Macroeconomic Consequences of Gender Differences in Job Search

Corinne Stephenson*

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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

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

1 Introduction

Gender disparities in labor market outcomes are well-documented, but much less is known about gender differences in the process of job search 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 an empirical analysis of job search data with an equilibrium model of on-the-job search. In doing so, I bring 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 of the Survey of Consumer Expectations, 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 application or per hour. By my estimates, women are about 23% less effective at generating job offers from their search efforts compared to men.

Second, the jobs women that 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 than the wage of the best offers received by men. This is after controlling for a rich set of worker and job attributes. The best job offer to women also is about 7% fewer hours on average. The lower wages offered to women are not offset by greater nonwage compensation – if anything, the opposite is true: women's offers are significantly more likely to lack fringe benefits such as health insurance or retirement plans. These patterns indicate that women, relative to men, tend to end up with job offers that are lower-paying and more likely to be part-time or lacking benefits.

Additionally, women appear to navigate the job search process differently: they often obtain more offers through referrals whereas men more frequently receive unsolicited offers. Women are also less likely to negotiate their starting salaries when they do get an offer. Taken together, these facts paint a consistent picture in which women's greater search activity does not translate into equally improved job outcomes.

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 current job satisfaction, proxied by current wage, affects search intensity. According to standard job-ladder models, workers in lower-paying jobs search harder for new jobs than 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 men's current wage is associated with about a 0.78% decrease in his search effort, whereas 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.

Indeed, additional evidence shows that women will turn down job opportunities that pay their expected 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 or convenience for pay implies that many women place substantial weight on job attributes like flexibility in schedule, 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, 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 parenthood. I find that the presence of children 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 current wage is similar to men's (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), meaning that mothers exhibit almost no decline in search effort as their current wage increases.

In other words, a mother will continue searching for a potentially better-fitting job regardless of how much she currently earns, presumably because wage isn't the only factor in what she considers a "better" job. Correspondingly, women with 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, and especially mothers, 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 absent overt discrimination.

Building on the empirical evidence above, the second part of the paper develops a structural model to quantify the macroeconomic impact 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 the 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 fertility choice of children, which temporarily interrupt careers and permanently shift a worker's valuation of job amenities. These features ensure the model replicates the empirical patterns: women search more intensively than men, value amenities more, and mothers differ from non-mothers in 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.

Overall, this paper's contributions 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, by embedding them in an equilibrium search model. The findings bridge two 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—gendered valuation of nonwage 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 outcomes of the job search process and job offer characteristics. Section 5 presents evidence on nonwage amenity valuation. Section 6 introduces the job search model. Section 7 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

The primary dataset for this paper is 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 supplement to the SCE and is fielded annually in October. It provides detailed cross-sectional data on job search behavior and job preferences. 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 presently 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. In terms of demographic characteristics, the respondents in the JSS tend to be more White, married, and homeowners compared to the CPS. Given these demographic 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). 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).

The definition of a respondent's labor force status in the JSS is the same as in the CPS. Respondents are in the labor force if they satisfy one of the following three criteria: working for pay at the time of the survey; not working for pay at the time of the survey but actively searched for a job in the last four weeks and reported being available for work; on temporary layoff. The definition of active search is the same as in the BLS. This is whether the respondent used one of the BLS job search methods in the last four weeks or sent an application (BLS, 2024). However the definition of unemployment in the JSS is slightly broader than that in the CPS. In the CPS, respondent's are only asked about active search behavior if they first respond that they "want work." Meanwhile in the JSS, respondents are asked about job search regardless of whether they state that they "want work."

2.1 Data on job search behavior

Most labor market surveys focus exclusively on the job search behavior of those who report being unemployed and out of the labor force. The JSS is distinct in that it asks about the job search behavior and outcomes of all respondents, regardless of their labor force or employment status. Having data on job search behavior of employed workers is central to estimating the elasticity of search effort with respect to one's current wage. Estimating this elasticity differentially by gender will provide a target for the weight on nonwage amenities in the later structural part of the paper.

In the JSS, employed respondents are asked about the characteristics of their current job such as hours, earnings, type of benefits, industry, occupation, firm size, tenure, and unionization. They are also asked retrospective questions about the job search process that lead to their current job (method of job search, wage setting characteristics, number of applications sent, number of offers, starting wage), as well as the characteristics of their previous job, where applicable. For those who report not being employed, they are asked questions about the nature and duration of their nonemployment. The non-employed are also asked the same job characteristics as the employed, except as it pertains to their most recent job, if applicable.

Respondents who indicate that they searched for work or would be open to a new job are asked various questions about the nature of their job search. Respondents are asked about their job preferences in terms of full-time or part-time work, and reasons for such preference. In terms of job search activities, respondents are asked their reasons for searching, methods used to look for work, whether they are pursuing a new job or additional work, the number of job applications sent, and time allocated to search activities in the last seven days.

2.2 Data on job search outcomes

The JSS has rich information on respondents' job search outcomes, including the number of offers and interviews received in the last four weeks, as well as characteristics of the "best" job offer received. This includes industry, occupation, pay, hours, and benefits. The characteristics included for respondents' best offer mirror the characteristics asked about respondents' current job if employed, or most recent job if non-employed.

The survey includes questions about the method by which respondents' received their best offer. Respondents are asked whether they have or plan to accept or reject the offer, and the factors influencing the decision to accept or reject the offer, such as pay, benefits, etc. The survey also includes questions about the wage setting process of the best offer such as the degree to which respondents' knew the wage of the job, whether they bargained, and whether the employer provided a counter-offer. To have a measure of how many jobs are censored by respondents, the survey asks whether employers were willing to make an offer but the respondent indicated they were not interested.

2.3 Data on nonwage amenities

I adopt three approaches to measuring the importance of nonwage amenities by gender. First, I estimate the elasticity of search effort with respect to employed workers' current wage. The magnitude of the elasticity reveals the importance that men versus women place on their current wage – as opposed to nonwage amenities – in explaining their search efforts.

Second, I harness a series of questions in the survey in which one feature of a hypothetical job offer is altered. The survey elicits the reservation wages and reservation hours of all respondents who indicated that they searched in the last four weeks or would be open to a new job. Respondents are then asked whether they would accept a hypothetical job offer at their stated reservation wage if it required one of the following job disamenities: working 10% more hours, doubling one's daily commute, relocating to another city, or not being provided health insurance.

Respondents' sensitivity to such job disamenities is measured on both the extensive and intensive margin. The extensive margin reflects whether respondents would accept such a hypothetical job offer. The intensive margin is the percentage by which their current would have to increase in order to accept such a hypothetical offer. In this paper I focus on the three amenity features that relate directly to the flexibility of a job: work hours, commute time, and relocation. Third and lastly, the survey asks respondents about their satisfaction with "other aspects of the job, such as benefits, maternity/paternity leaves, flexibility in work hours, etc?" Taken together with reported satisfaction with their current wage, I am able to construct indifference curves relating such amenities to wages.

3 Job Search behavior and outcomes

This section examines gender differences in job search behavior and outcomes. Using the JSS data, I document three facts. The first fact is that women are more likely to engage in job search activities than men, and do so with greater intensity as reflected in the number of applications sent or hours spent searching. Men and women also differ in the job search method and wage setting protocol for the best offer they receive. Women are significantly more likely to receive their best offer via a referral while men are more likely to receive an unsolicited offer. In terms of the wage setting process, women are less likely to bargain and have a comparatively poorer idea of the job's pay before accepting an offer.

The second fact is that women and men receive a similar number of job offers per search input and the share with at least one offer is likewise similar. Combined with the first fact, this second fact implies that women's offer yields—defined as the ratio of search outputs to inputs—are consistently lower than men. The features of the best offer also differ. The wage of women's best job offer is 12% less than men's after residualizing for extensive controls. In terms of benefits, women's are less likely to have an offer with various fringe benefits such as healthcare provision, life insurance, etc.

The third fact is that women's job acceptance behavior is more sensitive to nonwage amenities relating to flexibility. Women are much less likely to accept a hypothetical offer if it entails a bad job amenity such as longer working hours, longer commute time, or relocating. The differential valuation on nonwage amenities is also reflected in the elasticity of search effort with respect to their current wage. The magnitude of this elasticity is statistically significantly smaller for women, indicating that they place less value on their wage in guiding their search process.

In the discussion of nonwage amenities, I highlight the role of household children as a mechanism explaining differences in search behavior and amenity valuation. Women with children search statistically significantly more than women without children. Moreover, the differential magnitudes for the elasticity of search effort with respect to the current wage is driven largely by the presence of household children. Women are much more likely to search only for part-time work or an additional job, and have spent time without a job in the last five years. The main reasons given for the weaker labor force attachment are childcare availability and family obligations.

By distinguishing between search behavior, offer yields, and preferences for nonwage amenities, this section provides a detailed empirical foundation for understanding the mechanisms underlying gender differences in job search outcomes.

3.1 Job search behavior

When asked the reason for searching, men and women are aligned in the top two reasons: dissatisfaction with current pay or benefits and dissatisfaction with current job duties (Appendix Table 20). The two reasons why men and women differ the most in their reason for searching are that men are more likely to indicate not using their skills as a reason, while women list a long commute distance. When focusing on the subsample of men and women with children in the household, women are more likely to report commute time and low quality of work life while men list looking for a change and improper use of skills. In the subsample of respondents without children, commute time remains an important reason for women, though, in general, men and women are much more aligned in their reasons for searching in the absence of household children.

3.1.1 Extensive and intensive margin search

Drawing on the JSS, I document differences in job search behavior between men and women. For four different measures of extensive margin search, Table 2 shows the percent of men and women who reported such search as well as the differences between the two. Women are more likely to have actively searched across all time horizons. Women search nearly eight percentage points more than men across all extensive margin measures, reflected in the first differences column that shows the raw means. The second differences column controls for demographic and worker controls, and state and year fixed effects. The differences between men and women are smaller in magnitude after including controls but remain statistically significantly different.

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	16.96	24.70	7.74*** (1.29)	3.51*** (1.20)
Actively searched, last 4 weeks	20.25	28.82	8.57*** (1.42)	2.68** (1.28)
Actively searched, last 12 months	33.60	45.52	11.91*** (1.58)	5.62*** (1.50)
Sent application(s), last 4 weeks	16.94	25.63	8.69*** (1.35)	2.89** (1.22)
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.

Appendix Table 21 focuses on the two main extensive search measures of interest: active search in the last four weeks and having sent an application in the last four weeks. Each column varies the type of controls included in the specification. I follow the approach from Blau and Kahn (2017) and augment each subsequent model. The choice of controls is not innocuous as many of these controls – such as marital status and occupation – are likely endogenous with respect to women's search and labor-force decisions.

Appendix Table 22 and Table 23 report summary statistics of extensive margin search by demographic groups and industry and occupation, respectively. Younger men and women, ages 25-34 search the most. This is also reflect in Appendix Figure 2, which plots the incidence of search over the lifecycle. Until around the age of 30, men and women do not differ in their incidence of search. The statistical differences between men and women in terms of search emerge between the ages of roughly 30 and 45.

In terms of education, men with at least a college degree search more relative to men with less education. For example 19% of men with at least a college degree search actively in the last four weeks compared to 15% with only a high school degree or less. The percentage point difference is the same focusing on those who sent an application – 16%

versus 12%. By contrast, there are no differences in likelihood of searching by education level for women. When focusing on race, Black respondents search more than Hispanic or white respondents. This is driven primarily by Black women, who search on average 25 percentage points more than white women and 8 percentage points more than Hispanic women. Lastly, married respondents are roughly seven percentage points less likely to engage in job search compared to non-married respondents.

Turning to the probability of searching by industry and occupation, Appendix Table 23 shows that the three industries in which respondents are most likely to search are: health care, hospitality, and information services. The two occupations with consistently the highest probability of searching are administration and sales.

Appendix Table 24 breaks down the differences by employment status. Most of the differences in job search are driven by those who are currently employed. By definition, there are no differences in the share of unemployed who searched in the last four weeks. While there are no statistical differences in job search for the unemployed, this is likely due to the small sample of unemployed in the dataset.

Not only are women more likely to search in terms of the extensive margin, but they also search more on the intensive margin. This is reflected in the number of applications sent in the last four weeks and the total hours spent searching in the last seven days. Table 3 shows that women send 1.7 applications on average in the last four weeks compared to 1.0 applications for men. When focusing on applications solely for a new job, women send 1.4 compared to 0.8 for men in the last four weeks. In the past seven days, women spent 1.7 hours on job search compared to 1.1 hours for men. These differences remain statistically significantly difference after including controls.

Table 3: Intensive margin of job search

	Men	Women	Coefficient on women indicator from separate OLS regressions 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.

The same demographic patterns in terms of which respondents are more likely to search also hold on the intensive margin, reflected in Appendix Table 26. For men, the groups of respondents that search the most intensely in terms of the number of applications sent or hours spent searching are: young, educated, and not married. Search differences by race are less pronounced for men. Meanwhile, for women, those who search the most are similarly young, black, and not married. Once again, the level of education does not factor as importantly for women compared to men.

3.1.2 Search methods and wage setting protocols

Beyond the probability of searching and number of search efforts, men and women also differ in the search method by which they receive their best job offer. Table 4 shows the following four methods constitute how over 90% of offers were received for both men and women: via referral, unsolicited, online search, and employer's website. Where women and men differ is that women are more likely to receive their best offer through a referral and less likely to receive an unsolicited offer.

Table 4: Search method for best offer

	Men	Women	Coefficient on women indicator from separate OLS regressions	
			Difference	Difference
Method of best offer (percent):				
Referral	32.99	40.43	7.44*** (2.76)	7.17** (3.59)
Unsolicited	27.69	16.49	–11.21*** (2.90)	–7.58*** (2.93)
Online search	17.66	17.80	0.15 (2.72)	–2.81 (2.73)
Employer's website	16.17	16.32	0.15 (1.90)	–1.70 (1.98)
Enquired with employer directly	8.33	7.46	–0.87 (1.97)	–1.22 (1.92)
Previously worked for employer	7.80	9.87	2.07 (2.56)	2.55 (2.24)
Employment agency	5.48	4.92	–0.56 (1.66)	–1.35 (1.60)
Union	0.92	0.47	–0.45 (0.42)	0.23 (0.52)
Other means	2.91	4.10	1.19 (1.49)	1.01 (1.65)
Observations	582	640	1,222	1,222
Workers controls			no	yes
State and year fixed effects			no	yes

The difference in referrals is surprising in light of research on the relative importance of social networks by gender. A common finding across these papers is that women tend to be disadvantaged through the use of referrals. Focusing on the U.S., in experimental work Mengel (2020) finds that men's networks display more homophily than women's. Meanwhile, Zeltzer (2020) finds that doctors refer patients more to specialists of their own gender. When focusing on the nature of the referral, I find no differences in being referred by a friend or current employee. However, women are more likely to be referred by a former colleague.

The difference in unsolicited offers is less surprising in the context of the existing literature on discrimination. A close line of research to understanding unsolicited offers is experimental research on audit studies (for a comprehensive review, see Bertrand and Duflo, 2017). These papers tend to find that women are not hired or called back in male-dominated professions as well as very skilled positions (Booth and Leigh, 2010; Petit, 2007; Neumark et al., 1996). This is consistent with my finding that women's best offer is 9% less likely to be an unsolicited offer, controlling for both offer occupation and industry.

Understanding if and how the wage setting mechanism differs by gender is central for structural modeling if the goal is to understand gender wage dynamics. Table 5 shows features of the wage setting process for respondent's best job offer. Over 55% of both men and women had a good idea of the pay for their best job offer. This is consistent with the canonical wage posting model of Burdett and Mortensen (1998). Nevertheless, a significant share appear to not have a good idea of the pay, and this also differs by gender with men knowing more than women. A large share of respondents' best offer entailed bargaining. The degree to which men and women bargain also differs. The share of women who bargain is 7% less than men and remains statistically significant after controlling for various demographic and worker characteristics. This is consistent with research that men are more likely to negotiate for a higher wage (Biasi and Sarsons, 2022; Leibbrandt and List, 2015; Babcock et al., 2003).

Table 5: 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	67.28	55.69	–11.59*** (3.56)	–10.54*** (3.73)
Bargaining involved	42.72	33.96	–8.75** (3.56)	–7.52** (3.59)
Counter-offer involved	13.63	12.26	–1.37 (2.47)	–0.68 (2.49)
Employer knew applicant's recent salary	34.35	35.73	1.38 (3.53)	2.47 (3.57)
Observations	582	640	1,222	1,222
Workers controls			no	yes
State and year fixed effects			no	yes

4 Job search outcomes

4.1 Number of job offers

Table 6 shows job search outcomes that entail beginning a new job, i.e., excluding additional work. Although women search more than men on both extensive and intensive margins, they receive a similar number of offers in the last four weeks. When comparing raw means, the share of women with a formal offer is statistically larger than for men. However, after including controls, the difference is no longer significant. The share of men with an unsolicited offer is larger than that for women, though the difference is not statistically significant. Appendix Table 29 shows outcomes that include additional work, and the results are similar. When including the possibility of additional work, there are two additional measures of outcomes: offers over a longer horizon of six months and number of interviews in the last four weeks. By these measures as well, men and women are similar.

Table 6: 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.

Table 7 reports four different measures of job offer yields, reflecting two measures of outputs (number of job offers and share with at least one offer) and two measures of inputs (applications sent and hours spent searching). The offer yield is constructed as follows:

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

where input i is either number of hours or applications, and output j is either number of offers or the share with at least one offer.

Women have a lower offer yield than men across all four measures. The differences are larger when considering the number of offers as the output. When considering the share with at least one offer, men and women are more alike. These two outputs — number of offers and share with at least one offer — correspond to capturing the intensive and extensive margins, respectively. It is important to consider both, as some might stop their job search after receiving an offer while others continue to search longer.

Table 7: 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 shown how men and women differ in their job search efforts and outcomes, I next focus on the attributes of respondents' "best offer." Table 8 shows the differences in offered wages and hours between men and women. Women's raw offered wage is 25% lower than men's and drops to 15% after controlling for demographics, job offer characteristics, and state and year fixed effects. When additionally controlling for the respondent's most recent wage—defined as the current wage if employed or last wage if unemployed—the difference in offered wages drops slightly to 12% and remains statistically significant.

The differences in offered hours follow a similar pattern, except that once controlling for most recent hours, there is no longer a significant gender difference.

Table 8: 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.

Appendix Table 30 presents corresponding raw and residualized estimates for four wage measures: previous, current, reservation, and accepted wages. The residualized differences across these measures are similar, with women earning about 16% less than men. The reservation wage gap is slightly smaller: women's reservation wage is 11% lower than men's. Appendix Table 31 presents the analogous estimates for hours. Differences in raw means are consistently around 12%, while residualized differences are approximately 7%.

Two differences between the wage and hour estimates are worth highlighting. First, the magnitude of wage differences—both raw and residualized—is larger than that of the hour differences, consistent with the idea that wage differences are more convex in hours.

Second, the residualized difference in reservation wages remains statistically significant after controlling for most recent wage, whereas the difference in reservation hours becomes statistically insignificant after controlling for most recent hours.

Across all wage measures, women's distributions are more skewed and exhibit greater excess kurtosis compared to those of men. Appendix Figure 4 shows the kernel density of log weekly offered wages overlaid with a normal distribution. Men's offer distribution has a skewness of 0.37 and excess kurtosis of -0.03, while women's has a skewness of 0.65 and excess kurtosis of 0.68. Appendix Figure 5 shows skewness of 0.24 and kurtosis of 0.31 for men's current wage distribution, and 0.42 and 0.91 for women's. Appendix Figure 6 reports skewness of 0.33 and kurtosis of -0.46 for men's reservation wages, and 0.77 and 0.37 for women's.

Although women consistently report lower wages than men, fringe benefits might act as a compensating differential. To examine this possibility, Table 9 provides an exhaustive list of the benefits included in respondents' best job offer. The theory of compensating differentials suggests that workers may accept lower wages in exchange for desirable non-wage job characteristics. According to the BLS, in 2024, benefits made up 31% of total employment costs (BLS, 2024). If women place greater value on fringe benefits, this could partially explain their lower wages.

Table 9 shows that, with the exception of childcare assistance, women are less likely to receive any of the listed fringe benefits. Moreover, women are 10% more likely to receive a job offer with no benefits at all—a statistically significant difference. If the table captured all relevant non-wage job attributes, these findings would contradict the predictions of compensating differential theory. Hodges (2020) finds similar patterns using different datasets. One possibility is that the types of non-pecuniary amenities women value most—such as hours flexibility, commute time, and location—are not included among standard fringe benefits. These harder-to-measure amenities are explored further in subsequent sections.

Table 9: Job offer fringe benefits

	Men	Women	Coefficient on women indicator from separate OLS regressions Difference	Difference
Benefits included in best offer (percent):				
Health insurance	60.83	48.30	–12.53*** (2.77)	–10.52*** (3.36)
Dental insurance	54.80	43.37	–11.43*** (2.78)	–9.15*** (3.36)
Retirement contribution	47.02	33.58	–13.44*** (2.71)	–11.16*** (3.23)
Life insurance	32.53	28.97	–3.56 (2.58)	–2.42 (3.10)
Flex. Spending Accounts	24.48	18.65	–5.83** (2.29)	–3.29 (2.58)
Pension plan	15.76	14.01	–1.75 (1.99)	–0.90 (2.37)
Stock options	13.78	7.50	–6.29*** (1.69)	–5.77*** (2.09)
Quality of life benefits	10.80	10.28	–0.52 (1.72)	–0.19 (1.78)
Commuter benefits	9.08	5.50	–3.58** (1.44)	–2.98** (1.45)
Childcare assistance	2.76	3.47	0.70 (0.98)	1.20 (1.11)
Housing subsidy	1.71	0.83	–0.88 (0.61)	–0.71 (0.70)
No benefits	33.67	45.27	11.60*** (2.73)	9.29*** (3.36)
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.

5 Nonwage amenities

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

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

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

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

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

Table 10: 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 smaller elasticity for women suggests that nonwage job attributes play a more important role in their search decisions. To investigate this, I use survey questions on reservation wages and sensitivity to various job features.

Table 11 reports the percentage of men and women who would accept a job offer at their stated reservation wage if it entailed specific changes to nonwage aspects of the job. Women are less likely than men to accept offers involving relocation, longer commutes, or increased hours. This highlights the importance of incorporating nonwage amenities into job search models.

Table 11: 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	60.52	56.55	–3.97*** (1.33)	–7.06*** (1.37)
Double daily commute	34.98	29.50	–5.48*** (1.26)	–7.55*** (1.29)
Relocate	17.97	14.67	–3.30*** (1.00)	–4.49*** (1.02)
Observations	2,681	2,817	5,498	5,498
Worker controls			no	yes
State and year fixed effects			no	yes

5.1 Labor force attachment

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

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

Conditional on active search, Table 12 shows (Panel A) the percentage of individuals who seek only part-time or additional work, and (Panel B) the stated reasons for preferring part-time work. About 25% of women search only for part-time work compared to 15% of men. Men are more likely to cite additional income as their reason; women more often cite childcare responsibilities.

Table 12: Reasons for only seeking part-time work

	Men	Women	Coefficient on women indicator from separate OLS regressions: Difference	Difference
Panel A. Percent who searched for:				
An additional job	23.44	34.84	11.40*** (2.53)	7.94*** (2.45)
Part-time work	14.84	24.73	9.88*** (2.23)	8.14*** (2.39)
Panel B. Reasons for seeking part-time work (percent):				
Just want additional income	49.88	40.30	–9.59*** (3.50)	–7.47** (3.55)
Hours flexibility	7.20	7.28	0.09 (1.76)	0.19 (1.81)
Limited retirement income	6.84	6.68	–0.17 (2.13)	0.95 (2.10)
Child care availability	1.22	11.98	10.76*** (1.67)	8.55*** (1.41)
Other	5.91	7.82	1.91 (1.85)	–0.43 (1.81)
Observations	573	793	1,366	1,366
Worker controls			no	yes
State and year fixed effects			no	yes

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

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

Table 13: 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	2.50	2.77	0.27 (0.21)	0.03 (0.22)
Disabled or retired	5.97	5.98	0.01 (0.50)	–0.66 (0.45)
Enrolled in school	1.07	1.03	–0.03 (0.16)	–0.41** (0.17)
Family obligations	1.00	4.07	3.07*** (0.31)	2.61*** (0.32)
Discouraged	0.37	0.38	0.01 (0.09)	–0.06 (0.10)
Other reasons	1.08	1.65	0.57** (0.22)	0.55** (0.24)
Observations	2,044	2,267	4,311	4,311
Worker controls			no	yes
State and year fixed effects			no	yes

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

5.2 Role of children in the search process

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

Table **??** shows extensive margins of search and Table 15 the intensive margin. Women with children are about five percentage points more likely to be actively searching. On the intensive margin, they spend 55% more time and submit nearly twice as many applications compared to women without children.

Table 14: Extensive margin of job search, women with and without children

	No children	Children	Coefficient on children indicator from separate OLS regressions	
			Pooled	Pooled
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) (2.46)
Observations	977	530	1,507	1,507
Worker controls			no	yes
State and year fixed effects			no	yes

Table 15: Intensive margin of job search, women with and without children

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

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

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

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

Table 16: 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, I use survey data on job satisfaction with nonwage attributes. The question asks: "And how satisfied would you say you are with other aspects of the job, such as benefits, maternity/paternity leave, flexibility in work hours, etc.?"

Figure 1 shows binscatters of current log wage against satisfaction with nonwage amenities. For men and women without children, satisfaction is positively correlated with wages. For women with children, however, the relationship is flat. Appendix Table 32 confirms this pattern in regression format: for women with children under six, the coefficient is near zero and not statistically significant.

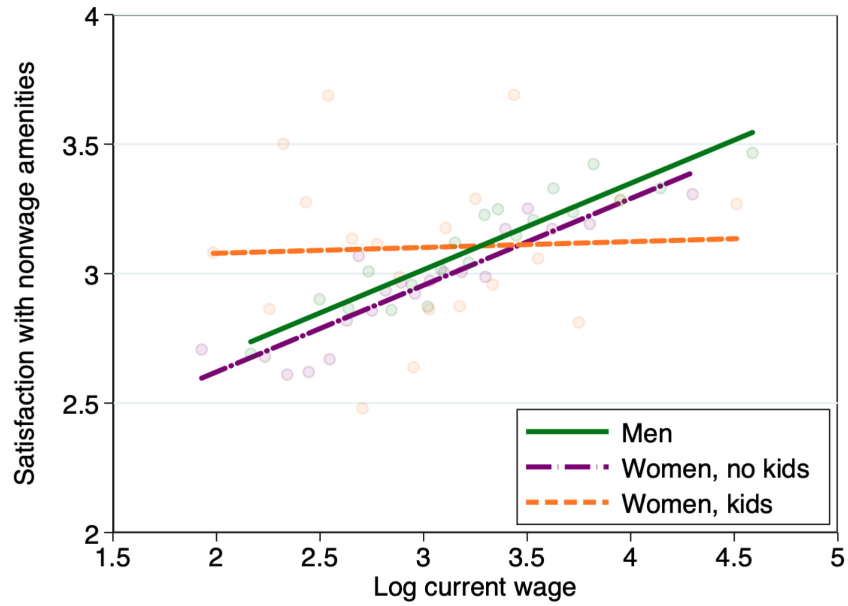

Figure 1: Current wage versus satisfaction with nonwage amenities

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

6 Model

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

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

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

6.1 Environment

The labor market is populated by unit mass of individuals. Time is continuous and the discount rate is r. Workers are female or male, denoted by gender status $g \in \{F, M\}$ and can have children or not, denoted by children status $c \in \{1, 0\}$. In addition, workers can either be employed or unemployed, denoted by employment status $e \in \{E, U\}$. Job matches are subject to exogenous separation shocks, δ_g. In addition to being employed or unemployed, individuals can also be on parental leave. Individuals enter parental leave either from employment or unemployment following an exogenous child shock, δ^c. Following the child shock, individuals' child status permanently changes from $c = 0$ to $c = 1$. To ensure that the population distribution of people with and without children remains balanced, workers permanently leave labor force and new workers enter at constant rates, δ^r. At the same rate, there is an inflow of new workers of each gender without children into unemployment. Below I describe the value functions in turn.

6.2 Employment

Workers receive utility $u_{g,c}(w, a) = w + \eta_{g,c} a$ from a job with wage w and amenity a. η is the weight placed on the nonwage amenity a. Workers choose search effort s that results in a job offer arrival rate $\lambda_g^e(s) = \alpha^e + \beta^e s$, where α_g^e is the rate of unsolicited offers and β_g^e is the rate of formal offers for a worker with employment status e. The cost to searching is $c_g^e(s) = \kappa_g^e s^{1+(1/\gamma)}$. Jobs are destroyed at rate δ_g. Workers have a child and enter parental leave at rate δ^c. Workers permanently leave the labor force at rate δ^r.

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

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

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

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

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

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

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

6.3 Unemployment

The value of unemployment is:

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

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

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

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

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

6.4 Parental Leave

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

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

7 Calibration

I calibrate my model to moments from the JSS for years 2013–2021 pooled together. Panel A of Table 17 lists the externally calibrated parameters and their source. I set the discount rate to match an annual interest rate of 5%. I set γ to equal 1, in other words to have a quadratic search cost. I set the exogenous child shock δ^c to the CDC birth rate and the labor force exit rate δ^r to the quit rate from the BLS. The flow value of parental leave b^p is normalized to one. In this version of the calibration I adopt the mean and dispersion of the wage and amenity offer from Hall and Mueller (2018). In the next iteration I plan to estimate the dispersion of amenities based on the acceptance function and difference between log reservation and offered wages.

Panel B of Table 17 lists the internally calibrated parameters and their calibration targets. There are 18 internally calibrated moments that were chosen to match the 18 moments in Table 18. The system is exactly identified.

Search technology in the model differs by gender and employment status. I assume a linear job offer arrival rate $\lambda_g^e(s) = \alpha^e + \beta^e s$, where the target for α_g^e is the rate of unsolicited offers and the target for β_g^e is the rate of formal offers.

I assume the same functional form for the cost of searching as in Christensen et al. (2005), Hornstein et al. (2011), and Faberman et al. (2022). This is: $c_g^e(s) = \kappa_g^e s^{1+(1/\gamma)}$. The cost of search differs by gender and employment status. κ_g^e is calibrated to match the average search effort in terms of number of applications sent.

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

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

Table 17: Calibrated parameter values

Symbol	Description	Value (M, W)	Source / Target
Panel A: Externally calibrated			
r	Discount rate	0.05	5% per year
γ	Elasticity of search cost	1.0	Quadratic search cost
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
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)
Panel B: Internally calibrated			
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
$\eta_{g,c}$	Weight on nonwage amenity	0.101, 1.000	Search-wage elasticity
b	Flow value of unemployment	1.002, 1.010	Acceptance rate of U
δ	Job separation rate	0.030, 0.038	Unemployment rate

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

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

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

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

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

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

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

Table 18: Targeted moments

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

The goal of the structural part of this paper is to conduct an accounting decomposition and quantify the different components of the gender wage gap. I carry out counterfactual exercises in which I equalize the following between men and women: equal search costs, equal job attachment, and equal weight on nonwage amenities. Table 19 shows the results. Of the three counterfactuals, I find that amenities play the largest role in explaining the wage differences. A significant part of the gender wage gap remains unexplained, however. This is likely due to aforementioned differences in the job search method and wage setting protocol such as bargaining.

Table 19: Contribution to gender wage gap

	Gender wage gap	
	Logs	Percent of gap
Raw gender gap in current wage	0.30	
Counterfactual		
Equal search costs	0.031	10.4%
Equal job attachment	0.042	14.1%
Equal weight on nonwage amenities	0.056	18.8%

8 Conclusion

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

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Appendix

Table 20: 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 21: 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 22: Extensive margin of search, by demographic characteristics

	Percent actively searched, last 4 weeks			Percent sent application, last 4 weeks		
	All	Men	Women	All	Men	Women
Panel A. Age groups						
25-34	26.36	24.73	27.65	23.31	21.76	24.54
35-44	21.80	17.56	25.77	18.64	14.38	22.62
45-54	20.72	17.88	23.74	17.92	14.61	21.45
55-64	14.72	12.20	17.57	12.52	10.39	14.92
Panel B. Education						
High school or less	20.20	15.55	24.48	17.54	12.83	21.88
Some college	19.43	16.59	21.96	17.35	14.23	20.14
College or more	21.52	19.48	23.87	18.09	16.46	19.95
Panel C. Race						
White	20.85	18.85	23.18	17.29	15.31	19.59
Black	40.16	24.73	47.42	37.27	19.96	45.40
Hispanic	32.30	25.13	38.23	31.26	24.28	37.03
Panel D. Marital status						
Not married	25.52	21.08	28.61	22.39	18.10	25.38
Married	17.72	15.86	19.91	15.16	13.23	17.44
Observations	7,769	3,913	3,856	7,769	3,913	3,856

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

Table 23: 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

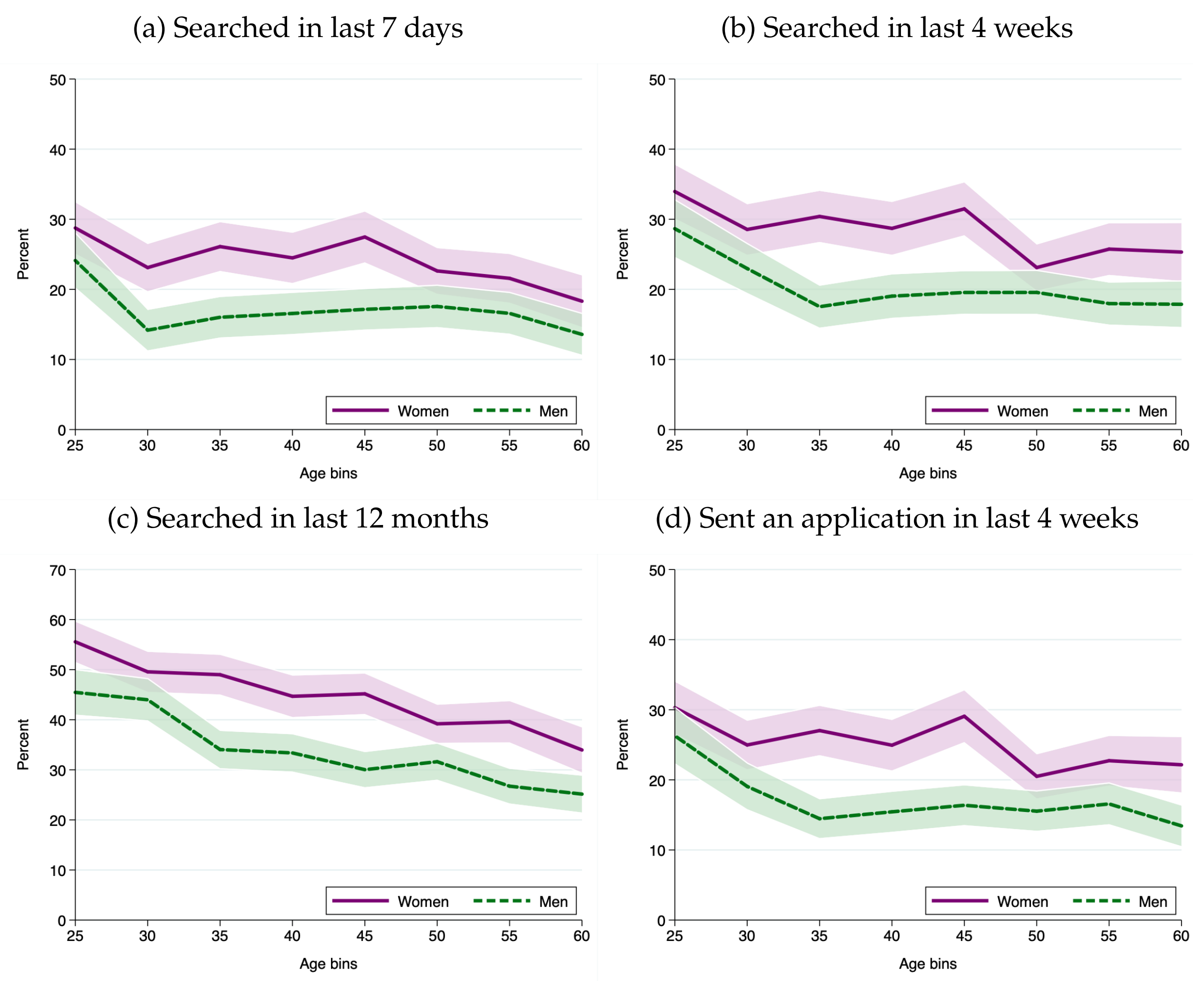
Source: October 2013–2021 waves of the SCE Job Search Supplement.

Table 24: 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 3 except broken down by employment status. Controls are not included. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *Source:* October 2013–2021 waves of the SCE Job Search Supplement.

Figure 2: Extensive margin search over the lifecycle



Notes: Figures show difference in measures of search incidence reported in Table 3 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

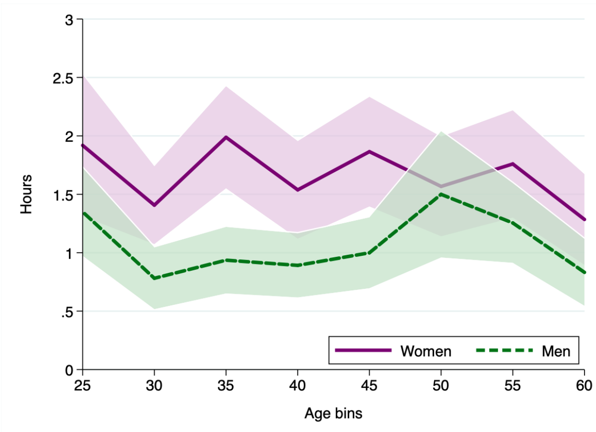
Table 25: Intensive margin search, different groups of controls

	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

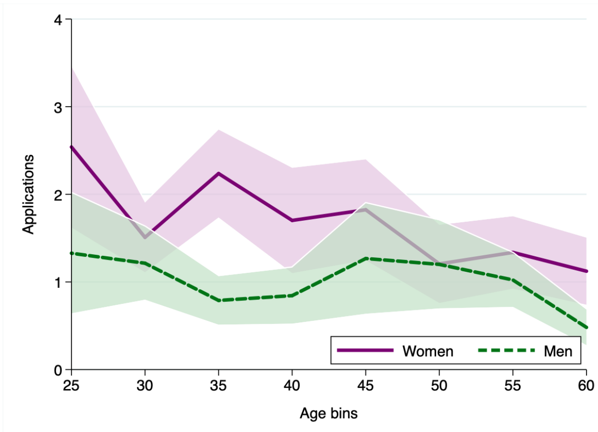
Source: October 2013–2021 waves of the SCE Job Search Supplement.

Figure 3: Intensive margin search over the lifecycle

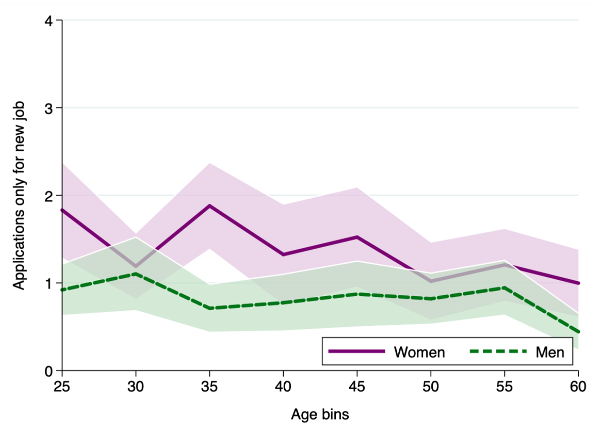
(a) Hours searching, last 7 days



(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 3 over the lifecycle. Confidence intervals are at the 90 percent level. *Source:* October 2013–2021 waves of the SCE Job Search Supplement.

Table 26: Intensive margin of search, by demographic characteristics

	Number of applications sent, last 4 weeks			Number of hours searching, last 7 days		
	All	Men	Women	All	Men	Women
Panel A. Age groups						
25-34	1.55	1.26	1.77	1.30	1.13	1.44
35-44	1.27	0.79	1.71	1.25	0.95	1.54
45-54	1.21	1.12	1.31	1.31	1.14	1.50
55-64	0.65	0.53	0.80	0.86	0.71	1.03
Panel B. Education						
High school or less	0.98	0.56	1.36	1.17	0.83	1.48
Some college	1.27	0.88	1.61	1.22	0.95	1.46
College or more	1.16	1.17	1.15	1.11	1.07	1.15
Panel C. Race						
White	0.83	0.77	0.90	0.88	0.87	0.88
Black	2.49	1.11	3.10	2.58	1.49	3.06
Hispanic	1.70	1.06	2.21	1.64	1.19	1.99
Panel D. Marital status						
Not married	1.45	0.97	1.78	1.58	1.29	1.79
Married	0.96	0.85	1.09	0.94	0.83	1.07
Observations	7,769	3,913	3,856	7,769	3,913	3,856

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

Table 27: 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 28: 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 29: 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 6 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 30: 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

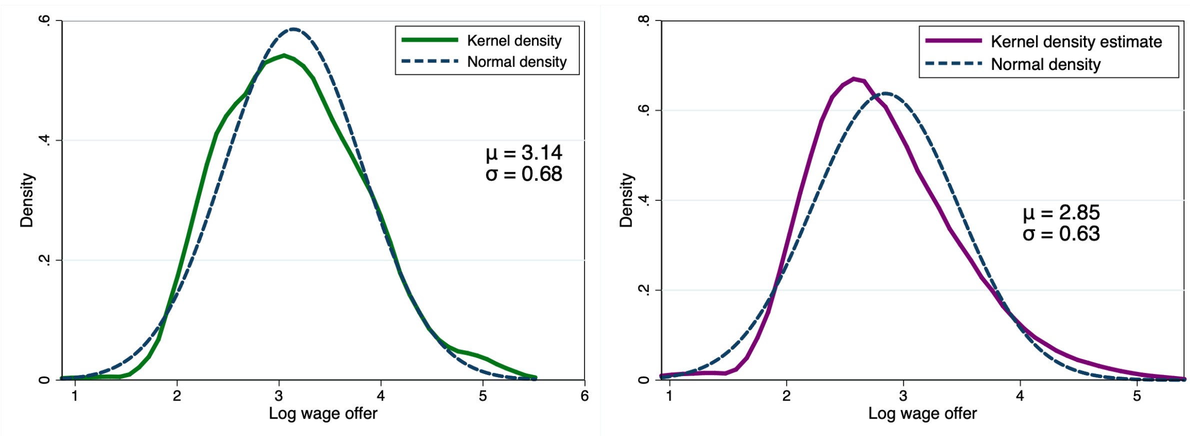


Figure 5: Kernel density of log current wage

(a) Men (b) Women

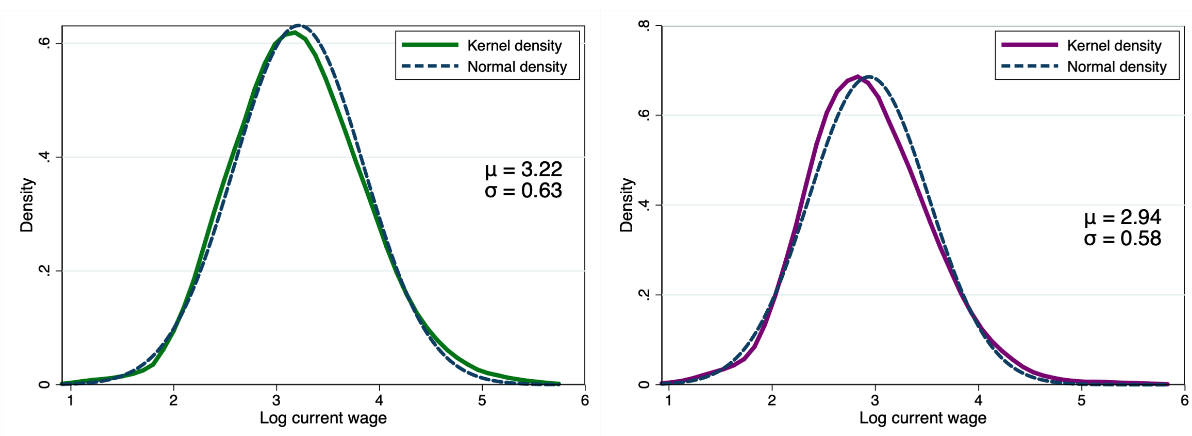


Figure 6: Kernel density of log reservation wage

(a) Men (b) Women

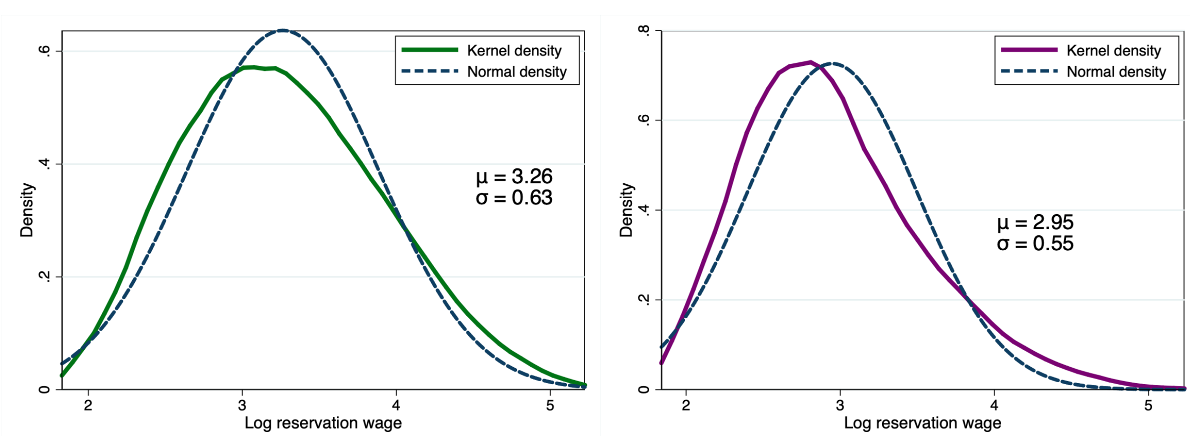


Table 31: Hours estimates

		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

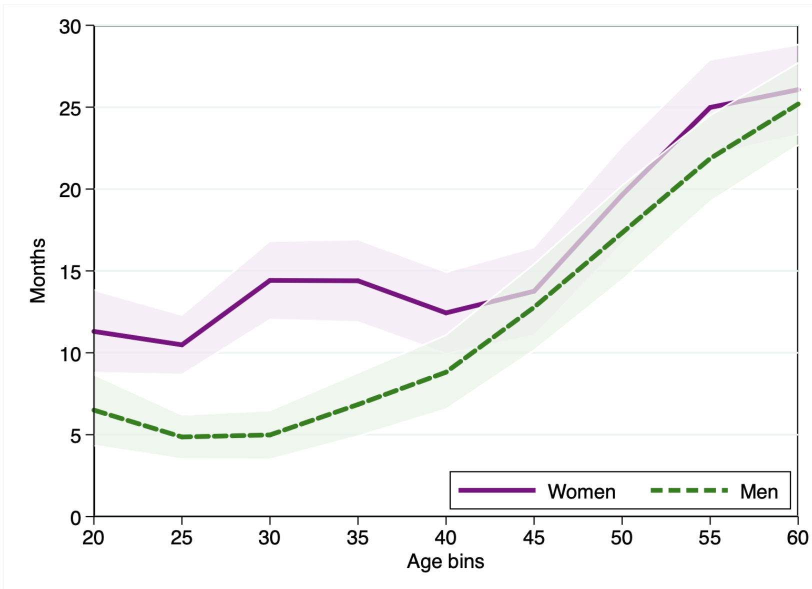
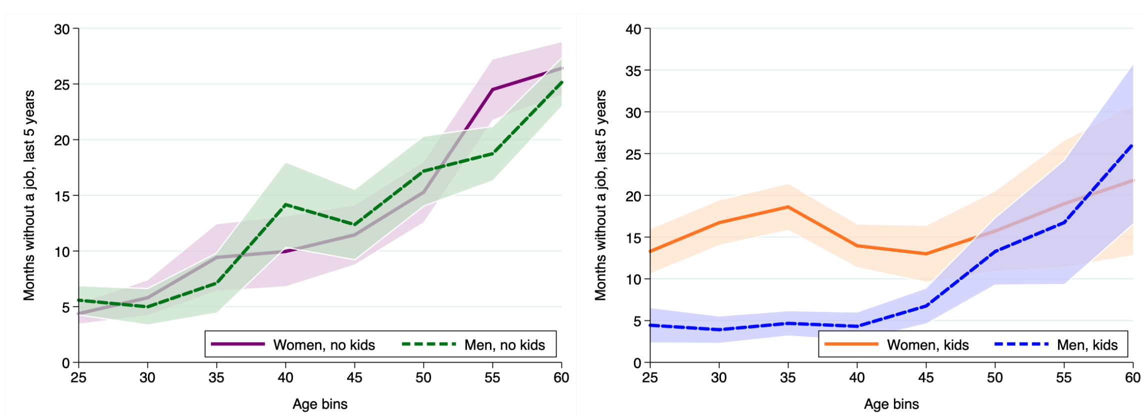


Figure 8: Months without a job in last 5 years, by presence of children

(a) No children

(b) Children



F Nonwage amenities

Table 32: 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 33: 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 34: 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 35: 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 36: 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.

G Job offer acceptance frequency

Figure 9: Acceptance frequency