Macroeconomic Consequences of Gender Differences in Job Search

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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

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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
Demographics (percent)						
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
Labor Force Statistics						
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
Observations	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 2: Extensive margin of job search

	Men	Women	Coefficient on women indicator from separate OLS regressions: Difference	Difference
Percent who:				
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.

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 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.

Table 3: Extensive margin of job search by demographic group

	Actively searched (%)			Sent application (%)		
	Men	Women	Difference	Men	Women	Difference
Panel A. Age groups						
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)
Panel B. Education						
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)
Panel C. Race						
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)
Panel D. Marital status						
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)

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.

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

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
Number of:				
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
Panel A. Age groups						
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)
Panel B. Education						
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)
Panel C. Race						
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)
Panel D. Marital status						
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. 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).

Table 6: Search method for best offer

	Men	Women	Coefficient on women indicator from separate OLS regressions: Difference	Difference
Method of best offer (percent):				
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

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 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
Wage setting of best offer (percent):				
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

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
Number of:				
Offers for new job, last 4 weeks	0.13	0.16	0.03 (0.03)	–0.01 (0.03)
Percent with:				
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:

$$\text{Offer Yield}(i, j) = \frac{\text{Output } j}{\text{Input } i}, \tag{1}$$

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

Outputs:	Number of offers		Share with at least one offer		Offer yield ratio: Women/Men	
	Men	Women	Men	Women	Men	Women
Inputs:						
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
Offered wage	Raw means	3.03	2.78	–0.25***
N=1,281		(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)
Offered hours	Raw means	3.53	3.35	–0.18***
N=1,281		(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
Benefits included in best offer (percent):				
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 compensation 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 finding of this paper is that women engage in job search more intensively than men, even though their search does not yield higher wages. One possible explanation is that women derive relatively greater value from nonwage amenities—attributes of a job other than pay. Just as income and substitution effects determine labor supply responses to wage changes, search effort may similarly depend on these effects (Shimer, 2004). A higher wage increases the opportunity cost of time spent searching (an "income effect" reducing search), but also raises the returns to finding a better job (a "substitution effect" increasing search). Standard job ladder models predict that as one's current wage rises, search effort declines because the expected gain from finding an even better job diminishes (Burdett, 1979; Benhabib and Bull, 1983; Pissarides, 2000; Shimer, 2004; Christensen et al., 2005).

In this section, I examine whether gender differences in preferences for nonwage job attributes can help explain why women continue to search more than men. I begin by estimating the elasticity of search effort with respect to the current wage, and then provide evidence on gender differences in the valuation of job attributes such as working hours, commute length, location, and flexibility. 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 do not distinguish by gender.

To test how search effort responds to current wages, I estimate the following regression for individual i in state s and year t:

$$\text{Search effort}_{ist} = \delta w_{ist} + \mathbf{X}_{ist}\beta + \alpha_s + \gamma_t + \varepsilon_{ist} \quad (2)$$

where the dependent variable is the number of job applications sent in the last four weeks. The key independent variable w_{ist} is the log of the worker's current wage. The vector $\mathbf{X}_{ist}$ includes demographic and human capital controls (age, education, race, etc.), and α_s and γ_t are state and year fixed effects. The coefficient δ measures the search–wage elasticity. If the job ladder mechanism holds, I expect $\delta < 0$ (higher current wages lead to less search).

Table 12 presents the estimation results separately for men and women, as well as for the pooled sample with an interaction for women. I find a clear inverse relationship between wages and on-the-job search effort for both genders. In the preferred specification with full controls (column 4), the coefficient on log current wage is about –0.38 for men and –0.35 for women, both highly significant. In other words, higher wages are associated with fewer job applications, consistent with the job ladder model. However, the magnitude of this effect is substantially larger for men. At the sample mean of the dependent variable, the implied search effort elasticity with respect to the current wage is approximately –0.78 for men, compared to –0.39 for women. This difference is statistically significant (at the 10% level) when tested in the pooled regression (Panel C of Table 12). Thus, men's job search intensity falls more sharply as their wages increase, whereas women's search effort is less sensitive to wage gains.

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

	Search effort$_{ist}$ = Number of applications			
Panel A. Men				
Log current wage	–0.29***	–0.44***	–0.43***	–0.38***
	(0.07)	(0.08)	(0.08)	(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
Panel B. Women				
Log current wage	–0.51***	–0.37***	–0.34***	–0.35***
	(0.12)	(0.12)	(0.12)	(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
Panel C. Statistical difference				
Women × Log current wage	–0.21**	–0.19	–0.20*	–0.24*
	(0.12)	(0.12)	(0.12)	(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 fact that women's search effort is less wage-elastic suggests that non-pecuniary job aspects play a more important role in their search decisions. In other words, women may continue to search for better job amenities even when their current wage increases, whereas men reduce search more readily once higher wages are secured. To investigate this idea more directly, I turn to survey evidence on workers' reservation job preferences—specifically, how willing they are to accept jobs with less-desirable nonwage attributes.

The survey asks employed job seekers whether they would accept a new job at their stated reservation wage if that job required certain sacrifices or changes in nonwage conditions. Table 13 summarizes the responses for three such hypothetical scenarios: (i) working 10% more hours than the current job, (ii) doubling the daily commute time, and (iii) relocating to a different area. The patterns reveal a clear gender gap. Women are significantly less likely than men to accept a job offer at their reservation wage if it comes with a longer workweek, a longer commute, or relocation. For example, 57% of women would accept a job at their reservation wage that requires 10% more hours, compared to 61% of men—an unconditional difference of –4 percentage points, which widens to –7 pp after controlling for worker characteristics (both differences are highly significant). Similarly, only 30% of women would accept a job that doubles their commute, versus 35% of men (a gap of –5 to –8 pp, depending on controls). Women are also less willing to relocate for a job. These findings underscore the importance of nonwage amenities like flexibility and commute length in women's job choices. Incorporating such amenities into job search models is likely essential for understanding gender differences in search behavior and outcomes.

Table 13: Acceptance rates of hypothetical job offer

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
Percent who would accept offer if required to:				
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 widely regarded as a key contributor to gender wage disparities, and are also closely linked to flexibility amenities. Weaker attachment to the labor market can affect wages through multiple channels, including slower human capital accumulation (Becker, 1964), statistical discrimination by employers (Phelps, 1972), signaling effects (Spence, 1978), loss of firm-specific capital (Mincer and Jovanovic, 1981), slower wage growth (Topel, 1991), and reduced bargaining power (Mortensen and

Pissarides, 1994). Women's labor force attachment tends to be weaker than men's, as documented by numerous studies (Light and Ureta, 1990; Light and Ureta, 1995; Waldfogel, 1998; Goldin, 2006; Manning and Petrongolo, 2008; Blau and Kahn, 2013; Kleven et al., 2019) In the context of job search, weaker attachment often manifests in preferences for part-time work or more frequent career breaks, which in turn can influence the types of jobs women search for and accept.

Using the JSS data, I examine two indicators of labor force attachment: (1) whether job seekers restrict their search to part-time or supplemental jobs, and (2) the length and reasons for recent nonemployment spells. Table 14 focuses on the first indicator, conditional on active job search. Panel A reports the share of actively searching individuals who are looking only for part-time work or an additional job (as opposed to full-time primary employment). Panel B reports the reasons these individuals give for preferring part-time hours. The gender differences are striking. About 25% of women job seekers limit their search to part-time opportunities, compared to only 15% of men.

Conversely, women are more likely to be searching for an additional job – 23% of male job seekers versus 35% of female job seekers are searching for an additional job, indicating women's search is more often focused exclusively on part-time roles. The reasons for seeking part-time work also differ by gender. Men who seek part-time jobs overwhelmingly cite "just want additional income" as their motivation (about 50% list this as the reason), whereas women are far more likely to cite child care constraints: 12% of women (versus only 1% of men) report "child care availability" as their primary reason for preferring part-time work. These patterns suggest that family responsibilities weigh more heavily on women's job preferences.

Table 14: Reasons for only seeking part-time work

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
Panel A. Percent who searched for:				
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)
Panel B. Reasons for seeking part-time work (percent):				
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.

Another indicator of labor force attachment is the amount of time individuals spend out of employment. Even among prime-age workers, women tend to have longer nonemployment spells. In the JSS data, prime-aged women report being without a job for an average of 13 months over the last five years, compared to 8 months for prime-aged men. Table 15 provides a detailed breakdown of the reasons for time spent without a job, along with the average number of months attributable to each reason, by gender. There are large gender differences tied to family responsibilities. Women spend 5 of those months out of work due to family obligations, on average, whereas men spend only 1 month on family-related career breaks. Consequently, family-related nonemployment accounts for a substantial portion of women's time out of the labor force but is a minor factor for men. Women also report slightly more time out for "other" non-market reasons (1.7 months vs. 1.1 for men). By contrast, men tend to spend marginally more time out of work for reasons such as education: men report about 1.1 months out due to enrolling in school, versus 1.0 months for women (a small but statistically significant difference in favor of men). Both genders spend a similar amount of time actively looking for work while unemployed (around 2.5–2.8 months) and time out due to retirement or disability (around 6 months). Overall, Table 15 highlights that women's weaker labor force attachment is closely linked to family-related career interruptions, whereas men's nonemployment spells are less driven by home responsibilities.

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

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
Reasons for not having a job in last 5 years (months):				
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.

In summary, women exhibit lower labor force attachment than men: they more often seek part-time roles and have longer nonemployment spells, largely due to family responsibilities. These gender differences in labor force attachment suggest that flexibility and other nonwage amenities are especially salient to female workers. Next, I examine how one major factor—childbearing and child care—contributes to these patterns.

5.2 Role of children in the search process

The evidence above indicates that nonwage job attributes (especially those related to flexibility and work–family balance) are more salient for women. A natural question is how parenthood influences women's job search behavior and preferences. In this subsection, I compare the search efforts of women with children to those without children, shedding light on the mechanisms behind women's higher demand for flexibility.

I first analyze the extensive margin of search behavior for these two groups. Table 16 shows the proportions of employed women who are actively searching for a job, separately for mothers and non-mothers. Women with children are about 5 percentage points more likely to be actively searching for new jobs than women without children. For instance, 24.9% of women with children reported actively searching in the last week, compared to 19.9% of women without children. A similar gap appears for search activity in the last four weeks (28.5% vs. 23.9%) and in the likelihood of having submitted an application in the last month (25.5% vs. 20.7%). These differences are statistically significant. Even after controlling for other characteristics, mothers remain roughly 5 pp more likely to engage in job search.

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
Percent who:				
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

Next, Table 17 examines the intensive margin of search—how much time and effort job seekers devote to searching—by motherhood status. Employed mothers not only search more frequently, they also search more intensively when they do search. Women with children spend about 55% more hours per week on job search than women without children (1.8 hours vs. 1.2 hours, a difference of 0.63 hours that is significant at the 5% level with controls). They also submit nearly twice as many job applications over a four-week period on average. Mothers sent about 2.2 applications in the past month compared to 1.3 applications for non-mothers. Even focusing only on applications for a *new* primary job (excluding those for an additional job), mothers sent roughly 2.0 applications vs. 0.9 for non-mothers. These gaps (approximately 0.8–1.0 additional applications) are statistically significant. The higher search intensity among women with children aligns with the idea that they have a stronger motivation to find jobs that fit their scheduling and flexibility needs. In particular, mothers may be actively seeking employers who offer better work–life balance policies, shorter commutes, or other amenities that help reconcile work and family responsibilities.

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

	No kids	Kids	Coefficient on children indicator from separate OLS regressions	
			Difference	Difference
Number of:				
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

The above results indicate that women with household children both participate more in job search and put in greater effort, suggesting they may be less deterred by high current wages if nonwage considerations are at stake. To probe this, I estimate the search–wage elasticity separately for women with and without household children. The regression specification is analogous to that in Table 12, but now the sample is split by child status (and includes a child-interaction test in Panel C). Table 18 shows the outcomes. For women without household children, the search effort elasticity with respect to the current wage is about –0.72 (column 3 of Panel A), which is only slightly less elastic than the figure for men (–0.78). In contrast, women with household children exhibit an elasticity that is effectively zero and statistically insignificant: across specifications in Panel B, the wage coefficient is close to 0 (e.g., –0.02 in column 2, not significant). In the fully controlled model (column 4), the point estimate for mothers is actually positive (0.14) though insignificant, implying virtually no decline in search effort as wages rise. The difference between mothers and non-mothers is confirmed in Panel C: the interaction term is positive and statistically significant. These results strongly support the view that women with household children value nonwage amenities so highly that their search effort is decoupled from wages. Unlike other workers, higher pay alone does not discourage mothers from continued job search—presumably because they are searching for jobs that better meet their nonwage needs rather than simply higher wages.

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

	Search effort$_{ist}$ = Number of applications			
Panel A. No children				
Log current wage	–0.89***	–0.77***	–0.72***	–0.76***
	(0.23)	(0.21)	(0.20)	(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
Panel B. Children				
Log current wage	–0.45*	–0.02	0.01	0.14
	(0.25)	(0.26)	(0.26)	(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
Panel C. Statistical difference				
Children × Log current wage	0.44	0.50*	0.51*	0.65**
	(0.30)	(0.28)	(0.28)	(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

To further assess the importance of nonwage amenities for different groups, I examine self-reported job satisfaction with nonwage aspects of the current job. The JSS asks employed respondents: "How satisfied are you with other aspects of the job, such as benefits, maternity/paternity leave, flexibility in work hours, etc.?" on a Likert scale. The idea is that if nonwage features are a key driver for certain workers, their satisfaction with those features might be less tied to their wage level.

Figure 1 provides a graphical summary, plotting satisfaction with nonwage amenities against the current log wage for three groups: men, women without children, and women with children. Each plot is a binned scatter (averaging satisfaction within small wage bins). A clear pattern emerges: for men and for childless women, satisfaction with nonwage job aspects is positively correlated with the wage. In other words, higher-paying jobs tend to also offer better nonwage amenities (or otherwise leave workers more satisfied with those amenities). However, for women with children, the relationship is almost flat – their satisfaction with nonwage aspects remains low on average and does not improve with higher wages. This suggests that many mothers, even those in relatively high-paying jobs, may still perceive their jobs as lacking in desirable amenities (such as flexibility or adequate leave policies). A formal regression analysis confirms this pattern: in Appendix Table 35, the coefficient on log wage for predicting amenity satisfaction is near zero and statistically insignificant for women with young children, whereas it is positive and significant for other groups.

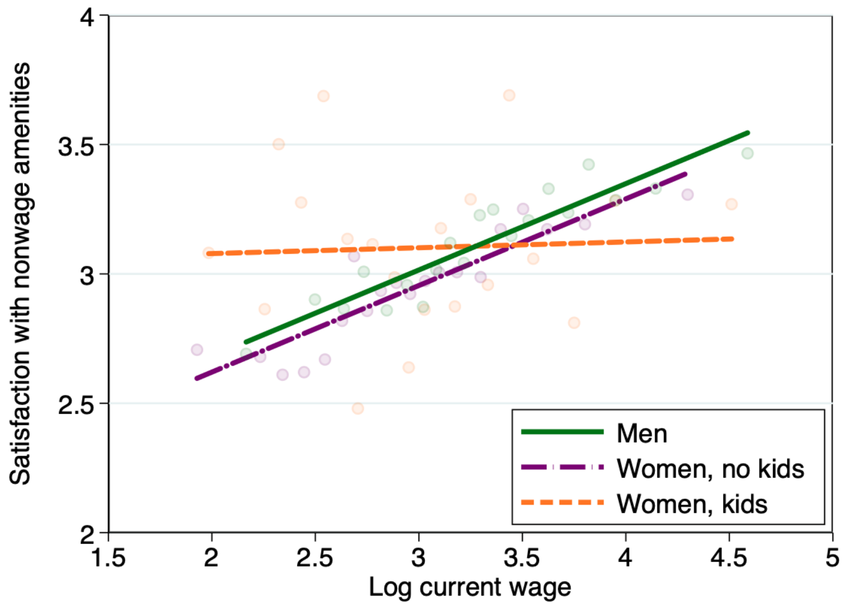

Figure 1: Current wage versus satisfaction with nonwage amenities

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.

The influence of household children is further evident when looking at women's willingness to accept jobs lacking in amenities. Table 19 mirrors the earlier Table 13 but focuses on women with vs. without household children. It reports the fraction of women who would accept a job at their reservation wage if it required more hours, a longer commute, or relocation. Women with household children are less willing to accept jobs with these nonwage drawbacks. For instance, 55% of women with children would accept an offer requiring a 10% increase in work hours, compared to 60% of childless women (a gap of –4.8 pp, which grows to –7.1 pp with controls, significant at 5%). Similarly, only 28.6% would accept a job that doubles their commute, versus 33.0% (–4.4 pp unadjusted, –5.0 pp with controls). Relocation is the least appealing condition for all, but especially for those with children: only 14.7% would relocate for a job at their reservation wage, compared to 20.6% of women without children (a significant –6 pp gap). These differences highlight that women with caregiving responsibilities place an even higher premium on flexible or convenient job conditions. In short, having children intensifies the importance of nonwage amenities in a woman's job decision calculus.

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
Percent who would accept offer if required to:				
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

Finally, Table 20 connects job search behavior back to job satisfaction with amenities. It shows the proportion of men and women who are actively searching or have recently applied for jobs, broken down by their reported satisfaction with their current job's nonwage amenities. Not surprisingly, workers who are dissatisfied with their job's amenities are much more likely to be job searching. Among those who are "very satisfied" with their nonwage conditions, only about 16% of women (and 11% of men) actively searched in the last week. By contrast, among those "not satisfied" (dissatisfied) with their job's amenities, 41% of women and 34% of men were actively job hunting. The gradient is monotonic – as satisfaction increases, the incidence of search falls – and it is present for both genders. Notably, at every satisfaction level, women have higher search rates than men, consistent with our earlier findings. The gender gap in search is particularly pronounced among workers who are already unhappy with their job's amenities (e.g., a 7 pp gap in the "not satisfied" group for active search). This suggests that poor nonwage conditions spur job search for everyone, but especially for women. In other words, women respond to unfavorable job amenities with an even greater propensity to search for a new job. This behavioral difference may further contribute to women's higher overall search rates observed in the data.

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)

The evidence in this section demonstrates that gender differences in preferences for job amenities are pronounced. Women, and especially those with household children, place greater importance on flexible working conditions, shorter commutes, and accommodating leave policies. These preferences manifest in higher search intensities and a lower sensitivity of search effort to wage, as well as in lower willingness to accept jobs lacking in such amenities. Men, in contrast, align their search behavior more closely with wage gains. These differences mean that women's job search outcomes (e.g., the types of offers they accept) diverge systematically from men's, even before considering employer-side behaviors. In the next section, I incorporate these gender-specific preferences and constraints into a structural job ladder model. The model will allow us to quantify the contribution of amenity valuations (versus other factors) to the gender wage gap and other labor market outcomes.

6 Model

In this section, I develop a partial-equilibrium on-the-job search model with endogenous search effort, building on previous job ladder models (Christensen et al., 2005; Hornstein et al., 2011; Bagger and Lentz, 2019; Faberman et al., 2022). The framework builds on standard job ladder models and extends them in several key ways to reflect the empirical findings in this paper. In particular, the model incorporates three new features in relation to Faberman et al. (2022).

First, I introduce amenities such that jobs are heterogeneous in both wage and nonwage amenity value, and workers derive utility from both components (not just wages). Second, I allow search technology reflected in search costs and the job offer arrival process to differ by gender and by employment status. Third, the model includes career interruptions due to parental leave and allows the value workers place on job amenities to change after having a child.

Men and women can differ in the model along several dimensions. In particular, I allow gender-specific differences in: preference for amenities, search costs, job separation rates, and job offer arrival rates. Additionally, two key parameters can change when a worker has a child compared to before having children: weight on nonwage amenities, value of nonemployment.

The primary goal of the structural model is to quantify the contribution of these gender differences to the gender wage gap. To that end, in the quantitative exercises we will perform counterfactual experiments that equalize certain parameters between men and women and measure the impact on outcomes. In particular, I examine the effects of equalizing: (i) search costs, (ii) the weight on non-wage amenities, and (iii) job attachment. By comparing these counterfactual scenarios, I can decompose the gender wage gap into components attributable to each source of difference.

6.1 Environment

The economy is populated by a unit mass of workers. Time is continuous, and all agents discount future payoffs at rate r per unit time. Workers are of two genders $g \in \{M, F\}$ (male or female), and each worker has a child status $c \in \{0, 1\}$ indicating whether they have at least one child (1) or not (0). At any point in time, a worker is either employed ($e = E$) or unemployed ($e = U$). I later consider a temporary parental leave state.

Job matches are subject to exogenous separation shocks: an employed worker of gender g loses her job at rate δ_g. I allow $\delta_F \neq \delta_M$ so that job attachment can differ by gender. Unemployed workers get a flow payoff $b_{g,c}$ while non-employed.

In addition to the usual employed and unemployed states, workers can enter a parental leave state after the birth of a child. Specifically, workers (employed or unemployed) experience an exogenous child arrival shock at rate δ^c. When this shock occurs, the worker's child status switches from $c = 0$ to $c = 1$ permanently. Following the child arrival, the worker goes into a parental leave spell: if the worker was employed, they temporarily leave their job (but remain attached to it while on leave), and if they were unemployed, they takes a leave from job search. I assume no job search takes place during the parental leave period.

To keep the population composition steady, I assume an outflow of workers from the labor force at rate δ^r, balanced by an inflow of new childless entrants at the same rate. In particular, each worker who permanently exits the labor force is replaced by a new young worker (with $c = 0$) entering unemployment, so that the total mass of workers (and the fraction with $c = 1$ versus $c = 0$) remains constant in steady state. Below I derive the value functions for each state in turn: employment, unemployment, and parental leave.

6.2 Employment

Job Utility Each job is characterized by two attributes: a wage w and a non-wage amenity value a. For example, a could represent job attributes such as a short commute, flexible hours, or other benefits. I assume the flow utility that a worker of gender g and child status c derives from a job (w, a) is given by a linear function of (log) wage and the amenity:

$$u_{g,c}(w, a) = w_g + \eta_{g,c} a \tag{3}$$

where w_g represents the log wage component (which could potentially depend on g due to gender differences in offered wages) and $\eta_{g,c}$ is the weight placed on the amenity value. This specification implies that wages and amenity values enter utility additively and is consistent with formulations used in other studies that incorporate amenities into job choice (Hwang et al., 1998; Dey and Flinn, 2008; Bonhomme and Jolivet, 2009; Sullivan and To, 2014; Hall and Mueller, 2018; Wiswall and Zafar, 2018; Le Barbanchon et al., 2021; Maestas et al., 2023). Intuitively, $\eta_{g,c}$ measures how much the worker values job amenities relative to wages. For example, one might expect $\eta_{F,1} > \eta_{F,0}$ if women value flexibility more after having children.

On-the-Job Search Employed workers can search for better job opportunities while working. Let s denote the worker's search effort on the job, which entails a cost and influences the arrival rate of outside job offers. I assume the job offer arrival rate for an employed worker of gender g is a linear function of s:

$$\lambda_g^E(s) = \alpha_g^E + \beta_g^E s \tag{4}$$

where the intercept, α_g^e, reflects a baseline level of offers. This can be thought of as offers arising in the absence of any search effort, and in the data corresponds to the rate at which respondents receive unsolicited offers. The marginal increase in offer arrival rate per unit of search effort β_g^E is analogous to the rate of formal offers that individuals receive in response to their search effort. I allow both parameters to differ by gender reflecting the differing offer rates in Table 8 and the offer yields in Table 9. Similarly, if a worker is unemployed, their offer arrival rate is:

$$\lambda_g^U(s) = \alpha_g^U + \beta_g^U s \tag{5}$$

with possibly different parameters α_g^U, β_g^U for the unemployed state.

Search Cost Exerting search effort incurs a disutility cost. I assume an isoelastic search cost function commonly used in the literature (Christensen et al. (2005); Gomme and Lkhagvasuren (2015)):

$$c_g^e(s) = \kappa_g^e s^{1+(1/\gamma)} \tag{6}$$

where $e \in E, U$ indicates the employment status. The parameter $\gamma > 0$ is the elasticity of the search cost and $\kappa_g^e > 0$ is a scale parameter that can differ by gender and by employment status. This cost specification implies diminishing returns to effort: as s increases, the marginal cost $c_g'(s)$ rises with an elasticity $1/\gamma$. I calibrate κ_g^E and κ_g^U to match observed average search intensities for employed and unemployed workers, respectively.

State Transitions While employed, a worker faces several possible transitions: (a) with an endogenous rate determined by $\lambda_g^e(s)$, they may receive a new job offer; (b) with an exogenous job destruction rate δ_g, their job may be destroyed and they become unemployed; (c) with an exogenous child arrival rate δ_c, they may enter parental leave due to childbirth; and (d) with an exogenous exit rate δ_r, they may permanently leave the labor force. These transitions are captured in the Bellman equation for the value of employment.

Employed Worker's Value Function Let $V_{g,c}(u)$ be the present discounted utility or value for a worker of gender g and child status c who is employed in a job that yields flow utility $u = u_{g,c}(w, a)$. This value satisfies the following Hamilton-Jacobi-Bellman (HJB) equation:

$$rV_{g,c}(u) = \max_s \left\{ \begin{array}{l} u_{g,c} - c_g(s) + \lambda_g^E(s) \int_{u'} \max\left\{V_{g,c}(u') - V_{g,c}(u), 0\right\} dF(u') \\ +\delta_g \left[U_{g,c} - V_{g,c}(u)\right] + \delta^c \left[P^E(u) - V_{g,c}(u)\right] - \delta^r V_{g,c}(u) \end{array} \right\}, \tag{7}$$

where the maximization is over the worker's on-the-job search effort s. In this expression, $u_{g,c}$ is the current flow utility from the job (wage plus amenity value). $c_g^E(s)$ is the cost of search effort s while employed.

The term $\lambda_g^E(s) \int_{u'} \max\left\{V_{g,c}(u') - V_{g,c}(u), 0\right\} dF(u')$ is the expected gain from receiving better job offers. Here, $F(u')$ is the distribution of potential job utilities in the market, and the integral is taken over all offers u' that exceed the utility of the current job u (since the worker will only accept an offer if it yields higher utility than their current position).

The term $\delta_g \left[U_{g,c} - V_{g,c}(u)\right]$ is the expected loss from exogenous job separation. With rate δ_g, the job ends and the worker transitions to unemployment, obtaining value $U_{g,c}$.

This results in a drop in value equal to $V_{g,c}(u) - U_{g,c}$.

The term $\delta^c \left[P^E(u) - V_{g,c}(u)\right]$ represents the effect of a childbirth event. At rate δ^c, the worker has a child and enters parental leave. $P_g^E(u)$ is the value of being on leave while attached to a job that had utility u, so the difference $P_g^E(u) - V_{g,c}(u)$ is the change in the worker's value when moving from working to parental leave.

Lastly, the term $\delta^r V_{g,c}(u)$ represents the possibility of permanent exit from the labor force at rate δ^r. In that case, the worker drops out, and I interpret the resulting value as going to zero, so this term effectively subtracts $\delta^r V_{g,c}(u)$ from the flow value (acting similarly to an additional discount factor).

The employed worker chooses search effort s to maximize $V_{g,c}(u)$. The first-order condition (FOC) for optimal search effort equates the marginal cost of effort to the marginal benefit:

$$c'(s^*) = \lambda'(s^*) \int_{u' \geq u} \left[V_{g,c}(u') - V_{g,c}(u)\right] dF(u') \tag{8}$$

The cost of slightly increasing search effort (left-hand side) equals the expected gain of finding a better job (right-hand side). This condition implicitly defines the optimal effort $s^*(u)$ as a function of the current job's utility u: workers in lower-utility jobs have more to gain from search and will typically search harder (unless constrained by very high cost).

Offer Acceptance Decision Since all employed workers of a given type (g, c) use the same search technology and face the same offer distribution, it is optimal for an employed worker to accept any job offer that provides higher utility than their current job. This implies a simple reservation property: given current utility u, any offer u' such that $u' > u$ will be accepted. In the HJB equation above, I incorporate this by integrating over $u' \geq u$. If an offer u' is below u, the term $V_{g,c}(u') - V_{g,c}(u)$ is negative, and the max operator in the integral would yield zero net gain since the worker declines the offer.

6.3 Unemployment

Now consider a worker who is currently unemployed. Let $U_{g,c}$ denote the value of being unemployed for a worker of gender g and child status c. An unemployed worker receives the flow benefit $b_{g,c}$ (which could include unemployment insurance or the value of leisure) and can exert search effort s to find a job. The Bellman equation for unemployment is:

The value of unemployment is:

$$rU_{g,c} = \max_s \left\{ \begin{array}{l} b_{g,c} - c_g(s) + \lambda_g^U(s) \int_{u'} \max\left\{V_{g,c}(u') - U_{g,c}, 0\right\} dF(u') \\ +\delta^p \left(P^U - U_{g,c}\right) - \delta^r U_{g,c} \end{array} \right\}, \tag{9}$$

Most terms have analogous interpretations to the employed case. The worker gains flow utility $b_{g,c}$ while searching and pays search cost $c_g^U(s)$. Job offers arrive at rate $lambda_g^U(s)$. However, unemployed workers may not accept every offer. In general, there will be some reservation utility level $\phi_{g,c}$ such that the worker accepts an incoming job offer if and only if the job's utility u' exceeds $\phi_{g,c}$. Offers below $\phi_{g,c}$ are rejected because the worker prefers to remain unemployed and search for a better opportunity. I have represented this in the integral $\int_{u' \geq \phi_{g,c}} [V_{g,c}(u') - U_{g,c}] dF(u')$, which accounts only for offers above the reservation threshold. The threshold $\phi_{g,c}$ is determined endogenously by an indifference condition: at $u' = \phi_{g,c}$, the worker is indifferent between accepting and rejecting, so $V_{g,c}(\phi_{g,c}) = U_{g,c}$.

Additional terms in the unemployment value function include $\delta_c[P^U - U_{g,c}]$, which is the effect of a childbirth shock while unemployed (moving the worker into the parental leave state P^U, defined below), and $\delta^r U_{g,c}$ for the possibility of exiting the labor force. As with employed workers, the optimal search effort s for unemployed workers satisfies a first-order condition balancing cost and benefit:

$$c_g' (s^*) = \lambda_g' (s^*) \int_{u' \geq \phi} \left[V_{g,c} (u') - U_{g,c} \right] dF (u') \tag{10}$$

meaning the marginal cost of search equals the expected marginal benefit of securing an acceptable job. Unemployed workers with higher $b_{g,c}$ or lower arrival rates will tend to have a higher reservation threshold $\phi_{g,c}$, since the value of waiting is relatively higher.

6.4 Parental Leave

Finally, I consider the parental leave state that occurs after a worker has a child. I distinguish between two parental leave value functions, depending on whether the worker had a job at the time the child was born or not. $P_g^E(u)$ is the value of being on parental leave for a worker of gender g who entered leave from employment, where u is the utility of their job at the moment they went on leave. In this case, the worker remains formally attached to her job while on leave (with the option to return). P^U is the value of being on parental leave for a worker who entered leave from unemployment with no current job to return to.

I first describe $P_g^E(u)$. During parental leave from a job, the worker is temporarily not working and not actively searching for new jobs. However, I assume they enjoys some benefits from her employer and the government during this period. Let b_p denote the baseline flow utility while on leave. This could be, for example, the value of spending time with the newborn, and I normalize $b_p = 1$ for calibration. In addition, I assume the worker receives a fraction of the utility from her job during the leave. For instance, many workers receive partial wage replacements and continue to receive certain job-related benefits while on leave. I capture this by assuming that the worker on leave receives 60% of their job's utility flow, under both their pre-child and post-child preferences. Formally, if the job's utility was u before the child and would be $u_{g,c}$ after the child (noting that having a child may change the amenity weight $\eta_{g,c}$), I include terms $0.6, u$ and $0.6, u_{g,c}$ in the flow value. This is a simplification intended to approximate the idea that the worker retains a portion of her wage and benefits during leave.

While on leave from a job, the worker faces two possible transitions: they can return to their job at an exogenous rate $\lambda_{p,E}$ or they can lose the job and effectively become unemployed at rate $\lambda_{p,U}$. I treat these as Poisson transition rates. They also continues to face the small probability δ^r of leaving the labor force permanently. The value of being on leave from employment thus satisfies:

$$rP_g^E(u) = b^p + 0.6(u) + 0.6(u_{g,c}) + \lambda^{p,U}\left(U_{g,c} - P_g^E(u)\right) + \lambda^{p,E}\left(V_{g,c}(u) - P_g^E(u)\right) - \delta^r P \quad (11)$$

The worker receives the leave benefit b_p plus a partial continuation of their job's utility ($0.6, u + 0.6, u_{g,c}$ as discussed). With rate $\lambda_{p,U}$, they separate from their job during leave, in which case they transitions to the unemployment state with value $U_{g,c}$. With rate $\lambda_{p,E}$, they return to work at their previous job, resuming the value $V_{g,c}(u)$. Finally, at rate δ_r they may exit the labor force. I have assumed that no active job search is conducted during leave, so there is no choice of s in the P_g^E equation.

For a worker who was unemployed when the child was born, the parental leave value P^U is determined similarly. In that case, the worker on leave has no current employer, so they simply remain non-employed for the leave duration, receiving b_p each period. I assume that after an equivalent leave period, they will resume job search as an unemployed parent. Thus, λ_p governs the transition from P^U back to the $U_{g,c}$ state. Below is the HJB for P^U:

$$rP^U = b_p + \lambda_p(U_{g,c} - P^U) - \delta_r P^U \quad (12)$$

The key point is that parental leave temporarily suspends job search and work, after which the worker either returns to their pre-leave job (P^E case) or returns to unemployment (P^U case).

Overall, this model provides a structure to evaluate how gender differences in search behavior, preferences (amenity valuation), and job continuity (separation rates and leave behavior) can lead to different labor market outcomes for men and women. In the next section, I calibrate the model parameters to empirical moments and then perform counterfactual exercises to quantify the impact of each channel on the gender wage gap.

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 the model parameters to match key empirical moments from the Job Search Supplement (JSS) data (2013–2021). The calibration uses a mix of externally set parameters from the literature and internally determined parameters chosen to replicate observed gender gaps in search behavior and outcomes. Table 21 summarizes the externally fixed parameters. The annual discount rate is set to $r = 0.05$, consistent with a 5% interest rate. The elasticity of the search cost function is set to $\gamma \approx 1.2$, following the estimate in Christensen et al. (2005), implying a mildly convex (near-quadratic) search cost. I adopt the mean and dispersion of job offer attributes from Hall and Mueller (2018). The mean offered log wage is about 2.75 with a standard deviation of 0.24, and the mean offered amenity value is 0.31 (std. dev. 0.35), with a wage-amenity correlation of roughly 0.25. The annual probability of having a child is set to $\delta^c = 0.01$, matching U.S. vital statistics, and the exogenous labor force exit rate is $\delta^r = 0.02$, consistent with the average quit rate in JOLTS (BLS). I normalize the flow value of being on parental leave b_p to 1.0.

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

The remaining parameters are calibrated internally to exactly match 18 targeted moments (see Table 22 for parameter values and Table 23 for targets). I allow these parameters to differ by gender. In particular, the job offer arrival rate is gender- and employment-status specific. For each gender g and employment state $e \in U, E$, the offer arrival function is $\lambda_e^g(s) = \alpha_e^g + \beta_e^g, s$, where s denotes search effort. I calibrate α_e^g and β_e^g to match the observed rates of unsolicited offers (offers that arrive without application) and formal offers (offers per application) for men and women, in both unemployment and employment. The calibrated values imply that unemployed men have a higher baseline offer arrival rate than unemployed women (e.g. $\alpha_M^U = 0.045$ vs. $\alpha_F^U = 0.029$), consistent with men receiving more unsolicited offers, while the returns to search effort are similar for men and women when unemployed ($\beta_M^U \approx \beta_F^U \approx 0.06$). Among the employed, I calibrate a slightly higher intercept for women's offer arrival ($\alpha_F^E = 0.034$ vs. $\alpha_M^E = 0.031$) but a lower slope ($\beta_F^E = 0.009$ vs. 0.013), reflecting that employed women receive fewer offers per unit of search effort than men. I also calibrate gender-specific search cost parameters κ_e^g in the search cost function $c_e^g(s) = \kappa_e^g s^{1+1/\gamma}$. These are chosen to fit the average search intensity (number of applications sent) by gender. The estimates indicate that unemployed women have slightly higher search cost scaling than men ($\kappa_F^U = 0.039$ vs. $\kappa_M^U = 0.035$), and especially so for on-the-job search ($\kappa_F^E = 0.014$ vs. 0.005 for men). In other words, holding other factors constant, it is somewhat more costly for women to search while employed, which helps match the fact that employed women's search effort—though higher than men's—is not dramatically higher given their circumstances.

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

I further allow two preference parameters to differ by gender. First, the weight on non-wage amenities in job utility, η_g, is calibrated to be much larger for women than for men. The estimated value for women is $\eta_F = 1.000$, versus $\eta_M = 0.101$ for men. This stark difference reflects that women exhibit a stronger revealed preference for job amenities relative to wages, as evidenced by their higher likelihood of accepting lower-wage jobs that offer desirable amenities. Second, I allow the flow value of nonemployment b_g (utility when unemployed) to differ slightly. The calibrated b is roughly 1 for both genders ($b_M = 1.002$, $b_F = 1.010$), which yields reasonable reservation wage behavior and matches the observed gender difference in job acceptance rates. Finally, to capture gender differences in job continuity (labor force attachment), I calibrate women's exogenous job separation rate to be higher than men's. The model assigns $\delta_F = 0.038$ for women vs. $\delta_M = 0.030$ for men, meaning women are more likely to separate from jobs in any given period. This difference in δ helps the model reproduce women's lower steady-state unemployment rate (since women who lose jobs are more likely to exit the labor force or take parental leave rather than become unemployed) as well as gender differences in employment stability.

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

$$V(u) = \max_s \left\{ \frac{u - c(s) + \lambda^E(s) \int_{u' \geq u} V(u')\, dF(u') + \delta U + \delta^p P^E(u)}{r + \delta + \delta^r + \delta^p + \lambda^E(s)\bar{F}(u)} \right\} \tag{13}$$

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

$$c'(s^*) = \beta \int_{u' \geq u} V(u')\, dF(u') - \frac{\beta \bar{F}(u) \left[u - c(s^*) + \lambda^E(s^*) \int_{u' \geq u} V(u')\, dF(u') + \delta U + \delta^p P^E(u) \right]}{r + \delta + \delta^r + \delta^p + \lambda^E(s^*) \bar{F}(u)} \tag{14}$$

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

$$U = \max_s \left\{ \frac{b - c(s) + \lambda^U(s) \int_{u' \geq \phi} V(u')\, dF(u') + \delta^p P^U}{r + \delta^r + \delta^p + \lambda^U(s) \bar{F}(\phi)} \right\} \tag{15}$$

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

$$c'(s^*) = \beta \int_{u' \geq \phi} V(u')\, dF(u') - \frac{\beta \bar{F}(\phi) \left[b - c(s) + \lambda^U(s) \int_{u' \geq \phi} V(u')\, dF(u') + \delta^p P^U \right]}{r + \delta^r + \delta^p + \lambda^U(s) \bar{F}(\phi)} \tag{16}$$

I solve the model given these parameters by iterating on the first-order conditions for optimal search effort until convergence. The calibrated model fits the targeted moments closely (Table 23). In the data, unemployed women send about 8% more applications on average than unemployed men, and the model reproduces this gap (approximately 7.3 vs. 6.0 applications in the model for women and men, respectively, against 9.4 vs. 8.7 in the data). Employed workers search much less intensively, but here too women exhibit higher search effort than men; the model matches this pattern (women send $\tilde{1}.10$ applications while employed, versus 0.85 for men, closely aligning with the data). The gender gap in job-offer outcomes is also captured: unemployed men receive unsolicited offers at a slightly higher rate (5% vs. 4% per period in the data), and the model matches this difference (5% vs. 3%). Formal offer arrival rates per application are about equal by gender in both data and model when unemployed (around 0.11–0.12), and slightly higher for women among the employed (around 0.09 for women vs. 0.07 for men, in both data and model). The model exactly replicates the higher offer acceptance rate of unemployed women (45%) compared to men (28%), indicating that the calibrated female reservation strategy is more yielding, consistent with women's greater emphasis on amenities and slightly higher nonemployment value. Lastly, the steady-state unemployment rates produced by the model are 5.3% for men and 3.1% for women, matching the empirical moments. In sum, the calibrated model provides a good fit to these salient gender differences in job search behavior and outcomes, giving confidence to use it for counterfactual analysis.

Table 23: Targeted moments

	Men		Women	
	Data	Model	Data	Model
Panel A: Unemployed moments				
Search effort	8.70	6.02	9.38	7.31
Unsolicited offer rate	0.05	0.05	0.04	0.03
Formal offer rate	0.12	0.12	0.11	0.11
Acceptance rate	0.28	0.28	0.45	0.45
Panel B: Employed moments				
Search effort	0.85	0.85	1.17	1.10
Unsolicited offer rate	0.03	0.03	0.02	0.02
Formal offer rate	0.07	0.07	0.09	0.09
Panel C: Other moments				
Unemployment rate	0.053	0.053	0.031	0.031
Search-wage elasticity	–0.58	–0.62	–0.22	–0.20

7.2 Calibration

With the model in hand, I conduct a series of counterfactual simulations to quantify the contribution of each gender-specific difference to the overall gender wage gap. The raw gender gap in average current wages is about 0.250 in log points (approximately a 25% gap). I ask how this gap changes when eliminating one difference at a time between men and women. In each counterfactual, I set a particular set of female parameters equal to the male values, while keeping all other parameters as calibrated, and then resolve the model to obtain a new wage gap. I consider three such experiments, corresponding to equalizing: (i) search costs, (ii) job attachment, and (iii) preference for amenities.

Equalizing Search Costs In this counterfactual, I remove gender differences in the search cost function and job offer arrival rates. In practice, I set women's search cost parameters (κ^U, κ^E) equal to men's, and likewise set the female offer arrival parameters (α^U, β^U, α^E, β^E) to the male values. This counterfactual effectively gives women the same job search technology and cost structure as men. As a result, women in the simulation search and find jobs under the same efficiency as men do. I find that eliminating search frictions specific to women yields a modest improvement in women's relative wages. The gender wage gap falls by about 0.026 log points, which corresponds to roughly 10.4% of the original gap (Table 24). In other words, differences in search efficiency and cost between men and women account for about one-tenth of the wage gap.

Equalizing Job Attachment Next, I equalize gender differences in job attachment and labor force continuity. Here I set women's exogenous job separation rate equal to men's ($\delta_F = \delta_M$). This removes the higher turnover that women experience. With women now just as likely as men to remain in their jobs, the wage gap narrows further. I estimate that equalizing job attachment reduces the wage gap by about 0.035 log points (14.1% of the total gap). This reflects the intuition that lower job separation rates (and thus longer job tenure and continuous experience) help women accumulate better wage outcomes, closing a portion of the gap that was due to their higher probability of career interruptions.

Equalizing Amenity Preferences In the third counterfactual, I remove gender differences in preferences for nonwage amenities. I set the weight on amenities in women's utility equal to the men's value ($\eta_F = \eta_M$), thus making women no more amenity-oriented than men. Intuitively, this experiment asks how the wage gap would change if women were not willing to trade off wages for flexible hours, shorter commutes, or other amenities. This turns out to have the largest effect on the wage gap. When women value job amenities the same as men, they become more focused on wages in their job search and acceptance decisions, leading them to achieve higher wages on average. The counterfactual gender wage gap drops by approximately 0.047 log points, about 18.8% of the original gap. This suggests that nearly one-fifth of the wage disparity can be attributed to women's stronger preferences for amenities that often come at the cost of lower wages.

Table 24: Contribution to gender wage gap

	Gender wage gap	
	Logs	Percent of gap
Raw gap in current wage	0.250	
Reduction in gap with:		
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%

Table 24 summarizes the contribution of each channel to the gender wage gap. In total, the model-based decomposition indicates that the three factors above – search frictions, labor force attachment, and amenity preferences – can explain around 43% of the observed gender wage gap (10.4% + 14.1% + 18.8%). The remaining majority (roughly 57%) of the gap is not accounted for by these channels within the model. This unexplained portion could be due to other differences outside our model's scope, such as gender disparities in bargaining power or wage setting, differences in networking and job search methods, or unmodeled heterogeneity in skill and experience. Nevertheless, our quantitative exercise makes clear that gender differences in job search behavior and preferences are important: for example, the way that women disproportionately value nonwage job attributes has a quantitatively significant impact on aggregate wage inequality. The counterfactuals underscore that addressing gender gaps in search and job-finding processes – in addition to more traditionally studied factors – is important for understanding and ultimately reducing the gender wage gap.

8 Conclusion

This paper examines how gender differences in job search behavior contribute to observed labor market disparities between men and women. Using data from the SCE Job Search Supplement, I document significant gender differences in job search intensity, outcomes, and preferences, especially regarding nonwage amenities relating to flexibility. Empirically, women search more intensively than men but receive fewer offers per unit of effort, and their search behavior is more strongly influenced by nonwage considerations. To quantify these mechanisms, I develop and calibrate a structural on-the-job search model incorporating heterogeneity in wages and amenities, gender-specific search frictions, and endogenous effort choices. The calibrated model successfully replicates key empirical regularities, including women's higher valuation of job amenities and differential search intensities. Counterfactual exercises show that differences in amenity preferences alone explain nearly one-fifth of the gender wage gap. Moreover, gender-specific search frictions and job attachment patterns each account for approximately 10% to 14% of the observed wage disparity. Together, these search-related factors explain roughly 43% of the overall gender wage gap, highlighting the substantial role that differences in job search behavior play in shaping aggregate labor market outcomes.

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Appendix

Table 25: Reasons for searching

	Men			Women		
Percent who list:	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				
Panel A. Extensive: Actively searched, last 4 weeks					
Women	9.21***	7.50***	6.63***	4.52***	3.38**
	(1.46)	(1.42)	(1.44)	(1.30)	(1.34)
R-squared	0.012	0.042	0.049	0.210	0.219
Panel B. Extensive: Sent an application, last 4 weeks					
Women	9.34***	7.45***	6.67***	4.69***	3.76***
	(1.39)	(1.35)	(1.35)	(1.23)	(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
Panel A. Industry						
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
Panel B. Occupation						
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)
Percent who:						
Actively searched,	17.03	100.00	24.02	100.00	6.99***	0.00
last 4 weeks	(0.65)	(0.00)	(0.76)	(0.00)	(1.00)	(0.00)
Sent an application,	14.15	90.48	20.97	95.42	6.82***	4.94*
last 4 weeks	(0.61)	(2.45)	(0.73)	(1.45)	(0.94)	(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.

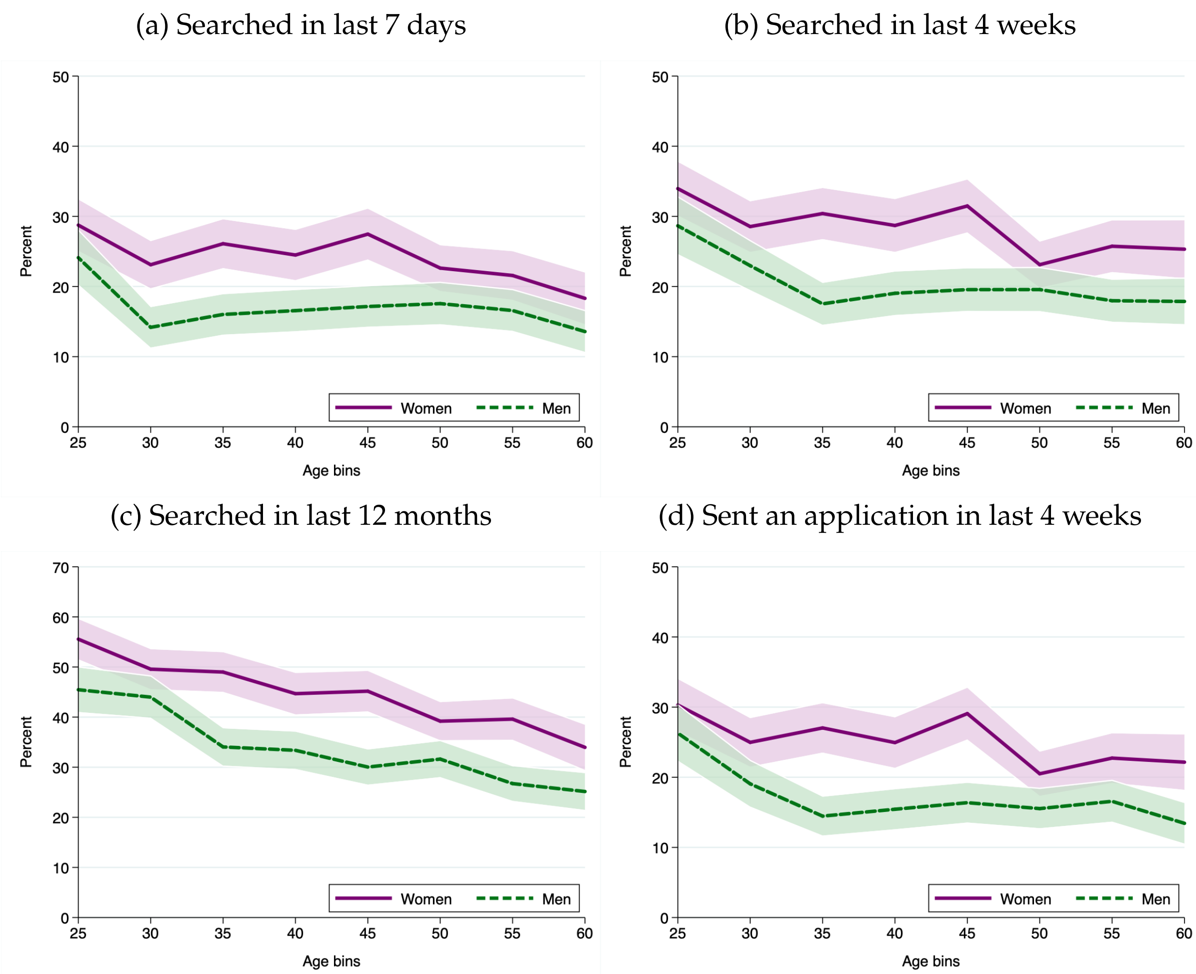
Figure 2: Extensive margin search over the lifecycle

(a) Searched in last 7 days

(b) Searched in last 4 weeks

(c) Searched in last 12 months

(d) Sent an application in last 4 weeks



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

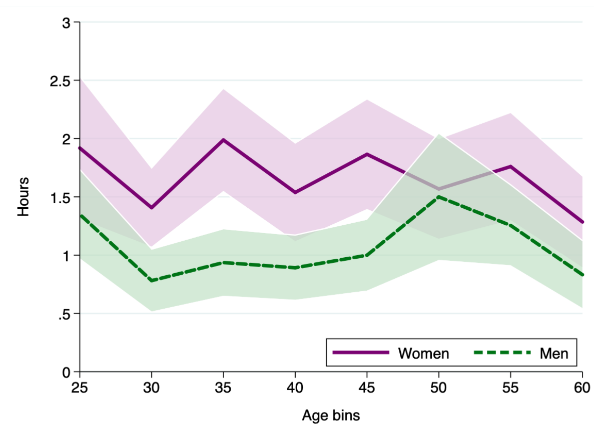
Table 29: Intensive margin search, different groups of controls

	Coefficient on women indicator from separate OLS regressions				
Panel A. Intensive: Number of applications sent, last 4 weeks					
Women	0.71***	0.54***	0.49***	0.26*	0.24
	(0.18)	(0.17)	(0.16)	(0.15)	(0.15)
R-squared	0.003	0.015	0.016	0.103	0.108
Panel B. Intensive: Number of applications for new job, last 4 weeks					
Women	0.60***	0.46***	0.43***	0.20	0.17
	(0.15)	(0.14)	(0.14)	(0.12)	(0.12)
R-squared	0.004	0.015	0.016	0.158	0.161
Panel C. Intensive: Hours spent searching, last 7 days					
Women	0.63***	0.50***	0.44***	0.19	0.16
	(0.18)	(0.16)	(0.17)	(0.15)	(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

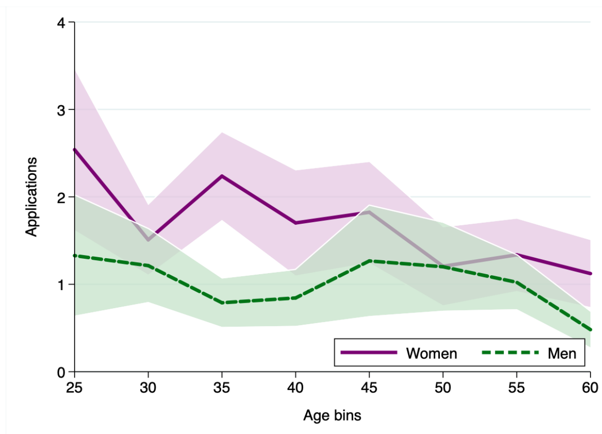
Source: October 2013–2021 waves of the SCE Job Search Supplement.

Figure 3: Intensive margin search over the lifecycle

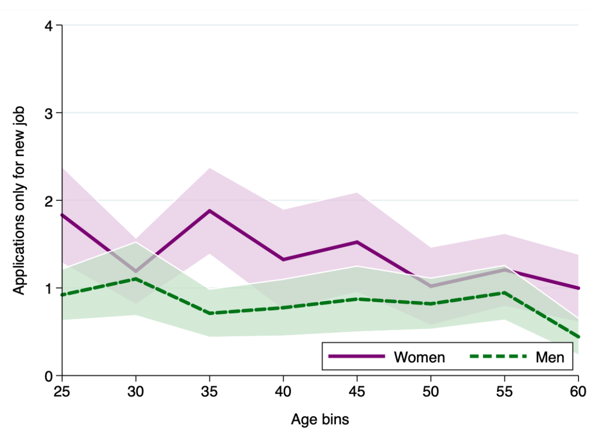
(a) Hours searching, last 7 days



(b) All applications, last 4 weeks



(c) Applications for a new job, last 4 weeks



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
Panel A. Industry						
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
Panel B. Occupation						
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***	0.02
					(0.11)	(1.29)
Applications sent, past 4 weeks	0.85	8.70	1.17	9.38	0.33**	0.68
					(0.15)	(1.61)
Applications for new job, past 4 weeks	0.59	8.00	0.80	9.38	0.21**	1.38
					(0.10)	(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

	Men	Women	Coefficient on women indicator from separate OLS regressions	
			Difference	Difference
Number of:				
Offers, last 4 weeks	0.25	0.29	0.04	0.00
			(0.04)	(0.03)
Offers, last 6 months	0.43	0.46	0.03	0.01
			(0.05)	(0.05)
Interviews, last 4 weeks	0.13	0.16	0.03	0.01
			(0.03)	(0.02)
Percent with:				
Formal offer	7.62	11.40	3.77***	1.41
			(1.04)	(0.98)
Unsolicited offer	2.58	2.36	–0.22	–0.29
			(0.52)	(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

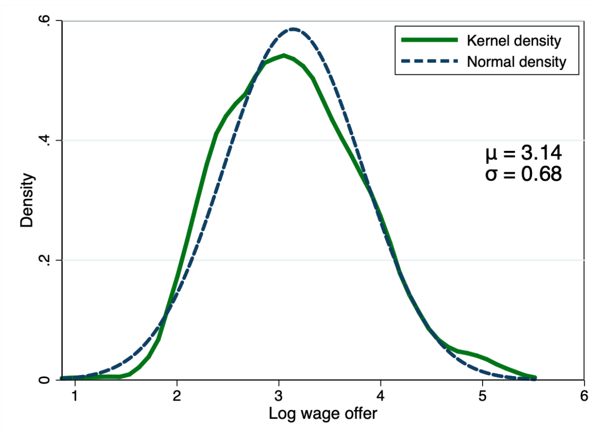
Table 33: Wage estimates

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

(a) Men



(b) Women

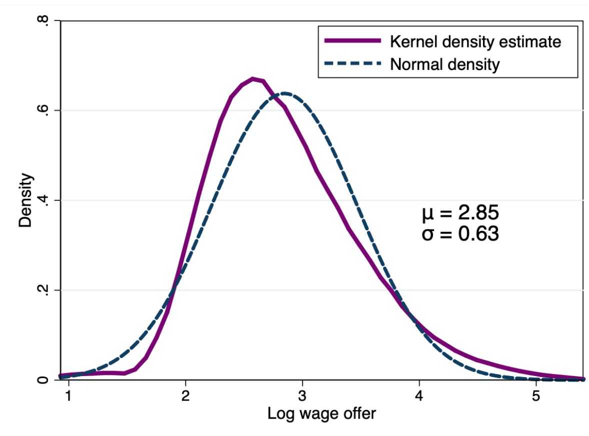
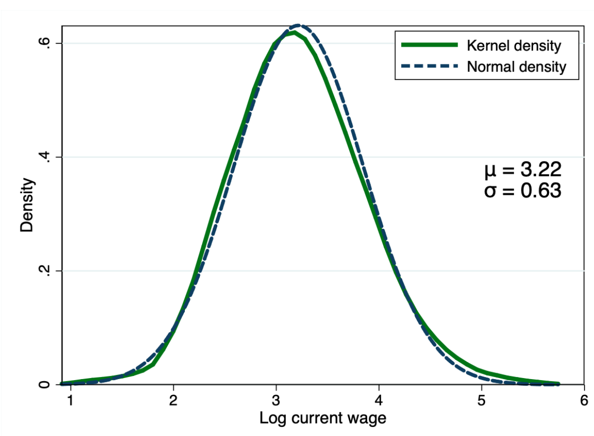


Figure 5: Kernel density of log current wage

(a) Men



(b) Women

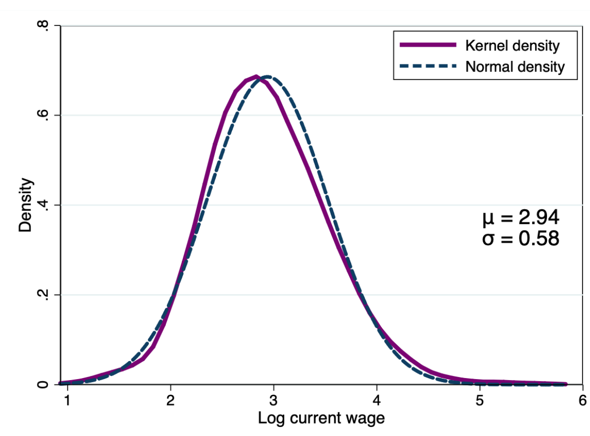
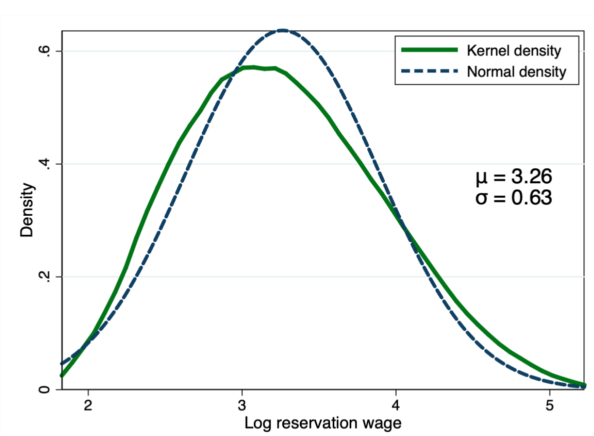


Figure 6: Kernel density of log reservation wage

(a) Men



(b) Women

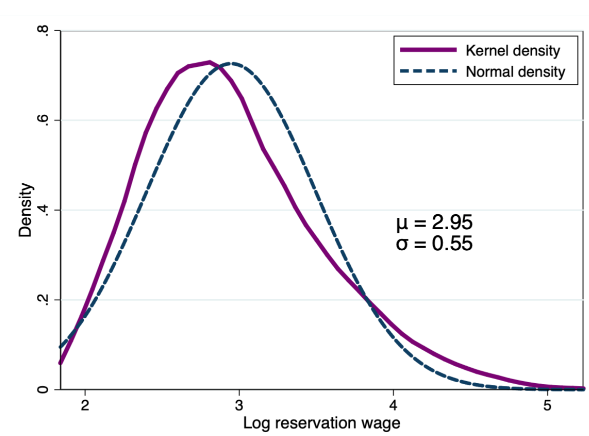


Table 34: Hours estimates

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

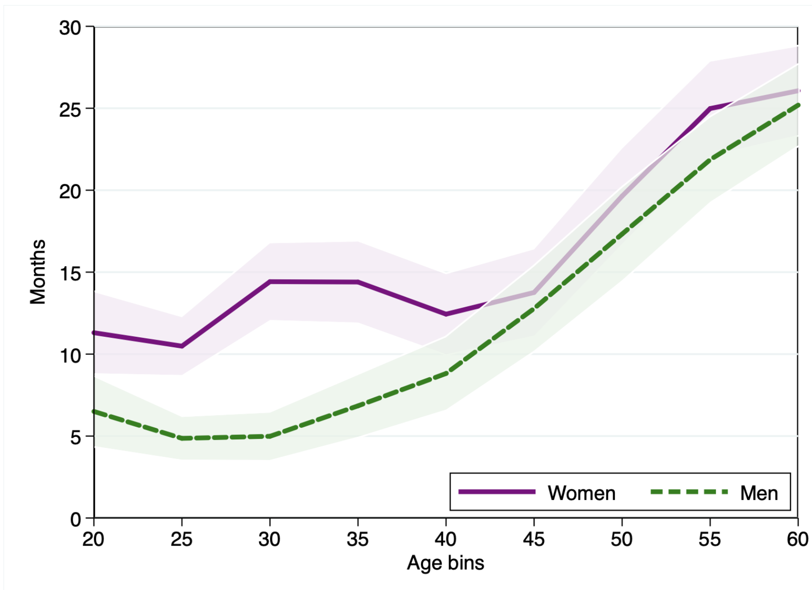
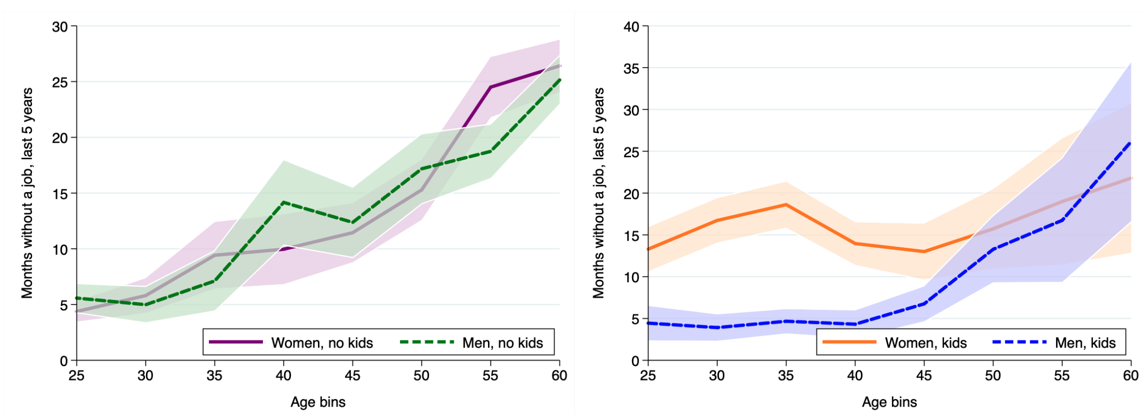


Figure 8: Months without a job in last 5 years, by presence of children

(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***	–0.002	–0.859***	–0.252
	(0.003)	(0.002)	(0.278)	(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

	No kids	Kids	Coefficient on children indicator from separate OLS regressions Pooled	Pooled
Percent who:				
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

	No kids	Kids	Coefficient on children indicator from separate OLS regressions Pooled	Pooled
Number of:				
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			
Panel A. No children				
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
Panel B. Children				
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
Panel C. Statistical difference				
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.