same search effort (intensive margin). These findings underscore the importance of measuring both margins—some job seekers stop searching once they receive an offer, while others continue searching. Examining only the probability of an offer potentially masks gender differences in search efficacy.

Table 9: Offer yields

<i>Outputs:</i>	Number of offers		Share with at least one offer		Offer yield ratio: Women/Men	
	Men	Women	Men	Women	Men	Women
<i>Inputs:</i>						
Hours	0.28	0.21	0.13	0.11	0.74	0.84
Applications	0.30	0.21	0.14	0.11	0.71	0.81

4.2 Features of best offer

Having established that women search more intensively yet obtain comparable numbers of offers (albeit with lower yield per effort), I now turn to the quality of the job offers received. In the survey, respondents who searched report details of their “best” job offer. I examine two aspects of these offers: (i) wages and hours and (ii) fringe benefits. Table 10 summarizes the gender gap in the wage and weekly hours of the best offer, under various specifications. Women’s offered wages are substantially lower than men’s. In raw terms, the average offered wage for women is about 25% less than that for men. This corresponds to a gap of 0.25 log points (log offered wage of 2.78 for women vs. 3.03 for men). Even

after controlling for demographic characteristics, job offer attributes, and state/year fixed effects (the “Residualized” specification), women’s offered wage remains roughly 15% lower than men’s. Adding a control for the worker’s most recent wage to account for prior earnings capacity narrows the offered wage gap slightly to about 12%, but remains statistically significant.

By contrast, the differences in offered hours are smaller and largely explained by controls. Women’s best offers involve about 18% fewer hours per week than men’s in the raw data (log weekly hours 3.35 vs. 3.53), but this gap shrinks to around 7% with demographic and job controls, and when we additionally control for the worker’s previous hours, the gender difference in offered hours is essentially zero and not significant. In short, women receive significantly lower wages in their job offers, even after adjusting for a rich set of covariates, whereas the hour differential is modest and disappears with controls for prior hours worked.

Table 10: Offered wage and hours

		Men	Women	Difference
<i>Offered wage</i> N=1,281	Raw means	3.03	2.78	−0.25***
		(0.02)	(0.02)	(0.04)
	Residualized	2.94	2.79	−0.15***
		(0.02)	(0.02)	(0.03)
	Including recent wage	2.91	2.79	−0.12***
		(0.02)	(0.02)	(0.04)
<i>Offered hours</i> N=1,281	Raw means	3.53	3.35	−0.18***
		(0.02)	(0.02)	(0.03)
	Residualized	3.44	3.37	−0.07**
		(0.02)	(0.02)	(0.03)
	Including recent hours	3.41	3.39	−0.02
		(0.02)	(0.02)	(0.03)

Notes: Table shows offered wage and hours estimates for men and women, and the difference between the two. Residualized estimates control for demographics and job offer features. Demographics include: age, age-squared, three education categories, four race categories, marital status, and number of children under six. Job offer features include: 2-digit SOC occupation, 2-digit NAICS industry, and three firm-size bins. State and year fixed effects are also included. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* Estimates are calculated using the October 2013–2021 waves of the SCE Job Search Supplement.

These wage and hours patterns are robust across alternative measures of pay and work intensity. Appendix Table 33 shows that women earn about 16% less than men in previous wages, current wages, and accepted wages (conditional on similar covariates), with the gender gap in reservation wages slightly smaller (around 11%). Likewise, Appendix Table 34 finds that women’s hours are about 7% lower than men’s, on average, after adjusting

for worker and job characteristics. These consistent gaps across various wage and hour measures reinforce the finding that women face a meaningful earnings disadvantage even at the job offer stage, whereas differences in desired or offered hours are more muted.

Two additional patterns in Table 10 are noteworthy. First, the gender gap in wages is quantitatively larger than the gap in hours, both before and after controls. This is consistent with the idea that wage differences widen disproportionately at higher hours (i.e. wages are convex in hours). For example, if women are more likely to seek shorter-hour jobs, the wage penalty they incur is greater than the proportional reduction in hours. Second, women's reservation wage remains significantly lower than men's even after controlling for their current wage, whereas the gender difference in reservation hours vanishes once current hours are accounted for. In other words, women's lower wage expectations are not fully explained by their current earnings, but their lower desired hours are explained by their current work hours. This again suggests that the wage gap is a more persistent phenomenon than any gap in hours preferences.

Wage offer distributions also differ by gender. Women's wage distribution is more skewed to the right and has heavier tails compared to men's. For instance, the distribution of log weekly offered wages for women has a skewness of 0.65 (versus 0.37 for men) and excess kurtosis of 0.68 (versus -0.03 for men), indicating that women's offered wages are more dispersed with a longer right tail (Appendix Figure 4). Similarly, women's distributions of current wages and reservation wages exhibit higher skewness and kurtosis than men's (Appendix Figure 5 and Appendix Figure 6). These distributional differences imply that a larger fraction of women receive very low or very high offers relative to the average, whereas men's offers are more tightly clustered around the mean.

Although women consistently receive lower wages than men, a natural question is whether they might be compensated through nonwage benefits or other job amenities. Economic theory of compensating differentials suggests that workers might accept lower pay in exchange for desirable job attributes. Fringe benefits are a prime example. As of 2024, benefits accounted for about 31% of total employment costs on average (BLS, 2024), so generous benefits could potentially offset a lower salary. To investigate this possibility, Table 11 provides the incidence of a wide range of fringe benefits in the best job offer, comparing men and women.

Strikingly, the data do not support the idea that women trade lower wages for better benefits. In fact, for nearly every benefit category, Table 11 shows that women's job offers are less likely to include the benefit than men's offers. For example, 61% of men's best offers include health insurance, compared to only 48% of women's—a gap of over 12 percentage points in favor of men. Similar gender gaps (on the order of 9–13 percentage

points) are observed for dental insurance (offered to 55% of men vs. 43% of women), retirement contributions (47% vs. 34%), and stock options (14% vs. 7.5%), among others. The only benefit that women receive slightly more often than men is childcare assistance (offered in 3.5% of women's offers vs. 2.8% of men's), but this difference is small and not statistically significant. Moreover, women are substantially more likely to receive no benefits at all: 45% of women's best offers come with zero fringe benefits, compared to 34% of men's offers, a difference of about 11 percentage points. These disparities remain pronounced and statistically significant even after controlling for worker characteristics and fixed effects. In sum, women not only receive lower pay, but also fewer fringe benefits in their job offers, relative to men.

Table 11: Job offer fringe benefits

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
<i>Benefits included in best offer (percent):</i>				
Health insurance	60.8	48.3	−12.5*** (2.8)	−10.5*** (3.4)
Dental insurance	54.8	43.4	−11.4*** (2.8)	−9.2*** (3.4)
Retirement contribution	47.0	33.6	−13.4*** (2.7)	−11.2*** (3.2)
Life insurance	32.5	29.0	−3.6 (2.6)	−2.4 (3.1)
Flex. Spending Accounts	24.5	18.7	−5.8** (2.3)	−3.3 (2.6)
Pension plan	15.8	14.0	−1.8 (2.0)	−0.9 (2.4)
Stock options	13.8	7.5	−6.3*** (1.7)	−5.8*** (2.1)
Quality of life benefits	10.8	10.3	−0.5 (1.7)	−0.2 (1.8)
Commuter benefits	9.1	5.5	−3.6** (1.4)	−3.0** (1.5)
Childcare assistance	2.8	3.5	0.7 (1.0)	1.2 (1.1)
Housing subsidy	1.7	0.8	−0.9 (0.6)	−0.7 (0.7)
No benefits	33.7	45.3	11.6*** (2.7)	9.3*** (3.4)
Observations	585	706	1,291	1,291
Worker controls			no	yes
State and year fixed effects			no	yes

Notes: Table shows features of job offers. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Estimates are calculated using the October 2013–2021 waves of the SCE Job Search Supplement.

The evidence thus far indicates that women do not receive compensating rewards for their greater search effort in the form of either higher pay or better fringe benefits. If anything, women end up with both lower wages and less generous benefits. This finding runs contrary to a simple compensating differentials story and is consistent with other studies. For instance, [Hodges \(2020\)](#) documents similar gender gaps in nonwage compen-

sation using different datasets. These results suggest that the amenities women value and possibly receive in lieu of higher pay may lie outside the scope of standard fringe benefits. In particular, women might place greater emphasis on non-monetary job attributes such as flexible working hours, shorter commute times, or convenient job location—factors not captured by the usual benefit metrics in Table 11. The next section explores these nonwage amenities and examines whether gender differences in preferences for job amenities can help explain the patterns observed in job search behavior and outcomes.

5 Nonwage amenities

The headline empirical fact of this paper is that women search more than men. They do so despite not receiving equivalent or higher wages. Just as income and substitution effects determine how much labor individuals supply in response to wage changes, search effort is subject to similar income and substitution effects (Shimer, 2004).

In this part of the paper, I explore whether men and women differ in their preferences for nonwage amenities, and how these preferences affect their search behavior. To do so, I begin by estimating the elasticity of search effort with respect to current log wages. Given the lack of data on employed workers' search behavior prior to the JSS, the only previous estimates of the search-wage elasticity are from Faberman et al. (2022) and Mueller (2010), both of which focus on all employed workers without distinguishing by gender.

A central tenet of job ladder models is the inverse relationship between search effort and wages. As one's wage increases, search effort declines, since the expected gains from search diminish. To test this, I estimate the following specification for individual i in state s at year t :

$$\text{Search effort}_{ist} = \delta w_{ist} + \mathbf{X}_{ist}\beta + \alpha_s + \gamma_t + \varepsilon_{ist}$$

Here, the dependent variable is the number of applications sent in the last four weeks. The variable w_{ist} is the log of current wages, \mathbf{X}_{ist} is a vector of demographic and worker characteristics, α_s are state fixed effects, γ_t are year fixed effects, and ε_{ist} is an error term. The coefficient of interest is δ . The negative and statistically significant coefficients in the first two columns of Table 12 indicate that this job ladder mechanism is present for both men and women. However, it is stronger for men, as reflected in their larger point estimates. I construct elasticities by gender by dividing the estimated coefficients by the mean of the dependent variable (the number of applications sent). The search effort-wage elasticity is -0.78 for men and -0.39 for women—a statistically significant difference at the 10% level. This is shown in the final column, which includes an interaction between

log current wage and a female indicator.

Table 12: Elasticity of search effort with respect to current wage

	Search effort _{ist} = Number of applications			
<i>Panel A. Men</i>				
Log current wage	−0.29*** (0.07)	−0.44*** (0.08)	−0.43*** (0.08)	−0.38*** (0.09)
R-squared	0.004	0.036	0.036	0.060
Observations	3,151	3,151	3,151	3,151
Mean of dependent variable	0.55	0.55	0.55	0.55
Elasticity (coefficient/mean)	−0.53	−0.80	−0.78	−0.69
<i>Panel B. Women</i>				
Log current wage	−0.51*** (0.12)	−0.37*** (0.12)	−0.34*** (0.12)	−0.35*** (0.11)
R-squared	0.009	0.079	0.081	0.102
Observations	2,928	2,928	2,928	2,928
Mean of dependent variable	0.89	0.89	0.89	0.89
Elasticity (coefficient/mean)	−0.57	−0.41	−0.38	−0.39
<i>Panel C. Statistical difference</i>				
Women × Log current wage	−0.21** (0.12)	−0.19 (0.12)	−0.20* (0.12)	−0.24* (0.13)
R-squared	0.033	0.052	0.053	0.072
Observations	6,079	6,079	6,079	6,079
State and year fixed effects	yes	yes	yes	yes
Human capital controls	no	yes	yes	yes
Family controls	no	no	yes	yes
Industry + occupation	no	no	no	yes

Notes: The table shows search-wage elasticities from separate OLS regressions for currently employed men, women, and the combined sample. The dependent variable is the number of applications sent in the last four weeks. Worker controls include: age, age-squared, education (3 categories), race (4 categories), marital status, presence of children under 6, and most recent 2-digit SOC occupation. Year and state fixed effects are included. Elasticities are calculated by dividing the estimated coefficient on log real current wage by the mean of the dependent variable. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* SCE JSS, October 2013–2021.

The smaller elasticity for women suggests that nonwage job attributes play a more important role in their search decisions. To investigate this, I use survey questions on reservation wages and sensitivity to various job features.

Table 13 reports the percentage of men and women who would accept a job offer at their stated reservation wage if it entailed specific changes to nonwage aspects of the job. Women are less likely than men to accept offers involving relocation, longer commutes, or increased hours. This highlights the importance of incorporating nonwage amenities into

job search models.

Table 13: Acceptance rates of hypothetical job offer

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
<i>Percent who would accept offer if required to:</i>				
Work 10% more hours	60.5	56.6	−4.0*** (1.3)	−7.1*** (1.4)
Double daily commute	35.0	29.5	−5.5*** (1.3)	−7.6*** (1.3)
Relocate	18.0	14.7	−3.3*** (1.0)	−4.5*** (1.0)
Observations	2,681	2,817	5,498	5,498
Worker controls			no	yes
State and year fixed effects			no	yes

5.1 Labor force attachment

Differences in labor force attachment are central to understanding gender wage disparities. Channels through which weaker labor force attachment can impact wages include: reduced human capital accumulation (Becker, 1964); statistical discrimination (Phelps, 1972); signaling (Spence, 1978); loss of firm-specific human capital (Mincer and Jovanovic, 1981); slower wage growth (Topel, 1991); and lower bargaining power (Mortensen and Pissarides, 1994).

Women’s weaker labor force attachment has been extensively documented (e.g., Kleven et al., 2019; Blau and Kahn, 2013; Manning and Petrongolo, 2008; Goldin, 2006; Waldfogel, 1998; Light and Ureta, 1995, 1990). Using the JSS, I examine women’s labor force attachment as reflected in their preference for part-time work and spells without employment.

Conditional on active search, Table 14 shows (Panel A) the percentage of individuals who seek only part-time or additional work, and (Panel B) the stated reasons for preferring part-time work. About 25% of women search only for part-time work compared to 15% of men. Men are more likely to cite additional income as their reason; women more often cite childcare responsibilities.

Table 14: Reasons for only seeking part-time work

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
<i>Panel A. Percent who searched for:</i>				
An additional job	23.4	34.8	11.4*** (2.5)	7.9*** (2.5)
Part-time work	14.8	24.7	9.9*** (2.2)	8.1*** (2.4)
<i>Panel B. Reasons for seeking part-time work (percent):</i>				
Just want additional income	49.9	40.3	−9.6*** (3.5)	−7.5** (3.6)
Hours flexibility	7.2	7.3	0.1 (1.8)	0.2 (1.8)
Limited retirement income	6.8	6.7	−0.2 (2.1)	1.0 (2.1)
Child care availability	1.2	12.0	10.8*** (1.7)	8.6*** (1.4)
Other	5.9	7.8	1.9 (1.9)	−0.4 (1.8)
Observations	573	793	1,366	1,366
Worker controls			no	yes
State and year fixed effects			no	yes

Notes: Panel A shows the percent of job seekers seeking part-time or additional work. Panel B reports reasons for preferring part-time work. Question asked of those interested in part-time only. Percentages may not sum to 100 due to nonresponse. Final column reports OLS coefficient on female indicator. Source: SCE JSS, October 2013–2021.

Prime-aged women report 13 months without a job in the last five years, compared to 8 months for men. Table 15 reports reasons and months without employment. Women are more likely to cite family obligations and other non-market reasons. Women spend 5 months without a job due to family obligations, compared to 1 month for men. In contrast, men are more likely to report school as a reason.

Table 15: Reasons and months without a job in last 5 years

	Coefficient on women indicator from separate OLS regressions			
	Men	Women	Difference	Difference
<i>Reasons for not having a job in last 5 years (months):</i>				
Looking for work	2.5	2.8	0.3 (0.2)	0.0 (0.2)
Disabled or retired	6.0	6.0	0.0 (0.5)	−0.7 (0.5)
Enrolled in school	1.1	1.0	−0.0 (0.2)	−0.4** (0.2)
Family obligations	1.0	4.1	3.1*** (0.3)	2.6*** (0.3)
Discouraged	0.4	0.4	0.0 (0.1)	−0.1 (0.1)
Other reasons	1.1	1.7	0.6** (0.2)	0.6** (0.2)
Observations	2,044	2,267	4,311	4,311
Worker controls			no	yes
State and year fixed effects			no	yes

Notes: Table shows reasons and average number of months respondents spent without a job in the past five years, including time unemployed or out of the labor force. *Source:* SCE JSS, October 2013–2021.

5.2 Role of children in the search process

The empirical results above suggest nonwage amenities are more salient for women, especially regarding flexibility. To explore mechanisms, I compare search behavior of women with and without children.

Table 16 shows extensive margins of search and Table 17 the intensive margin. Women with children are about five percentage points more likely to be actively searching. On the intensive margin, they spend 55% more time and submit nearly twice as many applications compared to women without children.

Table 16: Extensive margin of job search, women with and without children

	Coefficient on children indicator from separate OLS regressions			
	No kids	Kids	Difference	Difference
<i>Percent who:</i>				
Actively searched, last 7 days	19.91	24.92	4.12* (2.25)	4.87** (2.45)
Actively searched, last 4 weeks	23.90	28.51	4.79** (2.37)	5.21** (2.58)
Sent application, last 4 weeks	20.73	25.48	4.95** (2.27)	4.62* (2.46)
Observations	977	530	1,507	1,507
Worker controls			no	yes
State and year fixed effects			no	yes

Table 17: Intensive margin of job search, women with and without children

	Coefficient on children indicator from separate OLS regressions			
	No kids	Kids	Difference	Difference
<i>Number of:</i>				
Hours searching, past 7 days	1.16	1.79	0.63* (0.35)	0.69** (0.29)
Applications sent, past 4 weeks	1.28	2.23	0.95** (0.46)	0.82* (0.44)
Applications for new job, past 4 weeks	0.93	1.96	1.03** (0.45)	0.99** (0.42)
Observations	977	530	1,507	1,507
Worker controls			no	yes
State and year fixed effects			no	yes

Table 18 presents search effort elasticities with respect to current wage, estimated separately for women with and without children:

$$\text{Search effort}_{cst} = \delta w_{cst} + \mathbf{X}_{cst}\beta + \alpha_s + \gamma_t + \varepsilon_{cst}$$

For women without children, the elasticity is -0.72 , only 8% lower than men. For women with children, the coefficient is not statistically significant and close to zero (-0.02), indicating that their search effort is largely unresponsive to wages. This supports the view that women with children place greater value on nonwage job attributes.

To further assess the importance of nonwage amenities, I use survey data on job satisfaction with nonwage attributes. The question asks: "And how satisfied would you say you are with other aspects of the job, such as benefits, maternity/paternity leave, flexibility in work hours, etc.?"

Table 18: Elasticity of search effort with respect to current wage, women by children status

Search effort _{ist} = Number of applications				
<i>Panel A. No children</i>				
Log current wage	−0.89*** (0.23)	−0.77*** (0.21)	−0.72*** (0.20)	−0.76*** (0.20)
R-squared	0.098	0.064	0.068	0.086
Observations	973	973	973	973
Mean of dependent variable	1.01	1.01	1.01	1.01
Elasticity (coefficient/mean)	−0.53	−0.80	−0.78	−0.69
<i>Panel B. Children</i>				
Log current wage	−0.45* (0.25)	−0.02 (0.26)	0.01 (0.26)	0.14 (0.29)
R-squared	0.077	0.054	0.056	0.072
Observations	1,036	1,036	1,036	1,036
Mean of dependent variable	1.19	1.19	1.19	1.19
Elasticity (coefficient/mean)	−0.57	−0.41	−0.38	−0.39
<i>Panel C. Statistical difference</i>				
Children × Log current wage	0.44 (0.30)	0.50* (0.28)	0.51* (0.28)	0.65** (0.30)
R-squared	0.085	0.055	0.058	0.075
Observations	2,009	2,009	2,009	2,009
Human capital controls	no	yes	yes	yes
Marital status	no	no	yes	yes
Industry	no	no	no	yes

Figure 1 shows binscatters of current log wage against satisfaction with nonwage amenities. For men and women without children, satisfaction is positively correlated with wages. For women with children, however, the relationship is flat. Appendix Table 35 confirms this pattern in regression format: for women with children under six, the coefficient is near zero and not statistically significant.

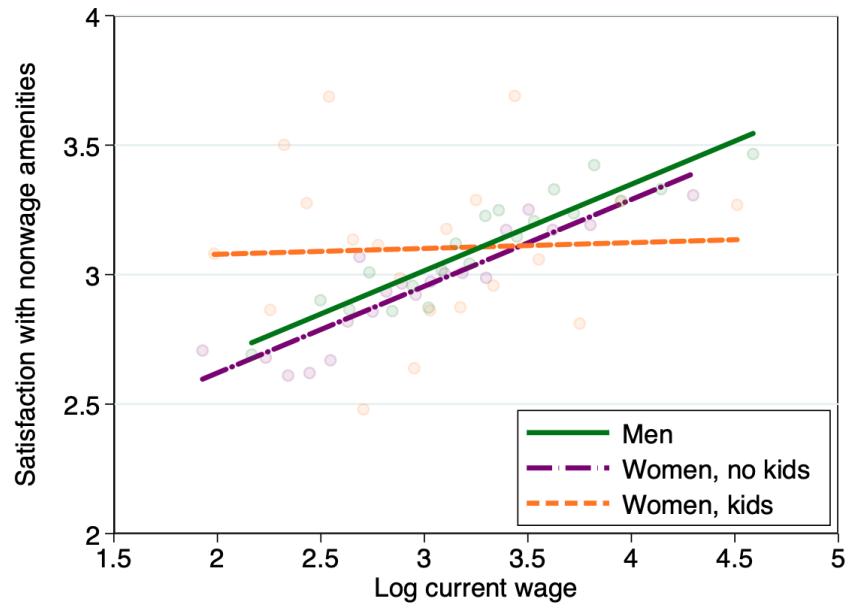


Figure 1: Current wage versus satisfaction with nonwage amenities

Notes: The graph plots a binscatter of satisfaction with nonwage amenities at respondents' current job against current log wage, for three groups: men, women without children, and women with children. Satisfaction is measured on a scale from 1 to 4: 1 = "Very dissatisfied", 2 = "Somewhat dissatisfied", 3 = "Somewhat satisfied", 4 = "Very satisfied". Source: Estimates are calculated using the October 2013–2021 waves of the SCE JSS.

Table 19: Acceptance rates of hypothetical job offer, women by children status

	Women		Coefficient on children indicator from separate OLS regressions	
	Kids	No kids	Difference	Difference
<i>Percent who would accept offer if required to:</i>				
Work 10% more hours	55.1	59.9	−4.8 (2.9)	−7.1** (2.9)
Double daily commute	28.6	33.0	−4.4 (2.9)	−5.0* (2.9)
Relocate	14.7	20.6	−6.0** (2.4)	−4.1* (2.3)
Observations	963	871	1,834	1,834
Worker controls			no	yes

Table 20: Search by satisfaction with nonwage amenities

Reported satisfaction with nonwage amenities	Actively searched (%)			Sent an application (%)		
	Women	Men	Difference	Women	Men	Difference
Not satisfied	40.7	33.7	7.01** (3.30)	36.1	27.6	8.45*** (3.18)
Neutral	26.9	20.5	6.38** (3.19)	23.8	18.7	5.15* (3.07)
Satisfied	21.7	14.5	7.22*** (1.73)	19.1	11.2	7.94*** (1.61)
Very satisfied	16.1	11.2	4.97*** (1.89)	13.7	9.7	3.94** (1.77)

6 Model

In this section, I build a partial equilibrium model job ladder model with endogenous search effort, building on previous models (Christensen et al., 2005; Hornstein et al., 2011; Bagger and Lentz, 2019; Faberman et al., 2022). More specifically, I extend the framework of Faberman et al., 2022 in three ways to reflect the empirical findings. First, I allow jobs to differ in their wage and nonwage amenity value. Second, I allow search technology to differ by employment status and sex. Third, I introduce career interruptions and change in the value of nonwage amenities due to the incidence of children.

Men and women differ in the model along the following dimensions: weight on nonwage amenities, search costs, job separation rate, and job offer arrival rates. In addition, I allow the following objects to also differ by child status: relative weight on nonwage amenities and flow value of unemployment.

The main goal of the structural part of this paper is to perform an accounting decomposition and quantify the different components of the gender wage gap. I perform counterfactual exercises in which I equalize the following between men and women: equal search costs, equal weight on non-wage amenities, and equal job attachment.

6.1 Environment

The labor market is populated by a unit mass of individuals. Time is continuous and the discount rate is r . Workers differ in two respects: they are female or male, denoted by gender status $g \in \{F, M\}$, and can have children or not, denoted by children status $c \in \{1, 0\}$. Workers can be employed or unemployed, denoted by employment status $e \in \{E, U\}$. Job matches are subject to exogenous separation shocks, δ_g .

In addition to being employed or unemployed, individuals can also be on parental leave. Individuals enter parental leave from employment or unemployment after an exogenous child shock, δ^c . Following the child shock, individuals' child status permanently changes from $c = 0$ to $c = 1$. To ensure that the population distribution of people with and without children remains balanced, workers permanently leave the labor force and new workers enter at constant rates δ^r . At the same rate, there is an inflow of new workers of each gender without children into unemployment. Below I describe the value functions in turn.

6.2 Employment

A job is characterized by both its wage w and its non-wage amenity value a , such as having a short commute time or flexible hours. The utility workers receive from their job is linear in log wages and amenity values, and given by $u_{g,c}(w, a) = w_g + \eta_{g,c}a$ where η is the weight placed on the nonwage amenity. This functional form for utility is consistent with other papers that incorporate amenities into jobs (Hwang et al., 1998; Dey and Flinn, 2008; Bonhomme and Jolivet, 2009; Sullivan and To, 2014; Hall and Mueller, 2018; Le Barbanchon et al., 2021; Maestas et al., 2023).

Workers choose a level of search effort s that results in a job offer arrival rate $\lambda_g^e(s) = \alpha_g^e + \beta_g^e s$, where α_g^e is the rate of unsolicited offers and β_g^e is the rate of formal offers for a worker with gender g and employment status e . The cost of searching is $c_g^e(s) = \kappa_g^e s^{1+(1/\gamma)}$. Jobs are destroyed at a rate δ_g . Workers have a child and enter parental leave at rate δ^c . Workers permanently leave the labor force at the rate δ^r .

The value of employment at utility is $V_{g,c}(u)$ and satisfies the following Hamilton-Jacobi-Bellman equation:

$$rV_{g,c}(u) = \max_s \left\{ \begin{array}{l} u_{g,c} - c_g(s) \\ + \lambda_g^E(s) \int_{u'} \max \{V_{g,c}(u') - V_{g,c}(u), 0\} dF(u') \\ + \delta_g [U_{g,c} - V_{g,c}(u)] \\ + \delta^c [P^E(u) - V_{g,c}(u)] - \delta^r V_{g,c}(u) \end{array} \right\},$$

where U is the value of unemployment and $P^E(u)$ is the value of being on parental leave from a job with utility u . Since all the employed workers of a given type use the same search technology, workers accept any job offer delivering higher flow utility than their

current job, so we can write

$$rV_{g,c}(u) = \max_s \left\{ \begin{array}{l} u_{g,c} - c(s) \\ + \lambda^E(s) \int_{u' \geq u} [V_{g,c}(u') - V_{g,c}(u)] dF(u') \\ + \delta [U_{g,c} - V_{g,c}(u)] \\ + \delta^c [P^E(u) - V_{g,c}(u)] - \delta^r V_{g,c}(u) \end{array} \right\},$$

The optimal policy choice s^* must satisfy the following first-order condition with respect to s :

$$c'(s^*) = \lambda'(s^*) \int_{u' \geq u} [V_{g,c}(u') - V_{g,c}(u)] dF(u')$$

This reflects the condition that the marginal cost of searching equals the marginal benefit from searching.

6.3 Unemployment

The value of unemployment is:

$$rU_{g,c} = \max_s \left\{ \begin{array}{l} b_{g,c} - c_g(s) \\ + \lambda_g^U(s) \int_{u'} \max \{V_{g,c}(u') - U_{g,c}, 0\} dF(u') \\ + \delta^p (P^U - U_{g,c}) - \delta^r U_{g,c} \end{array} \right\},$$

where $b_{g,c}$ is the flow value of unemployment, and P^U is the value of being on parental leave from unemployment. Since the unemployed use a different search technology than the employed, it no longer needs to be the case that workers accept any job offer that delivers higher flow utility than the flow value of unemployment. Still, there will be some reservation utility ϕ such that workers accept a job offer from unemployment iff $u \geq \phi$, so we can write

$$rU_{g,c} = \max_s \left\{ b_{g,c} - c_g(s) + \lambda_g^U(s) \int_{u' \geq \phi} [V_{g,c}(u') - U_{g,c}] dF(u') + \delta^p (P^U - U_{g,c}) - \delta^r U_{g,c} \right\}$$

The optimal policy choice s^* must satisfy the following first-order condition with respect to s :

$$c'_g(s^*) = \lambda'_g(s^*) \int_{u' \geq \phi} [V_{g,c}(u') - U_{g,c}] dF(u')$$

6.4 Parental Leave

The value of parental leave when entering it from employment is:

$$rP_g^E(u) = b^p + 0.6(u) + 0.6(u_{g,c}) + \lambda^{p,U} (U_{g,c} - P_g^E(u)) + \lambda^{p,E} (V_{g,c}(u) - P_g^E(u)) - \delta^r P$$

7 Quantitative Exercise

This section of the paper quantifies how much of the gender differences in wages can be explained by the valuation of nonwage amenities and search technology. I first estimate the model using the JSS, and then carry out counterfactual exercises.

7.1 Calibration

I calibrate my model to moments from the JSS for years 2013–2021 pooled together. Table 21 lists the externally calibrated parameters and their source. I set the discount rate r to match an annual interest rate of 5%. I set the elasticity of search cost γ to equal 1, in other words to have a quadratic search cost. I set the exogenous child shock δ^c to the CDC birth rate and the labor force exit rate δ^r to the quit rate from the BLS. The flow value of parental leave b^p is normalized to one. In this version of the calibration I adopt the mean and dispersion of the wage and amenity offer from Hall and Mueller (2018). Table 22 lists the internally calibrated parameters and their targets. There are 18 internally calibrated moments that were chosen to match the 18 moments in Table 23. The system is exactly identified.

Search technology in the model differs by gender and employment status. I assume a linear job offer arrival rate $\lambda_g^e(s) = \alpha^e + \beta^e s$, where the target for α_g^e is the rate of unsolicited offers and the target for β_g^e is the rate of formal offers. I assume the same functional form for the cost of searching as in Christensen et al. (2005), Hornstein et al. (2011), and Faberman et al. (2022). This is: $c_g^e(s) = \kappa_g^e s^{1+(1/\gamma)}$. The cost of search differs by gender and employment status. κ_g^e is calibrated to match the average search effort in terms of number of applications sent.

The steps to calibrate the model are as follows. First, I rewrite the value of employment as a contraction:

$$V(u) = \max_s \left\{ \frac{u - c(s) + \lambda^E(s) \int_{u' \geq u} V(u') dF(u') + \delta U + \delta^p P^E(u)}{r + \delta + \delta^r + \delta^p + \lambda^E(s) \bar{F}(u)} \right\}$$

Table 21: Externally calibrated parameter values

Symbol	Description	Value	Source
r	Discount rate	0.05	5% per year
γ	Elasticity of search cost	1.185	Christensen et al. (2005)
μ_w	Mean of offered wages	2.75	Hall & Mueller (2018)
σ_w	Std. dev. of offered wages	0.24	Hall & Mueller (2018)
μ_a	Mean of amenities	0.31	Hall & Mueller (2018)
σ_a	Std. dev. of amenities	0.35	Hall & Mueller (2018)
ρ	Correlation between w and a	0.25	Hall & Mueller (2018)
δ^c	Rate of having a child	0.01	CDC birth rate
δ^r	Labor force exit rate	0.02	Quit rate (JOLTS, BLS)
b^p	Flow value of parental leave	1.0	Normalization

Table 22: Internally calibrated parameter values

Symbol	Description	Value (M, W)	Target
κ^U	Search cost parameter U	0.035, 0.039	Search effort U
κ^E	Search cost parameter E	0.005, 0.014	Search effort E
α^U	Offer rate intercept U	0.045, 0.029	Unsolicited offer rate E
α^E	Offer rate intercept E	0.031, 0.034	Unsolicited offer rate E
β^U	Offer rate slope coefficient U	0.061, 0.062	Formal offer rate U
β^E	Offer rate slope coefficient E	0.013, 0.009	Formal offer rate E
η	Weight on nonwage amenity	0.101, 1.000	Search-wage elasticity
b	Flow value of unemployment	1.002, 1.010	Acceptance rate of U
δ	Job separation rate	0.030, 0.038	Unemployment rate

Taking the first-order condition with respect to s and rearranging yields:

$$c'(s^*) = \beta \int_{u' \geq u} V(u') dF(u') - \frac{\beta \bar{F}(u) \left[u - c(s^*) + \lambda^E(s^*) \int_{u' \geq u} V(u') dF(u') + \delta U + \delta^p P^E(u) \right]}{r + \delta + \delta^r + \delta^p + \lambda^E(s^*) \bar{F}(u)}$$

Similarly, the value of unemployment as a contraction is given by:

$$U = \max_s \left\{ \frac{b - c(s) + \lambda^U(s) \int_{u' \geq \phi} V(u') dF(u') + \delta^p P^U}{r + \delta^r + \delta^p + \lambda^U(s) \bar{F}(\phi)} \right\}$$

Taking the first-order condition with respect to s and rearranging yields:

$$c'(s^*) = \beta \int_{u' \geq \phi} V(u') dF(u') - \frac{\beta \bar{F}(\phi) \left[b - c(s) + \lambda^U(s) \int_{u' \geq \phi} V(u') dF(u') + \delta^p P^U \right]}{r + \delta^r + \delta^p + \lambda^U(s) \bar{F}(\phi)}$$

The algorithm to solve the model is as follows. First I start with a guess for V and U . Then I solve the first-order conditions for employment and unemployment for an optimal s using a solver tool. Then I update V and U with the new s . This process iterates until convergence.

Table 23: Targeted moments

Moment	Men		Women	
	Data	Model	Data	Model
Search effort, unemployed	8.70	6.02	9.38	7.31
Search effort, employed	0.85	0.85	1.17	1.10
Unsolicited offer rate, unemployed	0.05	0.05	0.04	0.03
Unsolicited offer rate, employed	0.03	0.03	0.02	0.02
Formal offer rate, unemployed	0.12	0.12	0.11	0.11
Formal offer rate, employed	0.07	0.07	0.09	0.09
Acceptance rate, unemployed	0.28	0.28	0.45	0.45
Unemployment rate	0.053	0.053	0.031	0.031
Search-wage elasticity	-0.58	-0.62	-0.22	-0.20

The goal of the structural part of this paper is to conduct an accounting decomposition and quantify the different components of the gender wage gap. I carry out counterfactual exercises in which I equalize the following between men and women: equal search costs, equal job attachment, and equal weight on nonwage amenities. Table 24 shows the results. Of the three counterfactuals, I find that amenities play the largest role in explaining the wage differences. A significant part of the gender wage gap remains unexplained, however. This is likely due to aforementioned differences in the job search method and wage setting protocol such as bargaining.

Table 24: Contribution to gender wage gap

	Gender wage gap	
	Logs	Percent of gap
Raw gap in current wage	0.250	
<i>Reduction in gap with:</i>		
Equal weight on nonwage amenities: η_g	0.047	18.8%
Equal job attachment: δ_g and λ_g^e	0.035	14.1%
Equal search costs: $c_g^e(s)$	0.026	10.4%

8 Conclusion

In this paper I first document a novel set of facts regarding job search behavior differences between men and women. I find that women search more on both extensive and intensive margins of search. Despite greater levels of search, women and men have similar job search outcomes in terms of the number of offers and the share with at least one offer. Combining these differential inputs with similar outputs implies that women are less effective in generating job offers compared to men. In addition, I find that women, particularly those with children, value nonwage amenities such as flexibility and commute time more than men. These preferences influence both their job search intensity and acceptance decisions. In the second part of the paper, I develop an on-the-job search model with endogenous search. I allow for the elasticity of search between wages and effort to differ by gender. I use the model to carry out counterfactual exercises and quantify the importance of search costs, labor force attachment, and nonwage amenities to explaining the gender wage gap.

References

- Armantier, Olivier, Giorgio Topa, Wilbert van der Klaauw, and Basit Zafar**, “An overview of the Survey of Consumer Expectations,” *Economic Policy Review*, 2017, 23 (2), 51–72.
- Babcock, Linda, Sara Laschever, and Iris Bohnet**, *Women Don’t Ask: Negotiation and the Gender Divide*, Princeton University Press, 2003.
- Bagger, Jesper and Rasmus Lentz**, “An empirical model of wage dispersion with sorting,” *Review of Economic Studies*, 2019, 86 (1), 153–190.
- Barbanchon, Thomas Le, Roland Rathelot, and Alexandra Roulet**, “Gender differences in job search: Trading off commute against wage,” *Quarterly Journal of Economics*, 2021, 136 (1), 381–426.
- Becker, Gary S.**, *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*, Chicago: University of Chicago Press, 1964.
- Bertrand, Marianne and Esther Duflo**, “Field Experiments on Discrimination,” in Abhijit Vinayak Banerjee and Esther Duflo, eds., *Handbook of Field Experiments*, Vol. 1 of *Handbook of Economic Field Experiments*, North-Holland, 2017, pp. 309–393.
- , **Claudia Goldin, and Lawrence F. Katz**, “Dynamics of the gender gap for young professionals in the financial and corporate sectors,” *American Economic Journal: Applied Economics*, 2010, 2 (3), 228–255.
- Biasi, Barbara and Heather Sarsons**, “Flexible wages, bargaining, and the gender gap,” *Quarterly Journal of Economics*, 2022, 137 (1), 215–266.
- Blau, Francine D and Lawrence M Kahn**, “Female labor supply: Why is the United States falling behind?,” *American Economic Review*, 2013, 103 (3), 251–256.
- BLS**, “Labor Force Statistics from the Current Population Survey: Concepts and Definitions (CPS),” *Bureau of Labor Statistics*, 2024.
- Bonhomme, Stéphane and Grégory Jolivet**, “The pervasive absence of compensating differentials,” *Journal of Applied Econometrics*, 2009, 24 (5), 763–795.
- Booth, Alison and Andrew Leigh**, “Do employers discriminate by gender? A field experiment in female-dominated occupations,” *Economics Letters*, 2010, 107 (2), 236–238.

- Chen, Kuan-Ming, Claire Ding, John A. List, and Magne Mogstad**, “Reservation wages and workers’ valuation of job flexibility: Evidence from a natural field experiment,” *Journal of European Economic Association*, 2024.
- Christensen, Bent Jesper, Rasmus Lentz, Dale T. Mortensen, George R. Neumann, and Axel Werwatz**, “On-the-job search and the wage distribution,” *Journal of Labor Economics*, 2005, 23 (1), 31–58.
- Cortés, Patricia and Jessica Pan**, “When time binds: Substitutes for household production, returns to working long hours, and the skilled gender wage gap,” *Journal of Labor Economics*, 2019, 37 (2), 351–398.
- Dey, Matthew and Christopher Flinn**, “Household search and health insurance coverage,” *Journal of Econometrics*, 2008, 145 (1-2), 43–63.
- Faberman, Jason R., Andreas I. Mueller, Aysegul Sahin, and Giorgio Topa**, “Job search behavior among the employed and non-employed,” *Econometrica*, 2022, 90 (4), 1743–1779.
- Goldin, Claudia**, “The quiet revolution that transformed women’s employment, education, and family,” *American Economic Review*, 2006, 96 (2), 1–21.
- , “A grand gender convergence: Its last chapter,” *American Economic Review*, 2014, 104 (4), 1091–1119.
- , “Nobel lecture: An evolving economic force,” *American Economic Review*, 2024, 114 (6), 1515–1539.
- **and Lawrence F. Katz**, “The cost of workplace flexibility for high-powered professionals,” *The Annals of the American Academy of Political and Social Science*, 2011, 638 (1), 45–67.
- **and —**, “A most egalitarian profession: Pharmacy and the evolution of a family-friendly occupation,” *Journal of Labor Economics*, 2016, 34 (3), 705–746.
- Hall, Robert E. and Andreas I. Mueller**, “Wage dispersion and search behavior: The importance of nonwage job values,” *Journal of Political Economy*, 2018, 126 (4), 1594–1637.
- Hodges, Leslie**, “Do female occupations pay less but offer more benefits?,” *Gender & Society*, 2020, 34 (3), 381–412.

- Hornstein, Andreas, Per Krusell, and Giovanni L. Violante**, “Frictional wage dispersion in search models: A quantitative assessment,” *American Economic Review*, 2011, 101 (7), 2873–2898.
- Hwang, Hae-shin, Dale T. Mortensen, and W. Robert Reed**, “Hedonic Wages and Labor Market Search,” *Journal of Labor Economics*, 1998, 16 (4), 815–847.
- Kleven, Henrik, Camille Landais, and Jakob Egholt Sogaard**, “Children and gender inequality: Evidence from Denmark,” *American Economic Journal: Applied Economics*, 2019, 11 (4), 181—209.
- Leibbrandt, Andreas and John A. List**, “Do women avoid salary negotiations? Evidence from a large-scale natural field experiment,” *Management Science*, 2015, 61 (9), 2016–2024.
- Light, Audrey and Manuelita Ureta**, “Gender differences in wages and job turnover among continuously employed workers,” *American Economic Review*, 1990, 80 (2), 293–297.
- and —, “Early-career work experience and gender wage differentials,” *Journal of Labor Economics*, 1995, 13 (1), 121–154.
- Maestas, Nicole, Kathleen J. Mullen, David Powell, Till Von Wachter, and Jeffrey B. Wenger**, “The value of working conditions in the United States and implications for the structure of wages,” *American Economic Review*, 2023, 113 (7), 2007–2047.
- Manning, Alan and Barbara Petrongolo**, “The part-time pay penalty for women in Britain,” *Economic Journal*, 2008, 118 (526), F28–F51.
- Mas, Alexandre and Amanda Pallais**, “Labor supply and the value of non-work time: Experimental estimates from the field,” *American Economic Review: Insights*, 2019, 1 (1), 111—26.
- Mengel, Friederike**, “Gender differences in networking,” *Economic Journal*, 2020, 130 (630), 1842–1873.
- Mincer, Jacob and Boyan Jovanovic**, “Labor Mobility and Wages,” in Sherwin Rosen, ed., *Studies in Labor Markets*, Chicago: University of Chicago Press, 1981, pp. 21–64.
- Mortensen, Dale T and Christopher A Pissarides**, “Job creation and job destruction in the theory of unemployment,” *Review of Economic Studies*, 1994, 61 (3), 397–415.

- Mueller, Andreas**, "On-the-job search and wage dispersion: New evidence from time use data," *Economics Letters*, 2010, 109 (2), 124–127.
- Neumark, David, Roy J. Bank, and Kyle D. Van Nort**, "Sex discrimination in restaurant hiring: An audit study," *Quarterly Journal of Economics*, 1996, 111 (3), 915–941.
- Petit, Pascale**, "The effects of age and family constraints on gender hiring discrimination: A field experiment in the French financial sector," *Labour Economics*, 2007, 14 (3), 371–391.
- Phelps, Edmund S.**, "The statistical theory of racism and sexism," *American Economic Review*, 1972, 62 (4), 659–661.
- Shimer, Robert**, "Search intensity," *mimeo*, University of Chicago, 2004.
- Sockin, Jason**, "Show me the amenity: Are higher-paying firms better all around?," Technical Report 3957002, Social Science Research Network November 2024.
- Spence, Michael**, "Job Market Signaling," in Peter Diamond and Michael Rothschild, eds., *Uncertainty in Economics*, New York: Academic Press, 1978, pp. 281–306.
- Sullivan, Paul and Ted To**, "Search and nonwage job characteristics," *Journal of Human Resources*, 2014, 49 (2), 472–507.
- Topel, Robert**, "Specific capital, mobility, and wages: Wages rise with job seniority," *Journal of political Economy*, 1991, 99 (1), 145–176.
- Waldfogel, Jane**, "Understanding the 'family gap' in pay for women with children," *Journal of Economic Perspectives*, 1998, 12 (1), 137–156.
- Wiswall, Matthew and Basit Zafar**, "Preference for the workplace, investment in human capital, and gender," *Quarterly Journal of Economics*, 2018, 133 (1), 457–507.
- Zeltzer, Dan**, "Gender homophily in referral networks: Consequences for the medicare physician earnings gap," *American Economic Journal: Applied Economics*, 2020, 12 (2), 169–197.

Appendix

Table 25: Reasons for searching

<i>Percent who list:</i>	Men			Women		
	All	No kids	Kids	All	No kids	Kids
Not satisfied with pay or benefits	48.8	58.16	40.53	56.50	55.77	57.35
Not satisfied with duties	46.5	52.48	42.83	46.10	51.99	53.07
Looking for change of careers	44.8	49.43	48.15	34.90	47.16	34.19
Not using experience or skills	42.4	48.69	31.65	29.80	37.51	21.30
Denied promotion or pay increase	22.9	30.22	18.07	18.90	20.04	14.89
Unsuitable work hours	18.1	20.30	11.47	10.80	13.37	10.74
Low quality of work life	15.9	24.33	14.29	20.10	16.54	25.83
Conflict with co-workers or boss	15.9	15.40	15.52	17.50	19.32	21.86
Concerned about job stability	14.1	14.45	6.22	11.70	7.57	16.73
Commute distance too long	10.4	7.60	13.21	19.30	17.95	26.35
Relocating for non-job-related reasons	5.5	7.71	5.31	8.50	10.54	7.38
Given notice that will lose job	3.5	2.00	3.44	3.00	1.54	1.45

Notes: Respondents can indicate multiple reasons for searching. *Source:* October 2013–2021 waves of the SCE Job Search Supplement.

A Extensive margin of search

Table 26: Extensive margin search, different groups of controls

	Coefficient on women indicator from separate OLS regressions				
<i>Panel A. Extensive: Actively searched, last 4 weeks</i>					
Women	9.21*** (1.46)	7.50*** (1.42)	6.63*** (1.44)	4.52*** (1.30)	3.38** (1.34)
R-squared	0.012	0.042	0.049	0.210	0.219
<i>Panel B. Extensive: Sent an application, last 4 weeks</i>					
Women	9.34*** (1.39)	7.45*** (1.35)	6.67*** (1.35)	4.69*** (1.23)	3.76*** (1.27)
R-squared	0.013	0.048	0.055	0.212	0.222
Observations	6,000	6,000	6,000	6,000	6,000
Human capital controls	no	yes	yes	yes	yes
Family controls	no	no	yes	yes	yes
Employment controls	no	no	no	yes	yes
Industry + broad occupation	no	no	no	no	yes

Source: October 2013–2021 waves of the SCE Job Search Supplement.

Table 27: Extensive margin of search, by industry and occupation

	Percent actively searched, last 4 weeks			Percent sent application, last 4 weeks		
	All	Men	Women	All	Men	Women
<i>Panel A. Industry</i>						
Agriculture, Extraction, Utilities	8.96	8.17	10.92	6.74	5.04	10.92
Construction	14.52	11.80	21.08	13.95	10.99	21.08
Manufacturing	18.90	15.52	26.82	16.65	13.75	23.44
Wholesale and Retail Trade	22.46	18.07	26.24	19.60	15.09	23.48
Transportation	15.30	13.73	19.22	12.71	10.87	17.32
Information Services	24.92	20.72	31.47	23.44	20.09	28.68
Finance	18.92	16.76	21.18	16.27	13.27	19.39
Real Estate	14.44	7.00	19.81	12.13	7.00	15.84
Professional, Technical, Business Services	19.66	17.94	21.61	16.64	14.92	18.58
Education	23.71	23.78	23.69	18.86	21.24	17.95
Health Care	26.01	25.22	26.29	23.94	23.39	24.14
Arts, Entertainment, Recreation	19.35	23.19	15.81	15.14	17.55	12.91
Hotel, Accommodation, Restaurant, or Food Services	25.14	26.53	24.15	20.76	19.90	21.37
Other Services	19.73	14.36	23.28	15.70	10.52	19.12
Government	15.89	13.10	18.06	14.08	11.67	15.95
<i>Panel B. Occupation</i>						
Management	17.30	16.40	18.47	14.19	12.14	16.83
Business and Financial Operations	18.37	17.96	18.75	15.72	14.88	16.51
Computer and Mathematical	21.92	21.23	23.86	17.72	17.44	18.54
Professional	16.62	13.77	20.45	13.50	12.20	15.25
Education	19.75	16.71	20.98	15.94	14.66	16.46
Arts	18.82	13.27	23.89	17.39	12.18	22.16
Healthcare, Technical	25.16	20.74	27.06	21.89	17.55	23.74
Healthcare, Support	23.42	23.05	23.48	22.39	21.73	22.50
Service Occupations	20.09	19.60	20.57	16.36	14.62	18.11
Sales	24.95	20.55	28.40	22.85	19.75	25.28
Administration	27.71	15.46	32.00	24.90	13.99	28.72
Construction and Installation	16.19	14.56	25.17	14.78	13.14	23.84
Production	13.79	10.90	18.92	11.32	7.80	17.56
Transportation	20.60	21.66	15.87	17.23	18.07	13.50
Observations	7,112	3,554	3,558	7,112	3,554	3,558

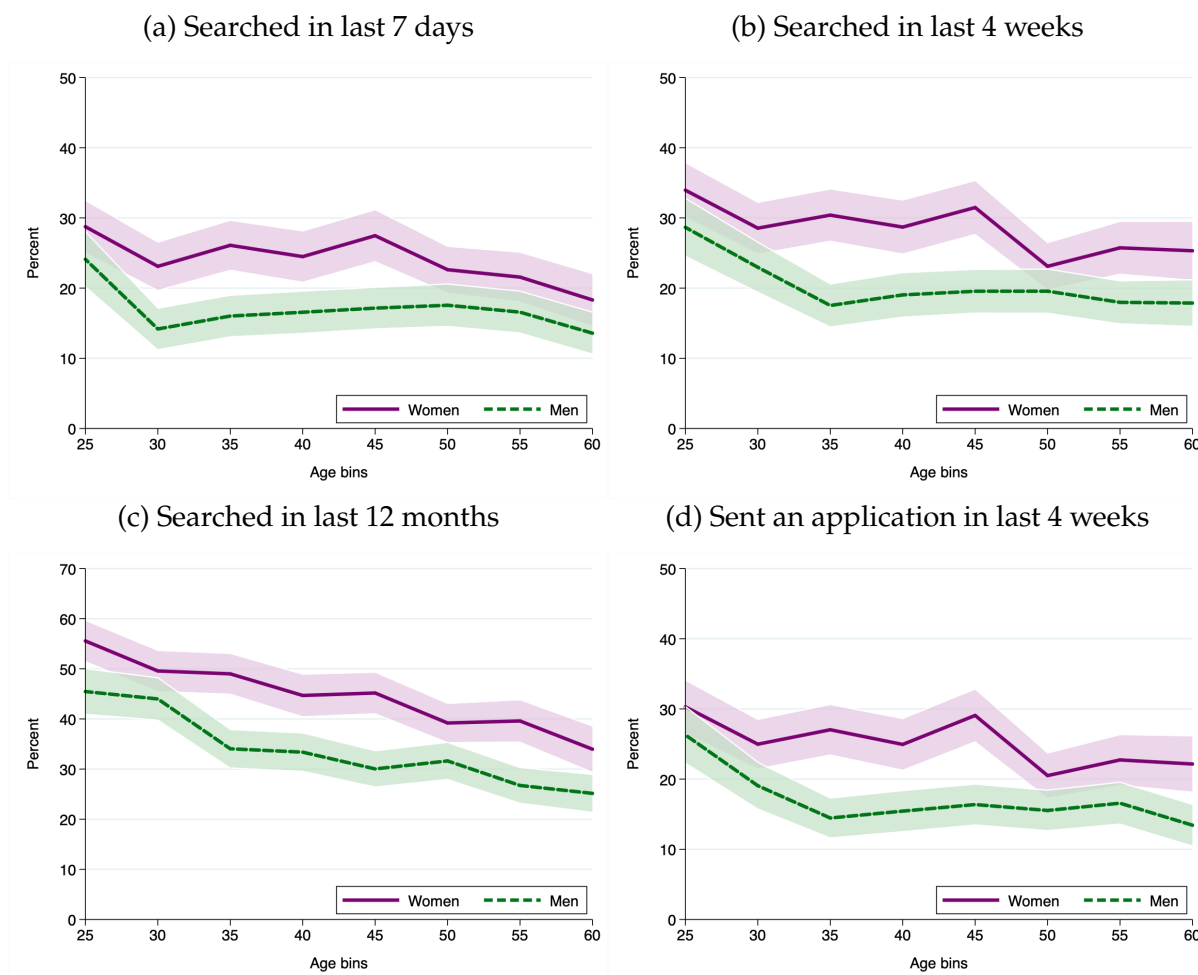
Source: October 2013–2021 waves of the SCE Job Search Supplement.

Table 28: Extensive margin of search, by employment status

	Men		Women		Difference	
	Emp.	Unemp.	Emp.	Unemp.	(1) v. (3)	(2) v. (4)
<i>Percent who:</i>						
Actively searched, last 4 weeks	17.03 (0.65)	100.00 (0.00)	24.02 (0.76)	100.00 (0.00)	6.99*** (1.00)	0.00 (0.00)
Sent an application, last 4 weeks	14.15 (0.61)	90.48 (2.45)	20.97 (0.73)	95.42 (1.45)	6.82*** (0.94)	4.94* (2.70)
Observations	3,299	144	3,124	208	6,423	352

Notes: This is analogous to Table 4 except broken down by employment status. Controls are not included. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: October 2013–2021 waves of the SCE Job Search Supplement.

Figure 2: Extensive margin search over the lifecycle



Notes: Figures show difference in measures of search incidence reported in Table 4 over the lifecycle. Confidence intervals are at the 90 percent level. Source: October 2013–2021 waves of the SCE Job Search Supplement.

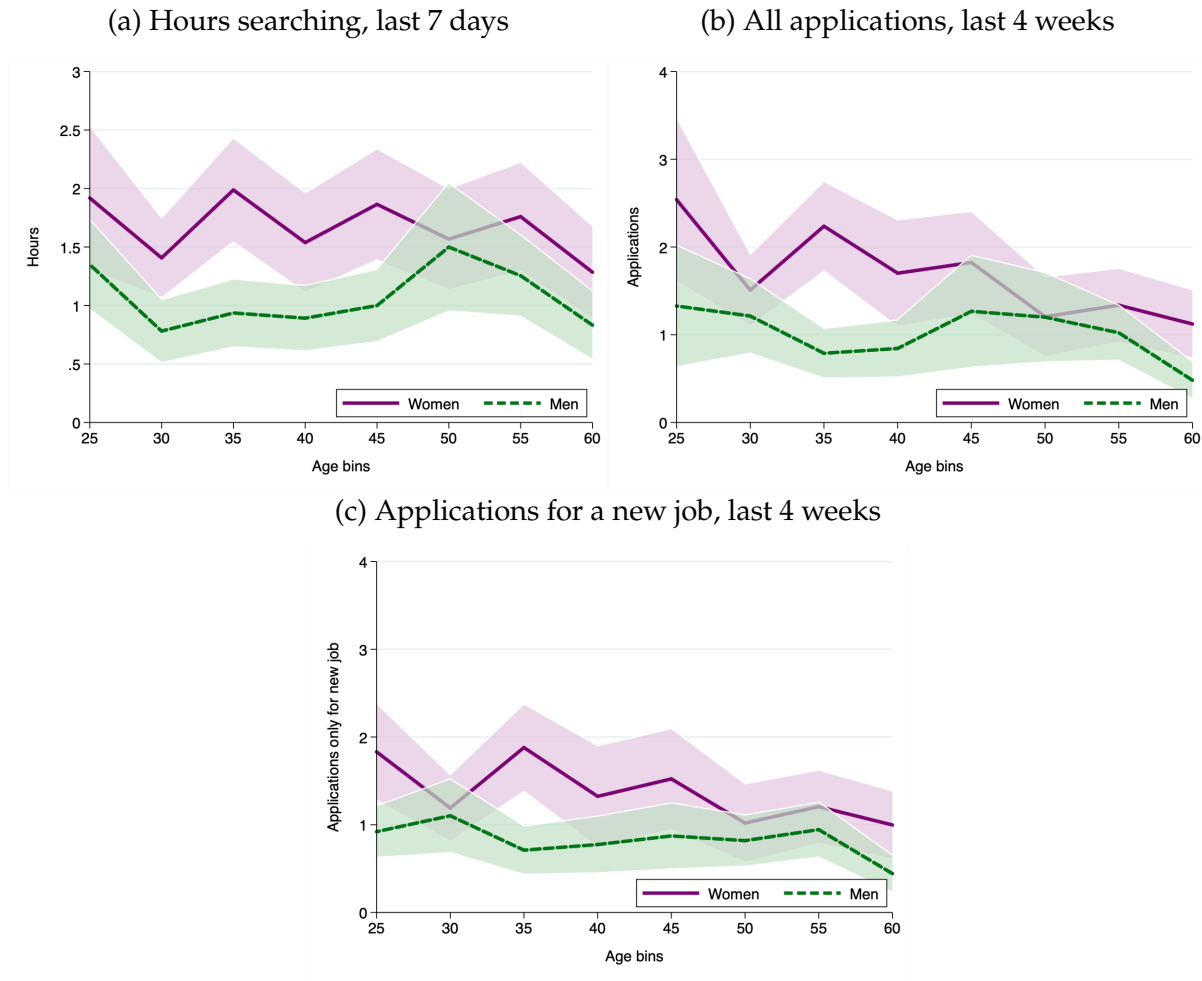
B Intensive margin of search

Table 29: Intensive margin search, different groups of controls

	Coefficient on women indicator from separate OLS regressions				
<i>Panel A. Intensive: Number of applications sent, last 4 weeks</i>					
Women	0.71*** (0.18)	0.54*** (0.17)	0.49*** (0.16)	0.26* (0.15)	0.24 (0.15)
R-squared	0.003	0.015	0.016	0.103	0.108
<i>Panel B. Intensive: Number of applications for new job, last 4 weeks</i>					
Women	0.60*** (0.15)	0.46*** (0.14)	0.43*** (0.14)	0.20 (0.12)	0.17 (0.12)
R-squared	0.004	0.015	0.016	0.158	0.161
<i>Panel C. Intensive: Hours spent searching, last 7 days</i>					
Women	0.63*** (0.18)	0.50*** (0.16)	0.44*** (0.17)	0.19 (0.15)	0.16 (0.16)
R-squared	0.004	0.021	0.024	0.184	0.189
Observations	6,000	6,000	6,000	6,000	6,000
Human capital controls	no	yes	yes	yes	yes
Family controls	no	no	yes	yes	yes
Employment controls	no	no	no	yes	yes
Industry + broad occupation	no	no	no	no	yes

Source: October 2013–2021 waves of the SCE Job Search Supplement.

Figure 3: Intensive margin search over the lifecycle



Notes: Figures show difference in measures of search incidence reported in Table 4 over the lifecycle. Confidence intervals are at the 90 percent level. Source: October 2013–2021 waves of the SCE Job Search Supplement.

Table 30: Intensive margin of search, by industry and occupation

	Applications sent, last 4 weeks			Hours spent searching, last 7 days		
	All	Men	Women	All	Men	Women
<i>Panel A. Industry</i>						
Agriculture, Extraction, Utilities	0.36	0.37	0.35	0.39	0.34	0.50
Construction	0.78	0.52	1.40	1.02	0.70	1.76
Manufacturing	1.01	0.79	1.51	1.17	1.05	1.45
Wholesale and Retail Trade	1.63	1.34	1.87	1.22	0.85	1.54
Transportation	0.76	0.59	1.19	0.59	0.53	0.72
Information Services	0.94	0.93	0.94	1.27	1.45	1.00
Finance	0.88	0.82	0.93	1.04	1.09	0.99
Real Estate	0.41	0.39	0.42	0.76	0.45	0.98
Professional, Technical, Business Services	1.27	1.12	1.44	0.93	0.75	1.15
Education	1.14	1.25	1.10	0.99	0.98	0.99
Health Care	1.36	0.76	1.58	1.23	0.53	1.49
Arts, Entertainment, Recreation	2.79	2.70	2.86	1.20	1.58	0.85
Hotel, Accommodation, Restaurant, or Food Services	1.24	1.34	1.16	1.84	1.10	2.36
Other Services	1.25	0.94	1.46	1.53	1.38	1.63
Government	1.12	0.50	1.60	0.91	0.90	0.93
<i>Panel B. Occupation</i>						
Management	1.54	1.20	1.99	0.98	0.76	1.26
Business and Financial Operations	1.16	1.14	1.18	1.06	1.10	1.02
Computer and Mathematical	1.04	1.05	1.01	0.86	0.86	0.84
Professional	0.62	0.44	0.86	0.99	1.04	0.93
Education	0.72	0.47	0.82	0.86	0.70	0.92
Arts	0.73	0.64	0.81	1.19	1.09	1.28
Healthcare, technical	0.82	0.41	1.00	0.59	0.54	0.61
Healthcare, support	1.75	1.16	1.84	1.83	0.65	2.01
Service Occupations	0.56	0.45	0.66	1.24	1.48	1.00
Sales	1.84	1.31	2.25	1.60	0.89	2.16
Administration	1.42	1.03	1.56	1.67	1.21	1.83
Construction and installation	0.73	0.65	1.15	0.86	0.71	1.70
Production	1.00	0.56	1.78	0.53	0.32	0.90
Transportation	1.18	1.25	0.90	1.00	0.96	1.16
Observations	7,108	3,552	3,556	7,108	3,552	3,556

Source: October 2013–2021 waves of the SCE Job Search Supplement.

Table 31: Intensive margin of search, by employment status

	Men		Women		Difference	
	Emp.	Unemp.	Emp.	Unemp.	(1) v. (3)	(2) v. (4)
Hours spent searching, past 7 days	0.82	9.83	1.18	9.85	0.36*** (0.11)	0.02 (1.29)
Applications sent, past 4 weeks	0.85	8.70	1.17	9.38	0.33** (0.15)	0.68 (1.61)
Applications for new job, past 4 weeks	0.59	8.00	0.80	9.38	0.21** (0.10)	1.38 (1.41)
Observations	2,909	144	2,854	208	5,760	351

Notes: The table shows search intensity by employment status for men and women. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* October 2013–2021 waves of the SCE Job Search Supplement.

C Job search outcomes

Table 32: Job search outcomes, including additional jobs

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
<i>Number of:</i>				
Offers, last 4 weeks	0.25	0.29	0.04 (0.04)	0.00 (0.03)
Offers, last 6 months	0.43	0.46	0.03 (0.05)	0.01 (0.05)
Interviews, last 4 weeks	0.13	0.16	0.03 (0.03)	0.01 (0.02)
<i>Percent with:</i>				
Formal offer	7.62	11.40	3.77** (1.04)	1.41 (0.98)
Unsolicited offer	2.58	2.36	−0.22 (0.52)	−0.29 (0.54)
Observations	3,291	3,132	6,423	6,423
Worker controls			no	yes
State and year fixed effects			no	yes

Notes: This is analogous to Table 8 except includes outcomes for jobs that are additional work to one's current job. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Estimates are calculated using the October 2013–2021 waves of the SCE Job Search Supplement.

D Wage and hours estimates

Table 33: Wage estimates

		Men	Women	Difference
<i>Previous wage</i> N=6,423	Raw means	3.00 (0.01)	2.77 (0.01)	-0.23*** (0.02)
	Residualized	2.97 (0.01)	2.80 (0.01)	-0.17*** (0.01)
<i>Current wage</i> N=6,423	Raw means	3.24 (0.01)	2.94 (0.01)	-0.30*** (0.02)
	Residualized	3.15 (0.01)	2.99 (0.01)	-0.16*** (0.01)
<i>Reservation wage</i> N=6,423	Raw means	3.26 (0.01)	2.95 (0.01)	-0.32*** (0.02)
	Residualized	3.22 (0.01)	3.01 (0.01)	-0.21*** (0.01)
	Including recent wage	3.17 (0.01)	3.05 (0.01)	-0.11*** (0.01)
<i>Accepted wage</i> N=574	Raw means	2.98 (0.03)	2.77 (0.03)	-0.22*** (0.05)
	Residualized	2.90 (0.03)	2.74 (0.03)	-0.16*** (0.05)
	Including recent wage	2.91 (0.03)	2.74 (0.03)	-0.16*** (0.05)

Notes: Table shows unconditional and conditional wage estimates for men and women, and the difference between the two. The conditional wage estimates for all different wage types control for the following demographics: age, age-squared, three education categories, four race categories, marital status, number of children under 6. State and year fixed effects are also included. In addition, the conditional wage estimates control for the relevant occupation at the two-digit level, industry, and firm size. For example, the current wage and reservation wage estimates control for the most recent of these variables. The offered and accepted wage estimates control for the occupation, industry, and firm size of the job offer. Lastly the previous wage estimates control for the previous of these. The log recent wage is also controlled for in the accepted wage estimates. The previous wage is also controlled for in the current wage estimates. When controlling for most recent wage in the offered wage estimates, the difference between men and women is 13%. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* Estimates are calculated using the October 2013–2021 waves of the SCE Job Search Supplement.

Figure 4: Kernel density of log offered wage

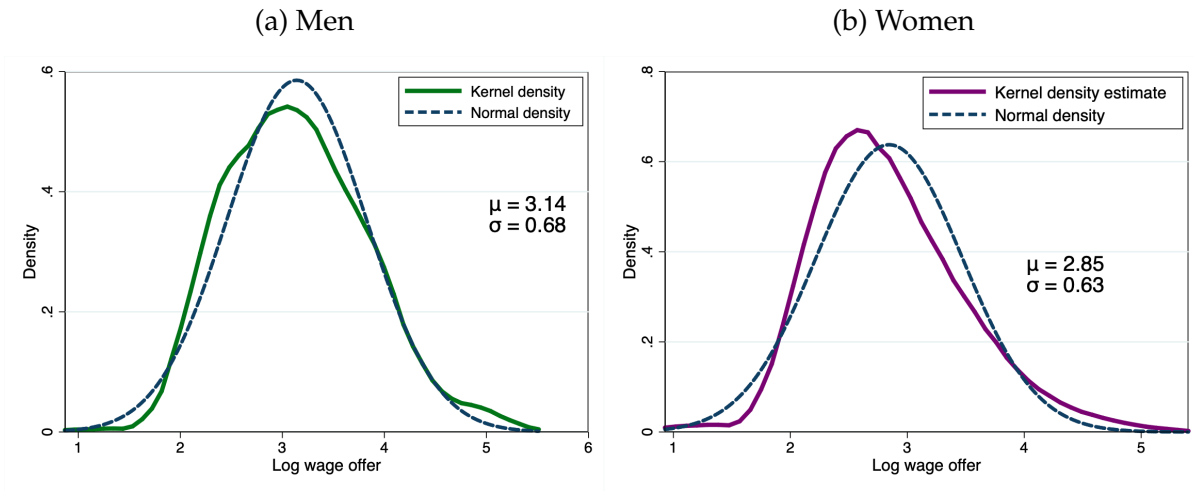


Figure 5: Kernel density of log current wage

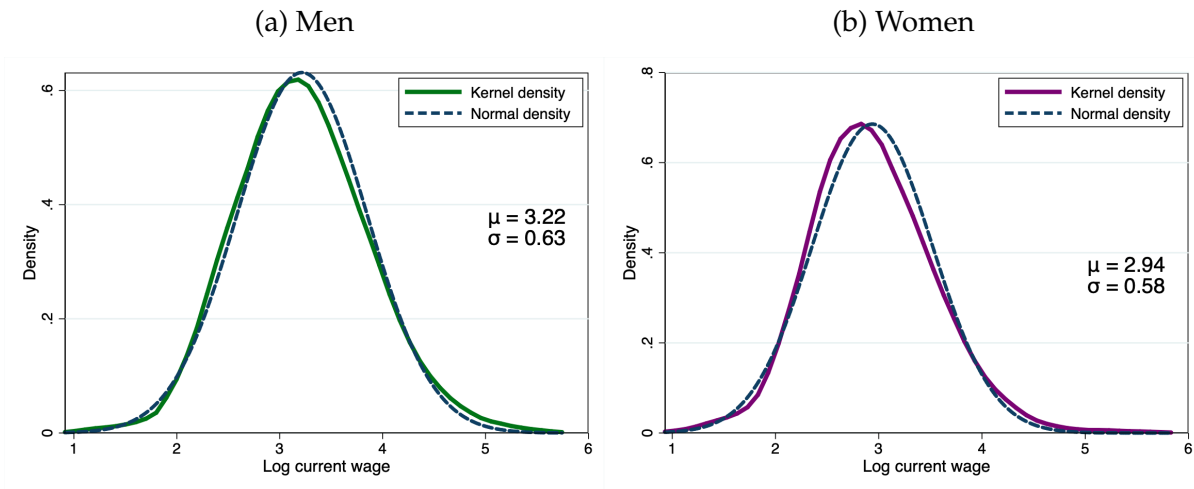


Figure 6: Kernel density of log reservation wage

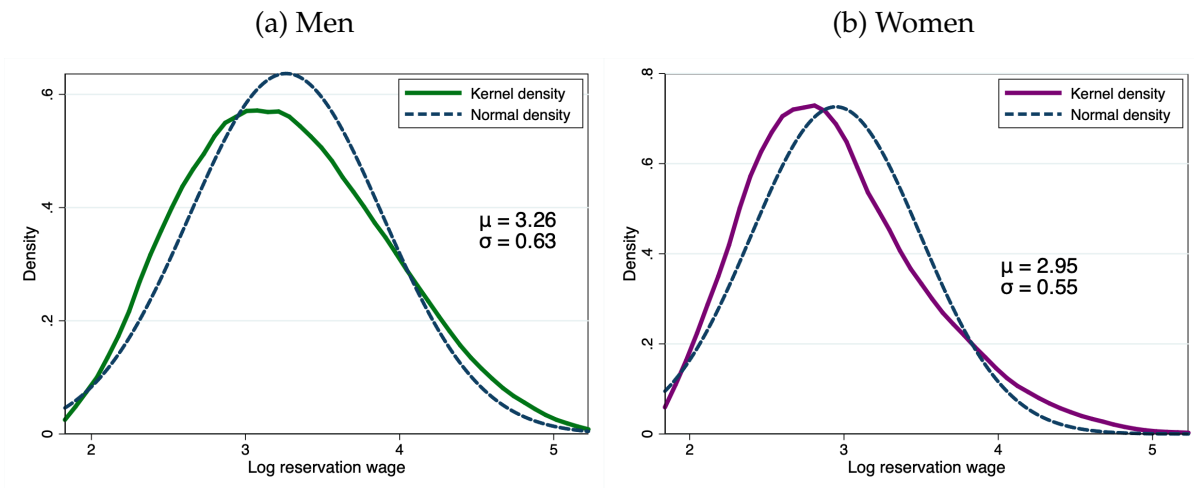


Table 34: Hours estimates

		Men	Women	Difference
<i>Previous hours</i> N=3,897	Raw means	3.66 (0.01)	3.54 (0.01)	-0.12*** (0.01)
	Residualized	3.57 (0.02)	3.51 (0.02)	-0.07** (0.03)
<i>Current hours</i> N=3,897	Raw means	3.71 (0.00)	3.60 (0.00)	-0.11*** (0.01)
	Residualized	3.63 (0.01)	3.53 (0.02)	-0.10*** (0.02)
<i>Reservation hours</i> N=3,897	Raw means	3.46 (0.01)	3.34 (0.01)	-0.12*** (0.02)
	Residualized	3.40 (0.02)	3.33 (0.02)	-0.07** (0.04)
	Including recent hours	3.39 (0.02)	3.34 (0.02)	-0.05 (0.03)
<i>Accepted hours</i> N=574	Raw means	3.45 (0.03)	3.29 (0.03)	-0.16*** (0.05)
	Residualized	3.32 (0.03)	3.24 (0.03)	-0.08* (0.05)
	Including recent hours	3.29 (0.03)	3.26 (0.03)	-0.03 (0.04)

Notes: Table shows raw means and residualized hours estimates for men and women, and the difference between the two. All the residualized estimates control for the following demographics: age, age-squared, three education categories, four race categories, home ownership, marital status, presence of children under 6. State and year fixed effects are also included. In addition, the residualized estimates control for the relevant 2-digit SOC occupation and 2-digit NAICS industry. For example, the current, reservation, and accepted hours estimates control for the most recent of these variables. The accepted hours estimates control for the occupation and industry of the job offer. Lastly the previous hours estimates control for the previous occupation and industry. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* Estimates are calculated using the October 2013–2021 waves of the SCE Job Search Supplement.

E Labor force attachment

Figure 7: Months without a job in last 5 years

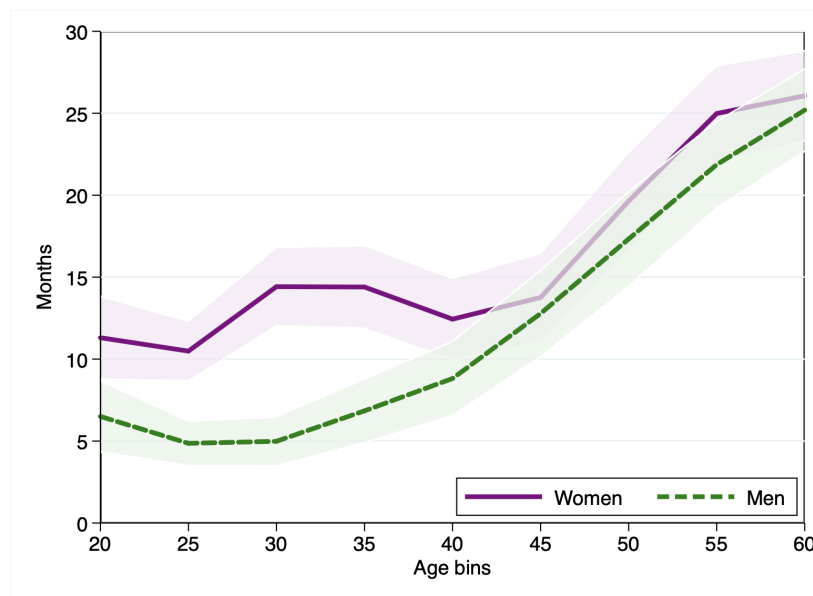
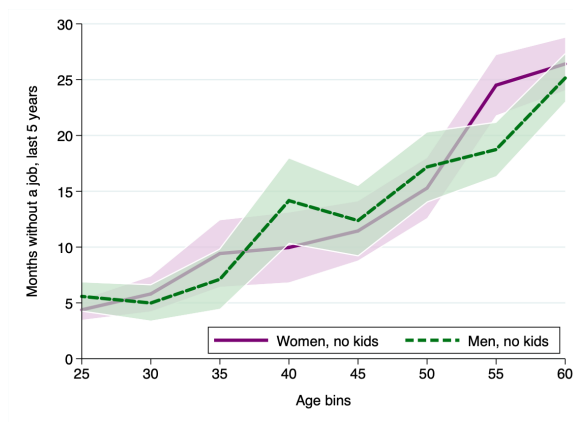
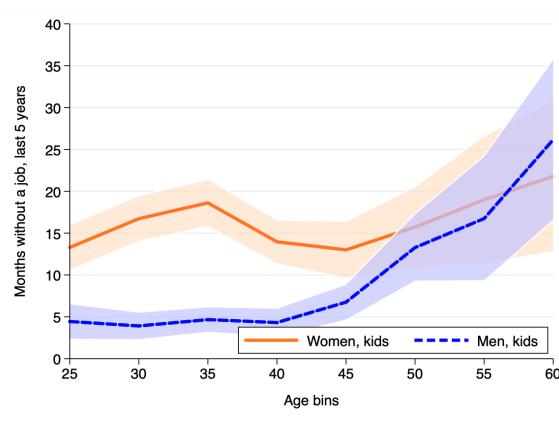


Figure 8: Months without a job in last 5 years, by presence of children

(a) No children



(b) Children



F Nonwage amenities

Table 35: Satisfaction with amenities at current job

	Dependent variable: log current wage			
	(1)	(2)	(3)	(4)
Men	0.120*** (0.015)			
Women, no kids		0.096*** (0.019)		
Women, kids under 6			0.009 (0.034)	
Women, kids 6-17				0.049* (0.028)
N	2,048	1,200	309	492
Adj. R-squared	0.424	0.379	0.561	0.393
Workers controls	yes	yes	yes	yes
State and year fixed effects	yes	yes	yes	yes

Table 36: Elasticity of job search, ATUS

	Searched, prior day		Minutes spent searching	
	Men	Women	Men	Women
Log real wage	-0.008*** (0.003)	-0.002 (0.002)	-0.859*** (0.278)	-0.252 (0.312)
N	10,694	12,443	10,694	12,443
Adj. R-squared	0.005	0.004	0.003	0.003
Worker controls	yes	yes	yes	yes
State + year FE	yes	yes	yes	yes

Notes: The table shows the relationship between job search measures and log real current wage. The dependent variable capturing incidence of search is an indicator for whether or not a respondent reported job searching in the prior day. Meanwhile minutes spent searching captures the intensity of search. Worker controls include: age, age-squared, three education categories, four race categories, presence of a spouse, and the presence of own household children under the age of 18. State and year fixed effects included. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* Estimates are calculated using the 2013–2021 waves of the American Time Use Survey (ATUS).

Table 37: Extensive margin of job search, men with and without children

		Coefficient on children indicator from separate OLS regressions		
	No kids	Kids	Pooled	Pooled
<i>Percent who:</i>				
Actively searched, last 7 days	16.53	13.99	-1.02 (2.30)	-0.43 (2.53)
Actively searched, last 4 weeks	19.89	16.49	-2.13 (2.37)	-0.25 (2.66)
Sent application, last 4 weeks	15.95	14.54	-1.77 (2.20)	0.16 (2.47)
Observations	1,077	357	1,434	1,434
Worker controls			no	yes
State and year fixed effects			no	yes

Notes: The sample includes individuals aged 25–64 who are currently in the labor force and do not have missing data on education, race, marital status, or number of children under six. Worker controls include log recent wage (current wage if employed and most recent wage if unemployed), age, age-squared, employment status, three education categories, four race categories, marital status, presence of children under six. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* Estimates calculated using the October 2013–2021 waves of the SCE Job Search Supplement.

Table 38: Intensive margin of job search, men with and without children

		Coefficient on children indicator from separate OLS regressions			
		No kids	Kids	Pooled	Pooled
<i>Number of:</i>					
Hours spent searching, past 7 days	1.04	0.82	−0.22 (0.24)	−0.14 (0.28)	
Applications sent, past 4 weeks	1.07	0.83	−0.24 (0.28)	−0.01 (0.35)	
Applications for new job, past 4 weeks	0.85	0.80	−0.05 (0.25)	0.25 (0.28)	
Observations	1,077	357	1,434	1,434	
Worker controls			no	yes	
State and year fixed effects			no	yes	

Notes: The sample includes individuals aged 25–64 who are currently in the labor force and do not have missing data on education, race, marital status, or number of children under six. Worker controls include log recent wage (current wage if employed and most recent wage if unemployed), age, age-squared, employment status, three education categories, four race categories, marital status, presence of children under six. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* Estimates calculated using the October 2013–2021 waves of the SCE Job Search Supplement.

Table 39: Elasticity of search effort with respect to current wage, men with and without children

Search effort _{ist} = Number of applications				
<i>Panel A. No children</i>				
Log current wage	−0.28*	−0.51***	−0.51***	−0.48***
	(0.15)	(0.15)	(0.16)	(0.17)
R-squared	0.033	0.021	0.021	0.037
Observations	967	967	967	967
Mean of dependent variable	0.78	0.78	0.78	0.78
Elasticity (coefficient/mean)	−0.35	−0.65	−0.65	−0.61
<i>Panel B. Children</i>				
Log current wage	−0.48***	−0.52***	−0.52***	−0.57***
	(0.15)	(0.18)	(0.18)	(0.20)
R-squared	0.094	0.027	0.027	0.044
Observations	1,108	1,108	1,108	1,108
Mean of dependent variable	0.51	0.51	0.51	0.51
Elasticity (coefficient/mean)	−0.96	−1.01	−1.01	−1.11
<i>Panel C. Statistical difference</i>				
Children × Log current wage	−0.20	−0.16	−0.14	−0.18
	(0.21)	(0.19)	(0.19)	(0.21)
R-squared	0.058	0.022	0.022	0.038
Observations	2,075	2,075	2,075	2,075
Human capital controls	no	yes	yes	yes
Marital status	no	no	yes	yes
Industry	no	no	no	yes

Notes: The table shows the search-wage elasticity from separate OLS regressions for currently employed women without children, women with children, and combined. The dependent variable is the number of applications sent in the last four weeks. Worker controls include: age, age-squared, three education categories, four race categories, marital status, presence of children under 6, and most recent 2-digit SOC occupation. Year and state fixed effects are included. The elasticity in the bottom row is calculated by dividing the estimated coefficient on the log real current wage by the mean of the dependent variable. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* Estimates are calculated using the October 2013–2021 waves of the SCE Job Search Supplement.

G Job offer acceptance frequency

Figure 9: Acceptance frequency

