Macroeconomic Consequences of Gender Differences in Job Search

Corinne Stephenson*

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Abstract

This paper explores how differences in job search behavior and preferences contribute to the gender wage gap. Using data from the Job Search Supplement of the Survey of Consumer Expectations, I find that women are more likely to search for jobs and do so more intensively than men. Despite differential search inputs, men and women receive a similar number of job offers, implying a lower job offer yield for women. Women's best job offer has lower wages and hours, and fewer fringe benefits. Women are more sensitive to nonwage features of a job, such as commute time, hours worked, and location of a job. Lastly, women are more likely to search only for part-time work and have not worked in recent years. Building on these findings, I develop an on-the-job search model with endogenous search effort. I allow jobs to differ in their wage and amenity value. I incorporate the incidence of children and parental leave into the model, as the empirical facts show this is an important mechanism accounting for differences in search behavior, preferences, and labor force attachment by gender. Through the lens of the model I find that gender differences in amenity valuation can explain close to 20% 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 grateful for guidance from my advisors Pascual Restrepo, Kevin Lang, and Tarek Hassan. Seminar participants at the Boston and Philadelphia Federal Reserves provided very helpful feedback.

1 Introduction

Much research and policy attention has been directed towards differences in labor market outcomes between men and women. However, relatively little attention has been cast towards how inputs into the job search process differ by gender, and how these relate to outcomes. This paper aims to fill that gap. Recent evidence suggests that men and women navigate the job search process differently, with potentially important implications for labor market outcomes, particularly wages, job satisfaction, and labor force attachment. In this paper I examine the role of gender differences in job search behavior and preferences, particularly nonwage job attributes, in shaping observed wage differentials between men and women.

Using data from the Job Search Supplement (JSS) of the Survey of Consumer Expectations (SCE), I document key patterns that distinguish the job search process by gender. Women are significantly more likely to search for a job than men, and do so more intensely as measured by the number of applications they send or hours devoted to search. Despite these differences in search frequency and effort, men and women receive a similar number of job offers. I construct four measures of offer yields using two measures of search inputs (applications sent and hours spent) and two measures of outputs (number of offers and share with at least one offer). Women are on average 23% less effective in generating job offers than men.

The best job offer that men and women receive also differs across several dimensions. The wage offered to women is 15% lower and hours offered are 7% lower, after controlling for extensive worker and job offer characteristics. This lower wage offer is not compensated by more fringe benefits. In fact women are significantly more likely to have a job that does not offer any fringe benefits. In terms of search mechanisms resulting in the best job offer, women are significantly more likely to receive their offer through a referral while men are more likely to receive an unsolicited offer. The wage setting protocol also differs by gender. Women are less likely to negotiate their wage and have a weaker sense of the job's wage prior to accepting the offer.

A central implication of job ladder models is that search effort is a function of one's current wage, or position on the job ladder. Those who are further down the job ladder search more intensely, as they have more to gain from finding a new job. Prior to the JSS, robustly testing this implication was not possible as it requires data on search effort for those who are currently employed, and most labor market surveys focus exclusively on search effort of the unemployed. I provide novel estimates of the elasticity of search intensity with respect to the log real current wage broken down by gender. I find that the elasticity is double in magnitude for men compared to women: -0.78 and -0.39, respectively.

The large gender difference in elasticity of search effort with respect to the current wage indicates that women place greater value on nonwage amenities of a job in guiding their search behavior. Not only is women's search behaviour relatively more influenced by nonwage amenities, but so too are their job acceptance decisions. Compared to men, women are significantly less likely to accept a hypothetical job offer at their stated reservation wage if it requites a longer commute, longer working hours, or relocating.

The type of nonwage amenities referred to in this paper are job features impacting flexibility, which might or might not be related to fringe benefits. When asked the reason for searching, the top two reasons women cite more than men are precisely those relating to flexibility: a low quality of work life "such as inflexibility with child care and family responsibilities" and having too long of a commute. Research shows that even in the absence of discrimination, a gender gap in earnings can emerge if women have flexible jobs with lower-earning while men have inflexible jobs with earnings that are convex in hours (Goldin, 2024; Cortés and Pan, 2019; Goldin and Katz, 2016; Goldin and Katz, 2011; Bertrand et al., 2010).

At the heart of this paper is the finding from exisiting research that wages and nonwage amenities differ in their degree of dispersion. Hall and Mueller (2018) show that the dispersion of nonwage amenities is approximately 40% larger than that of wages. In consequence, workers who place greater weight on nonwage amenities will exert greater search effort as nonwage amenities are harder to find.

Women's greater sensitivity to nonwage amenities is consistent with the literature (Chen et al., 2024; Le Barbanchon et al., 2021; Mas and Pallais, 2019; Wiswall and Zafar, 2018; Goldin, 2014). Where the literature is still nascent is in understanding the mechanisms contributing to differential nonwage amenity valuations by gender. To explore one possible mechanism, I examine how search behavior differs for women with and without children. For women without children, the elasticity of search effort with respect to the current wage is similar in magnitude to men's (-0.72). Meanwhile the elasticity for women with children is much smaller in magnitude, (-0.02). At least by this measure, the presence of children is the chief differentiating factor between men and women.

Consistent with women with children placing greater value on nonwage amenities of a job, I find that women with children search significantly more than those without children on extensive and intensive measures. Moreover women are significantly more likely to search only for part-time or additional work. When citing reasons for desiring only part-time work, the reason with the largest difference between men and women is childcare availability.

To quantify the impact of gender-specific search behaviors and preferences on wage outcomes, I build a partial equilibrium model of endogenous job search building on Faberman et al. (2022). I extend their models in three ways. 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. With the calibrated model in hang, I quantify different components to explaining the gender wage gap. To do so, 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. I find that

1.1 Related Literature

This paper builds on a few strands of literature. The first is a vast literature on the gender wage gap. There is a growing consensus that much of the gender wage gap is a motherhood penalty (Adams-Prassl et al., 2023; Kleven et al., 2019a; Kleven et al., 2019b; Adda et al., 2017; Angelov et al., 2016). Within this literature, the most immediately relevant papers are those that focus on gender differences in the search process. Drawing on the universe of unemployment insurance recipients in Denmark, Fluchtmann et al. (2024) find that women apply to jobs with an average wage that is 4.5% lower than men. Meanwhile Philippe and Skandalis (2024) examine explicitly how job search behavior changes following motherhood in a dataset of French workers who involuntarily lost their job. Consistent with my paper, they find that mothers are more selective on nonwage dimensions of a job compared to non-mothers.

This paper also adds to a burgeoning literature on the importance of nonwage amenities in the labor market. Working conditions vary substantially across the U.S. and are a central component of worker's compensation (Maestas et al., 2023). For one-third of workers, nonwage amenities have a more pronounced effect on job satisfaction than wages (Sockin, 2024). As aforementioned, the distribution of nonwage amenities is more dispersted than the distribution of wages, implying that nonwage amenities are harder to find (Hall and Mueller, 2018).

Within the literature on nonwage amenities, some papers underscore the relative importance of nonwage amenities for labor market outcomes by gender. For example, Women have a higher willingness to pay for jobs that offer flexibility while men have a higher willingness to pay for jobs with greater earnings potential (Wiswall and Zafar, 2018). Meanwhile women with young children have the highest willingness to pay for working from home and avoiding irregular schedules (Mas and Pallais, 2017). Women also value their commute 20% more than men and are willing to accept shorter commute times relative to men (Le Barbanchon et al., 2021; Petrongolo and Ronchi, 2020). These papers are consistent with the finding of Morchio and Moser (2024) that men sort into employers with higher pay while women sort into employers with better amenities. They find that compensating differentials explain half of the gender wage gap. I build on these papers by studying how differential valuations of nonwage amenities affect job search behavior.

Lastly, this paper builds on models featuring on-the-job search and endogenous search effort such as Christensen et al. (2005), Hornstein et al. (2011), Bagger and Lentz (2019), and Faberman et al. (2022). Relative to these papers, I introduce gender differences in search behavior. I allow search costs and search efficiency to differ by gender.

The paper proceeds as follows: Section 2 describes the data. Section 3 presents the empirical evidence on gender differences in job search behavior. Section 4 details the theoretical framework. Section 5 presents the quantitative results. Section 6 concludes.

2 Data

The primary dataset for this paper is the Job Search Supplement (JSS) of the Survey of Consumer Expectations (SCE), a nationally representative survey conducted by the Federal Reserve Bank of New York. The SCE, fielded monthly, surveys approximately $1,300$ household heads on their expectations about future macroeconomic and personal economic conditions. The JSS, which is a component of the SCE, is fielded annually in October and provides detailed cross-sectional data specifically focused 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 and fielded annually in October. The results in this paper pool data from all available years, which spans 2013–2021. The JSS was designed by the authors of Faberman et al. (2022).

Table 1 presents demographic and labor force statistics for the JSS and Current Population Survey (CPS) for the month of October, for all respondents and broken down by gender. In terms of demographics, of respondents in the JSS tend to be more White, married, and homeowners compared to the CPS. Given these differences in demographics, throughout the paper I present two sets for results: raw means by gender, and differences controlling for demographic characteristics. All results are weighted using given survey weights.

In terms of labor force statistics, the JSS and CPS are very similar. Comparing the JSS and CPS, the labor force statistics vary more for women than for men. For example, the unemployment rate in the JSS is one percentage point higher for women and 0.5 percentage points lower for men. The labor force participation rate is about five percentage points higher for women in the JSS, but similar across both surveys 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).

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

Notes: Table shows summary statistics for the Job Search Supplement and the Current Population Survey. Survey weights used throughout. *Source:* October 2013–2021 waves of the SCE Job Search Supplement, and monthly October 2013–2021 waves of the Current Population Survey.

2.1 Data on job search behavior

Relative to most labor market surveys, the JSS is distinct in that it asks about search behavior and outcomes regardless of the respondent's labor force or employment status. Most surveys, including the CPS, ask about job search behavior exclusively to those who report being non-employed. 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 their reason(s) for searching, method(s) of job search, whether they are pursuing a new job or additional work, how many applications they sent in the past four weeks, and how many hours they spent searching in the last seven days.

2.2 Data on search outcomes

In addition to being a distinct dataset on account of asking all respondents of their job search behavior, it is uncommon to have detailed information about job outcomes. In terms of search outcomes, respondents are asked about the number of offers and interviews they received, as well as various characteristics of their "best" job offer. The characteristics questions asked about respondents' best job offer are the same as the characteristics asked of their current job (for the employed) or most recent job (for the non-employed). Mirroring the questions on respondents' method of job search, the survey asks about the manner in which the respondent received the offer. Respondents are asked whether they have or plan to accept or reject the offer, and the reasons for doing so. The survey also includes questions about the wage setting process of the best offer. This include the degree to which the respondent knew the wage of the job, whether there was bargaining involved, and whether the employer provided a counter-offer. To have a measure of how many jobs were 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 preferences

The last part of the survey elicits reservation wages and reservation hours of all respondents who indicated they searched in the last four weeks or would be open to a new job.

After eliciting the respondent's reservation wage, the survey poses questions about sensitivity to nonwage amenities of a hypothetical job offer. At their stated reservation wage, respondent's are asked whether they would accept a hypothetical job offer if it required one of the following bad job amenities: relocating, doubling one's daily commute, relocating to another city, or not being provided health insurance. After eliciting the extensive margin of such bad amenities (i.e. whether the respondent would accept the hypothetical offer or not), they are then asked by what percentage the hypothetical wage offer would have to be increased in order for them to accept.

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 and includes whether the respondent used one of the BLS' job search methods in the last four weeks or sent an application (BLS, 2024). The definition of unemployment in the JSS and Faberman et al. (2022) is slightly broader than that in the CPS. In the CPS, respondent's are only asked about active search 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."

3 Job search behavior and outcomes

This section examines gender differences in job search behavior, preferences, and outcomes. Using the JSS data, I document three primary findings: (1) women are more likely to engage in job search activities than men, and do so with greater intensity; (2) despite their increased search efforts, women have lower job offer yields compared to men; and (3) women's job search behavior is more sensitive to non-wage job amenities, such as commute length and flexibility.

I begin by analyzing gender differences in search frequency and intensity, illustrating that women are more active in their job search across all time horizons. Next, I compare job search outcomes, showing that men and women receive a similar number of offers, but that women's offer yields—defined as the ratio of offers received to search inputs—are consistently lower. I then explore gender-specific characteristics of job offers, including the methods by which offers are received, differences in wage-setting practices, and benefit provision. Finally, I examine how labor force attachment and preferences for non-wage amenities, such as flexible hours, affect search behavior differently by gender, with an emphasis on how children shape these dynamics for women.

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

3.1 Search frequency

When asked the reason for searching, men and women are aligned in the top two reasons. These are dissatisfaction with one's current pay or benefits and dissatisfaction with one's current job duties. However men are more likely to indicate looking for a change of environment or not using their skills as a reason for searching. Meanwhile women are more likely to list a long commuting distance as a reason. Appendix Table 19 shows all options and results.

Drawing on the JSS, I document differences in job search behavior between men and women. Table 2 shows the extensive margin of search. Women are more likely to have actively searched across all time horizons. In the last seven days, 25 percent of women reported actively searching compared to 17 percent of men. In the last four weeks, 29 percent of women reported looking for work compared to 20 percent of men. In addition, women are more likely to have sent an application for a job in the last four weeks (26 percent of women compared to 17 percent of men). 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. Appendix Figure 2 plots the measures of search incidence plotted over the lifecycle. Until 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 occurs between the ages of 30 and 45.

Appendix Table 20 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. On account of the small sample size, I compare job search behavior between unemployed men and women from the CPS over the same time period. Those results are shown in Appendix Table 20.

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, 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.

Not only are women more likely to search, but they also search more intensely in terms of the number of applications sent in the last four weeks and the total hours spent searching in the last seven days. Table 3 shows the intensive margin of search. In the past seven days, women spent 1.7 hours on job search compared to 1.1 hours for men. Women also send more applications, whether for jobs that include additional work or exclusively for a new job. Over the past four weeks, women sent 1.7 applications compared to 1.0 application for men. As for the extensive margin, these differences in hours and applications remain significant even 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: 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.

3.2 Job search outcomes

Table 4 shows job search outcomes that entail beginning a new job, i.e. excluding additional work. Although women search more than men on 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 men. However after including controls, the difference is no longer significant. The share of men with an unsolicited offer is larger than for women, though the difference is not statistically significant. Appendix Table 22 shows outcomes that include additional work and the results are the same. 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 4. Job search outcomes for a new job

	Men	Women	Coefficient on women indicator from separate OLS regressions	
			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, 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 5 reports four different measures of job offer yields, reflecting the two measures of outputs (number of job offers and share with at least one offer) and inputs (applications sent and hours spent searching). I construct the offer yield as follows:

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

where input i is the number of hours or applications and output j is the 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 – are akin 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 5. 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

3.3 Features of best offer

Having shown how men and women differ in their job search efforts and outcomes, next I hone in on the attributes of respondents' "best offer." Table 6 shows the difference in offered wages and hours between men and women. Women's raw offered wage is 25% less than men's and drops to 15% after being residualized for demographics, characteristics of the job offer, and state and year fixed effects. When controlling for respondent's most recent wage – one's 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 are similar except that when controlling for most recent hours, there is no difference between men and women.

Table 6. 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. The residualized estimates control for demographics and job offer features. Demographics included are: age, age-squared, three education categories, four race categories, marital status, number of children under 6. Job offer features include: 2-digit SOC occupation of the job offer, 2-digit NAICS industry, and three firm-size bins of the job offer. 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 23 presents corresponding raw and residualized estimates for different wages: respondent's previous, current, reservation, and accepted wage. The magnitudes of these various residualized wages are similar, with a 16% difference between men and women. The gap in reservation wages is slightly smaller, with women's reservation wage being 11% less than men's. Appendix Table 24 shows the analogous estimates for hours. The difference in raw means are consistently around 12% while the difference in residualized hours are around 7%.

Two differences are worth highlighting between the wages and hours estimates. The first difference is that the magnitude of raw and residualized wage differences is larger than for the corresponding hours estimates. This is in line with hours being convex in hours such that the difference in wages diverges more than for hours. The second difference is between reservation wages and reservation hours. After accounting for respondent's most recent wage, the residualized difference in reservation wages is 11% and remains statistically significant. However after accounting for respondent's most recent hours, the difference is not statistically significant.

Across all wage measures, women's wage distributions are more skewed and have a higher excess kurtosis compared to men's distributions. Appendix Figure 3 shows the kernel density of the log weekly offered wage overlaid with a normal distribution. Men's wage offer distribution has a skewness of 0.37 and excess kurtosis of -0.03 while women's offer distribution has a skewness of 0.65 and excess kurtosis of 0.68. Appendix Figure 4 shows men's current wage distribution has a skewness of 0.24 and excess kurtosis of 0.31. Women's current wage distribution has a skewness of 0.42 and excess kurtosis of 0.91. Appendix Figure 5 men's reservation wage distribution has a skewness of 0.33 and excess kurtosis of -0.46. Women's reservation wage distribution has a skewness of 0.77 and excess kurtosis of 0.37.

Although consistently women have lower wages than men, benefits might be a compensating differential. To explore this further, in Table 7 I provide an exhaustive list of the different benefits included in respondent's best job offer. The theory of compensating differentials stipulates that the wages of nearly identical workers differ because jobs have different characteristics and workers differ in their willingness to forgo wages and take advantage or avoid these non-wage characteristics of a job. Fringe benefits are one type of non-pecuniary attributes that might lead workers to accept lower wages. According to the BLS, in 2024 all benefits constituted 31% of total employment costs (BLS, 2024). If women place greater utility on fringe benefits, then that could explain their relative difference in wages.

Table 7 shows that with the exception of childcare assistance, women are less likely to receive any of the listed benefits. Moreover, women are 10% more likely to have a job offer that does not include any benefits, and this difference is statistically significant. If the table reflected all the possible non-pecuniary aspects of a job, then the results would stand against the predictions of compensating differentials theory (Hodges (2020) finds similar results in terms of wages and benefits using different datasets). One possibility is that the type of non-pecuniary attribute that women value is not included in the fringe benefits below. The nonwage amenities that are at the heart of this paper and that I explore below cannot be included in employment costs as easily and include hours flexibility, commute time, and location.

Table 7. Job offer 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.

3.4 Mechanisms of search and wage setting

In addition to being able to compare different wage and hours estimates after residualizing for extensive controls, the JSS also allows for comparing the method by which men and women receive their best job offer. Table 8 shows the following four methods constitute how over 90% of offers were received: 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.

The difference in referrals is surprisingly 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. I mention here two papers whose setting is also the U.S. In experimental work Mengel (2020) finds that men's networks display more homophily than women's. Focusing on doctor referrals, 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 co-worker.

The difference in unsolicited offers is less surprisingly in the context of 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 tend to not be hired or called back in male-dominated professions as well as higher-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, and this estimate controls for differences in the offer occupation and industry (both at the two-digit level).

Table 8. Job search method

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	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

Notes: Demographics controls include: age, age-squared, three education categories, four race categories, marital status, presence of children under 6, 2-digit SOC occupation of most recent job, 2-digit NAICS industry of most recent job. 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.

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 9 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). In future work I plan to adapt the framework herein to be in a general equilibrium framework with a wage setting protocol that allows for these differences by gender.

Table 9. 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

Notes: Demographics controls include: age, age-squared, three education categories, four race categories, marital status, presence of children under 6, 2-digit SOC occupation of most recent job, 2-digit NAICS industry of most recent job. 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.

3.5 Labor force attachment

Differences in labor force attachment are central to understanding why wages might differ by gender. The canonical channels by which weaker labor force attachment can impact wages include: reduced human capital accumulation (Becker, 1964); statistical discrimination (Phelps, 1972); signaling effects to employers (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 in the literature.[1] Building on existing work, I examine women's labor force attachment in the con-

[1] A few papers include: Kleven et al., 2019a; Blau and Kahn, 2013; Manning and Petrongolo, 2008; Goldin, 2006; Waldfogel, 1998; Light and Ureta, 1995; Light and Ureta, 1990.

text of the Job Search Supplement. Women's tenuous labor force attachment is reflected in the their preference for part-time work and time spent without a job. Conditional on active search, Table 10 shows the percent of people who seek only part-time work or an additional job (Panel A) as well as the reasons for searching for part-time work (Panel B). 25% of women search for only part-time work compared to 15% of men. When indicating the reasons for only desiring part-time work, men are significantly more likely to want additional income while women list child care availability.

Table 10. Reasons for only seeking part-time work

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
Panel A. Percent who searched for:				
An additional job	23.44	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 who sought out part-time work and additional work. Panel B shows shows main reason respondents list for being interested in part-time and not full-time work. The question is asked to those who looked for work in the last four weeks or would want a job, and indicated being interested in only part-time work. Some respondents do not list any reason and hence the percentages do not sum to 100. The last column report the coefficient on a women indicator from and OLS regression. *Source:* October 2013–2021 waves of the SCE Job Search Supplement.

Prime-aged women report spending 13 months without a job in the last five years compared to 8 months for men. Table 11 shows reasons and time for not having a job. Women are statistically more likely to not have had a job due to family obligations and other reasons. Women spend nearly 5 months without a job due to family obligations compared to 1 month for men. When including controls, men are more likely to not have had a job on account of being in school.

Table 11. 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 the reason and average total months respondents spent without a job in the last five years. This includes those who were both unemployed and out of the labor force. The tabulations do not condition on having spent a positive amount of time without a job. *Source:* October 2013–2021 waves of the SCE Job Search Supplement.

3.6 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 than men. 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 have differing preferences for nonwage amenities of a job, and how this affects 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 search behavior of the employed prior to the JSS, the only papers to previously estimate the search-wage elasticity are Faberman et al. (2022) and Mueller (2010). Both these papers focus on all employed workers and do not differentiate between men and women.

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

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

where the measure of search effort is the number of applications sent in the last four weeks, w_{ist} is log 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 estimated coefficient of interest in this case is δ. The negative and statistically significant coefficients in the first two columns of Table 12 show this job ladder motive is present for both men and women. However the job ladder motive is stronger for men than women, reflected in the smaller point estimates for men. I construct elasticities by gender by dividing the estimated coefficients by the mean of the dependent variable, which in this case is the number of applications sent. The search effort-wage elasticity for men is nearly two times greater than the elasticity for women, -0.78 compared to -0.39. This difference is statistically significant at the 10% level, as reflected in the last column, which includes an interaction between the log current wage and an indicator for women.

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

	Search effort$_{ist}$ = Number of applications		
	Men	Women	Difference
Log current wage	–0.430***	–0.337***	–0.284***
	(0.083)	(0.103)	(0.084)
Women			0.253
			(2.484)
Women × Log current wage			–0.199*
			(0.117)
Mean of dependent variable	0.554	0.853	0.698
Elasticity	–0.775	–0.394	
N	3,151	2,928	6,079
Adj. R-squared	0.015	0.059	0.034
Workers controls	yes	yes	yes
State and year fixed effects	yes	yes	yes

Notes: The table shows the search-wage elasticity from separate OLS regressions for currently employed men, women, 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.

The smaller elasticity for women compared to men is suggestive that non-wage features of a job factor more importantly into the job search behavior and preferences of women. To explore this further, I exploit questions in the survey that ask for respondent's their reservation wage and sensitivity to various job features. Table 13 shows the percentage of men and women that would accept a job offer at their stated reservation wage if it required certain changes in the nonwage aspects of the job. Women are less likely to accept a job offer at their reservation wage if it entails relocating, doubling their daily commute, or working 10 percent more hours. For this reason, it is especially important to include non-wage amenities into a model of search.

Table 13. Acceptance rates of hypothetical job offer

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	Difference	Difference
Percent who would accept offer if required to:				
Work 10% more hours	60.52	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

3.7 Role of children in search process

The empirical results above show that nonwage amenities are relatively more important for women than men in the job search process. This is reflected most clearly in that women's search effort is less a function of their current wage relative to men, and that women are more sensitive to nonwage features of jobs pertaining to flexibility. To explore potential mechanisms for this differences, I repeat the analysis above on search behavior and elasticity, comparing women with and without children. Table 14 shows the extensive (Panel A) and intensive (Panel B) margins of search. Across all extensive margins of search, women with children search roughly five percentage points more than women without children. On the intensive margin, women spend around 55% more time searching and send nearly double the number of applications (where applications here includes for additional work).

Table 14. Job search of women, by children status

			Coefficient on children indicator from separate OLS regressions	
	No children		Children	Difference
Difference				
Panel A: Extensive margin				
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)
Panel B: Intensive margin				
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

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.

In Table 15 I estimate a very similar specification to that above, except for women with and without children. I estimate the following econometric specification for women with children status c in state s at year t: Search effort$_{cst} = \delta w_{cst} + \mathbf{X}_{cst}\beta + \alpha_s + \gamma_t + \varepsilon_{cst}$. Once again the parameter of interest is δ. For women without children, the elasticity is -0.72, which is only 8% less than men's elasticity. Meanwhile the estimated coefficient of δ is not significant for women with children however is close to zero and weakly positive. This is consistent with the argument of this paper that women place higher value on nonwage amenities, and this is largely driven by the presence of children. The elasticity for women with children is -0.02, which is by far the smallest in magnitude. this is further corroboration that women with children care more about the nonwage aspects of the job.

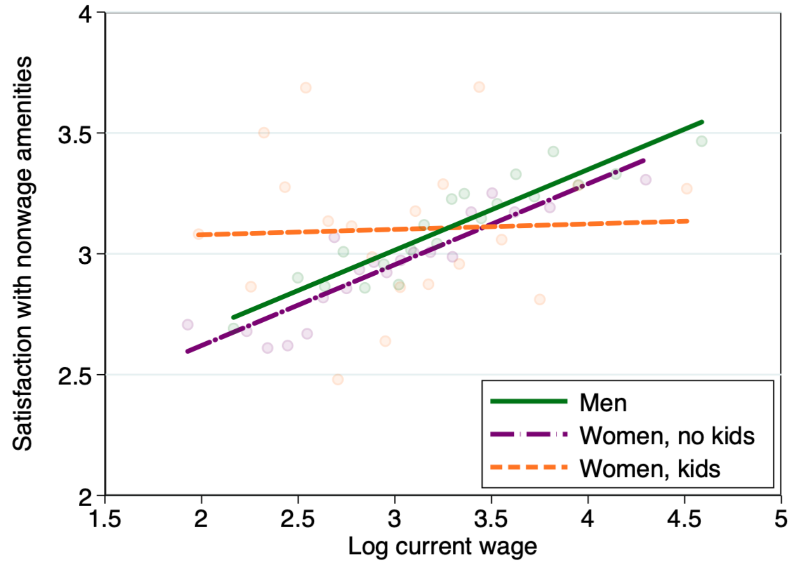
Table 15. Elasticity of search effort with respect to current wage, children

	Search effort$_{ist}$ = Number of applications		
	No children	Children	Difference
Log current wage	–0.730***	0.027	–0.600***
	(0.187)	(0.251)	(0.213)
Children			–0.752
			(0.922)
Children × Log current wage			0.487*
			(0.277)
Mean of dependent variable	1.016	1.166	1.096
Elasticity	–0.718	–0.023	
N	973	1,036	2,009
Adj. R-squared	0.015	0.059	0.034
Workers controls	yes	yes	yes
State and year fixed effects	yes	yes	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.

The relationship between search effort and one's current wage provides evidence as to the relative importance of wages versus nonwage amenities. The JSS asks respondent's directly about their satisfaction with nonwage amenities. The relevant question is: "And how satisfied would you say you are with other aspects of the job, such as benefits, maternity/paternity leaves, flexibility in work hours, etc?" Based on this question, Figure 1 plots a binscatter and linear fit of one's current log wage against satisfaction with nonwage amenities. The slope for men and women without children is parallel and upward sloping, indicating that wage growth and satisfaction go hand-in-hand for these two groups. Meanwhile the current wage and satisfaction with nonwage amenities is not correlated for women with children. Appendix Table 26 shows these results in a regression framework controlling extensively for individual observables. The relationship is close to zero and not statistically significant for women with children under six. For women with children who are slightly older, the relationship is half in magnitude compared to men or women without children and significant at the 10% level.

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. The range of satisfaction is from 1 to 4 with the following representing each number: 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 Job Search Supplement.

4 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.

4.1 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.

4.2 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 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:

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

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

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

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.

4.3 Unemployment

The value of unemployment is:

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

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

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

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

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

4.4 Parental Leave

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

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

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

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

5 Calibration

I calibrate my model to moments from the JSS for years 2013–2021 pooled together. Panel A of Table 16 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 16 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 17. 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.

Table 16. 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	0.1	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

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

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

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 the following:

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

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

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

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 17. 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 18 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 18. 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%

6 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 19. Reasons for searching

Reasons for searching (percent)	**Men**	**Women**
Not satisfied with pay or benefits	48.8	56.5
Not satisfied with duties	46.5	46.1
Looking for change of environment or careers	44.8	34.9
Not using experience or skills	42.4	29.8
Denied promotion or pay increase	22.9	18.9
Unsuitable work hours	18.1	10.8
Low quality of work life	15.9	20.1
Conflict with co-workers or boss	15.9	17.5
Concerned about job stability	14.1	11.7
Commute distance too long	10.4	19.3
Relocating for non-job-related reasons	5.5	8.5
Given notice that will lose job	3.5	3.0

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

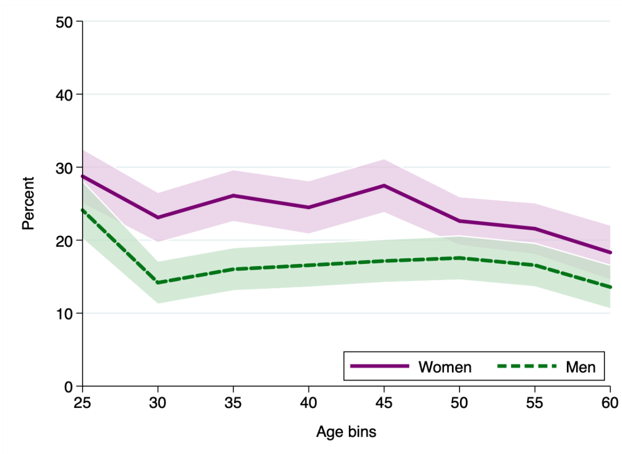
Table 20. Extensive margin of search, by employment status

	Men		Women		Difference	
	Emp.	Unemp.	Emp.	Unemp.	(1) v. (3)	(2) v. (4)
Percent who:						
Actively searched, last 7 days	13.87	91.20	20.06	84.64	6.19***	-6.56*
	(0.60)	(2.37)	(0.72)	(2.51)	(0.93)	(3.72)
Actively searched, last 4 weeks	17.03	100.00	24.02	100.00	6.99***	0.00
	(0.65)	(0.00)	(0.76)	(0.00)	(1.00)	(0.00)
Actively searched, last 12 months	31.27	100.00	41.91	100.00	10.64***	0.00
	(0.81)	(0.00)	(0.88)	(0.00)	(1.19)	(0.00)
Sent application(s), last 4 weeks	14.15	90.48	20.97	95.42	6.82***	4.94*
	(0.61)	(2.45)	(0.73)	(1.45)	(0.94)	(2.70)
Actively searched and are available	9.50	100.00	14.68	100.00	5.18***	0.00
	(0.51)	(0.00)	(0.63)	(0.00)	(0.81)	(0.00)
Observations	3,299	144	3,124	208	6,423	352

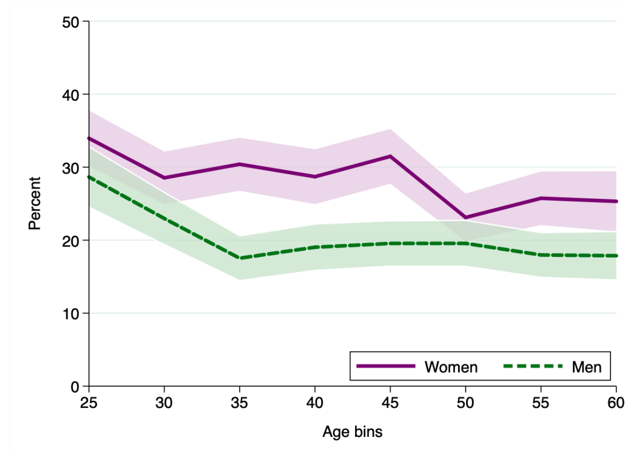
Notes: This is analogous to Table 3 except broken down by employment status. Controls are not included. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *Source:* October 2013–2021 waves of the SCE Job Search Supplement.

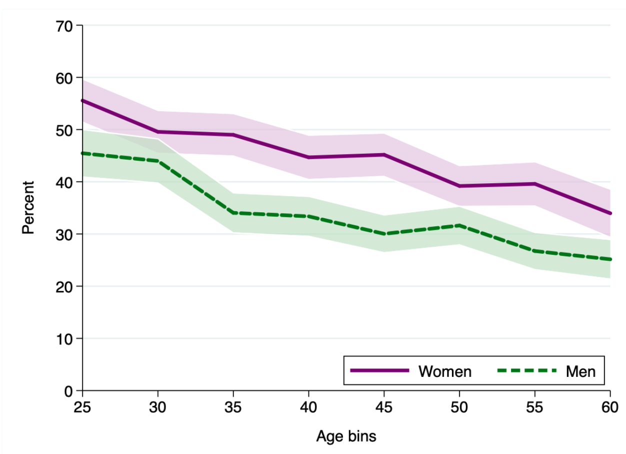
Figure 2. Extensive margin search over the lifecycle

(a) Searched in last 7 days

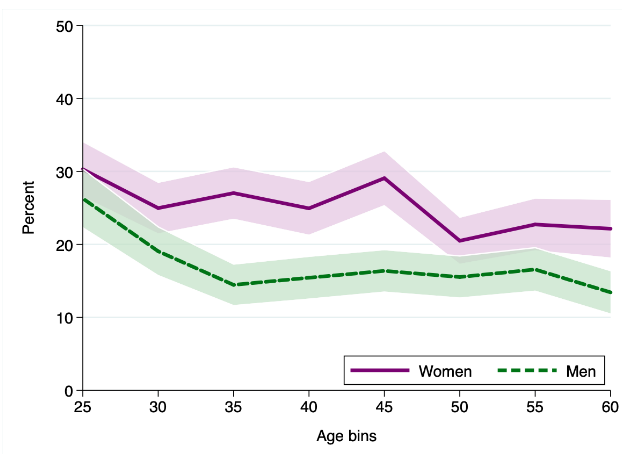


(b) Searched in last 4 weeks





(c) Searched in last 12 months



(d) Sent an application in last 4 weeks

Notes: Figures show difference in measures of search incidence reported in Table 3 over the lifecycle. Confidence intervals are at the 90 percent. *Source:* October 2013–2021 waves of the SCE Job Search Supplement.

Table 21. 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.

Table 22. Job search outcomes, including additional jobs

			Coefficient on women indicator from separate OLS regressions	
	Men	Women	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 4 except includes outcomes for job 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.

Table 23. 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. And 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 3. Kernel density of log offered wage

(a) Men **(b)** Women

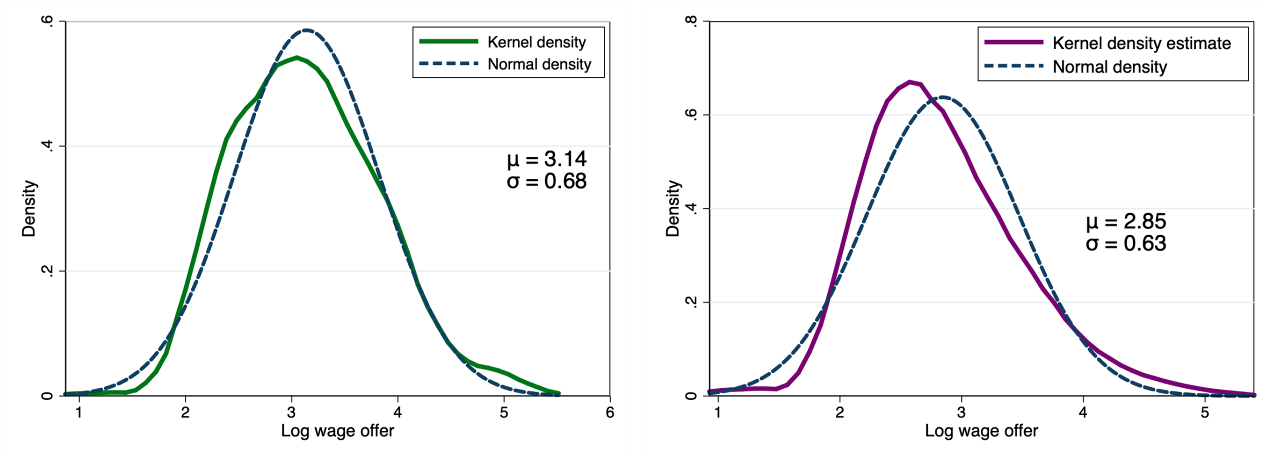


Figure 4. Kernel density of log current wage

(a) Men **(b)** Women

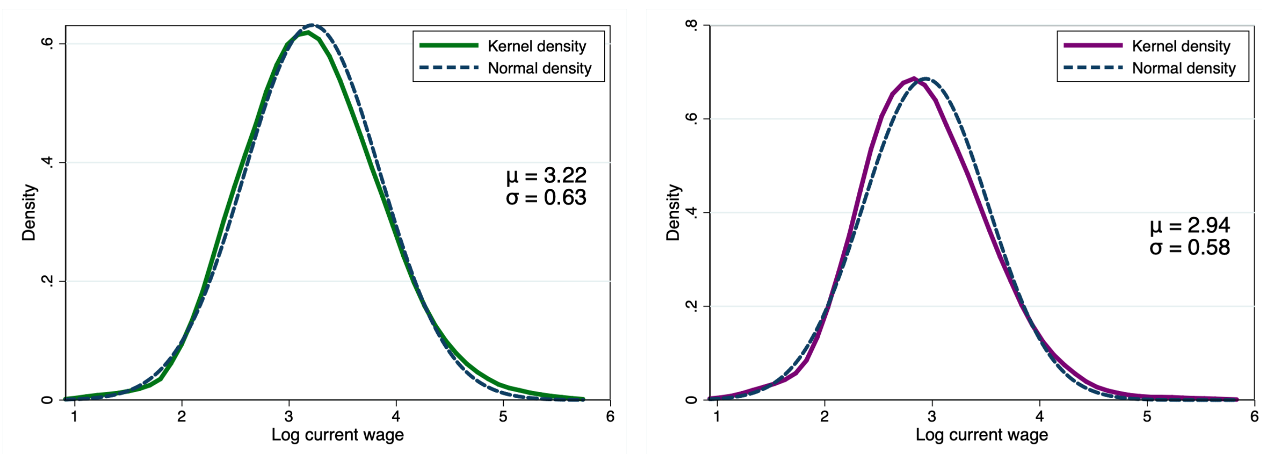


Figure 5. Kernel density of log reservation wage

(a) Men **(b)** Women

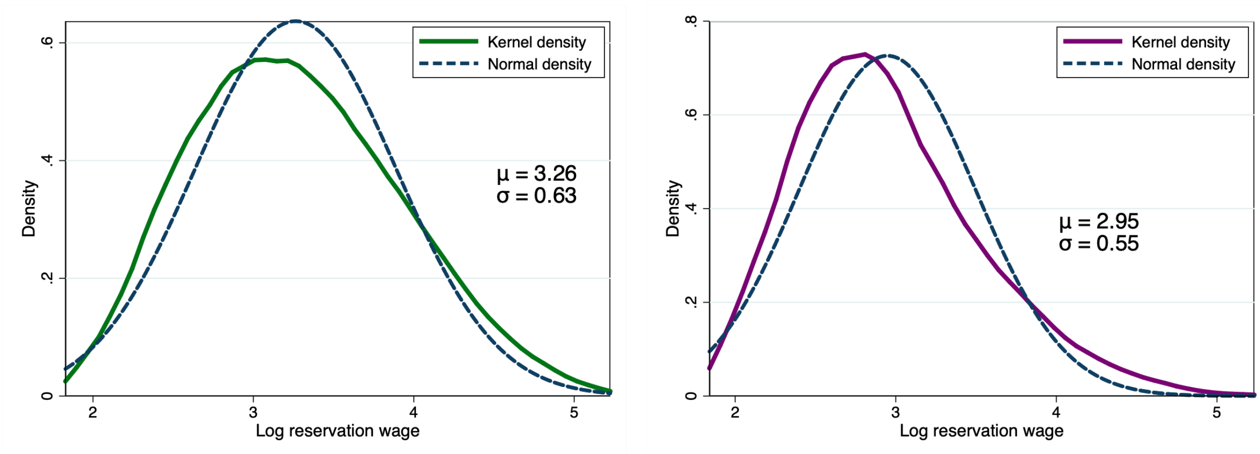


Table 24. Hours estimates

		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.

Table 25. 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).

Figure 6. Months without a job

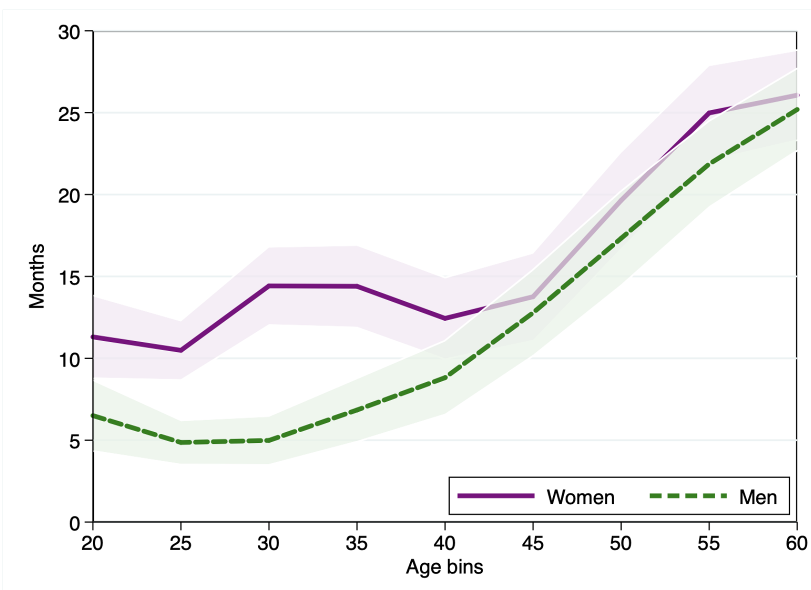


Table 26. Satisfaction with amenities at current job

	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

Figure 7. Acceptance frequency