Macroeconomic Consequences of Gender Differences in Job Search

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October 25, 2024

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Abstract

This paper explores how differences in on-the-job search behavior and job preferences contribute to the gender wage gap. To do so, I leverage the Job Search Supplement of the Survey of Consumer Expectations (SCE). I document five facts pertaining to how the job search process differs between men and women. First, women search more than men across several measures capturing both incidence and intensity of job search. Second, men and women receive a similar number of job offers, implying a lower job offer yield for women compared to men. Third, women are more sensitive to non-wage features, or amenities, of a job. Fourth, women are less attached to the labor force than men, but reenter with greater frequency than previously measured. Based on these facts, I build an on-the-job search model with endogenous search effort and allow for jobs to differ not only in the wage but also amenity value. I then calibrate the model to moments from the survey to evaluate how much of these differences in search behavior and job preferences contribute to the gender wage gap.

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

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

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1 Introduction

Recent research has shown that when men and women face identical pay in a gender-blind setting, women earn 20% less per hour on average (Adams-Prassl et al., 2023). This difference is driven almost entirely by the presence of children in the household. Moreover, women with children are willing to accept at most a commute that is 24% less than men (Le Barbanchon et al., 2021).

In this paper I explore the importance of labor market interruptions and the value of nonwage amenities for job search behavior. To do so, I begin by documenting three facts relating to job search behavior and outcomes for men and women. The first fact is that that women are more likely to engage in job search activities than men. The second fact is that despite searching more, they realize similar job search outcomes. Using the differential inputs and outputs into the job search process, I construct job offer yields. I find that women are on average 23% less effective in generating offers than men. This difference is driven by children. Men and women without children are equally effective in generating offers. Meanwhile, the mean wage that women are offered is 15% less than men and the offered work hours is 22% less. The third fact is that women are more sensitive to the nonwage amenities of a job. They are more likely to reject a job offer if it requires relocating, a longer commute, or working longer hours. I estimate an elasticity of search intensity with respect to the log real current wage of -0.59 for men and -0.22 for women.

Based on these facts, I build a model to quantify the importance of labor market interruptions and nonwage amenities in explaining differences in search behavior between men and women. My model features endogenous search effort and extends the framework of Faberman et al. (2022) in three ways. First, I allow for search efficiency to differ by gender. Second, I allow for jobs to differ in both their wage and nonwage amenity value. Third, I introduce a state of parental leave to incorporate the incidence of children.

With the calibrated model, I carry out a decomposition to understand the factors that cause women to search more. I carry out a series of counterfactual exercises in which I given men and women the following equal features of the model: search cost function, wage offer distribution, job offer rate, and lastly equalize the dispersion in the distribution of amenities and wages.

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 6 describes the calibration and model decomposition. Section 7 concludes.

2 Data

The main data source for this paper is the Job Search Supplement of the Survey of Consumer Expectations (SCE). The SCE is a nationally representative online survey fielded monthly by the Federal Reserve Bank of New York. The Job Search Supplement is fielded annually in October as part of the SCE and was designed by the authors of Faberman et al. (2022). Most surveys focusing on job search behavior ask questions to the unemployed. The Job Search Supplement is distinct in that it includes not only unemployed respondents but also those who are currently employed and out of the labor force. The survey has detailed information on the number of offers that respondents receive, as well as attributes of their best offer.

Table 1. Summary statistics: Job Search Supplement and Current Population Survey

	JSS	CPS	JSS		CPS	
	All	All	Men	Women	Men	Women
Demographics (percent)						
Aged 25-54	68.2	68.4	67.1	69.3	68.6	68.2
White non-Hispanic	72.1	63.2	76.5	67.9	65.1	61.3
Education: high school	33.8	34.3	32.2	35.3	36.2	32.4
Education: some college	30.8	29.2	29.4	32.1	27.5	30.9
Education: college or more	35.5	36.5	38.4	32.7	36.4	36.7
Married	64.6	50.5	70.9	58.6	55.9	44.9
Children under 6	15.9	13.1	15.3	16.5	12.3	13.9
Homeowner	66.6	59.7	72.8	60.6	62.7	56.6
Renter	31.4	39.0	25.6	36.9	36.0	42.2
Male	49.0	51.1				
Labor Force Statistics						
Labor force participation rate	81.0	79.0	83.7	78.5	84.6	73.2
Employment to population ratio	77.7	75.7	81.1	74.3	81.4	69.7
Unemployment rate	4.2	4.2	3.1	5.3	3.5	4.1
Observations	7,941	333,331	3,978	3,963	168,291	165,040

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

3 Job search behavior and outcomes

Below I document gender differences in job search behavior in terms of search frequency and desired job attributes and outcomes. When asked the reason for searching, men and women are aligned in the top two most common reasons. These are dissatisfaction with one's current pay or benefits (above 50 percent indicated this as a reason), and dissatisfaction with job duties (above 45 indicated this as a reason). The reasons that elicit the largest differences between men and women are: not using one's skills on the job (47 percent of men listed this compared to 27 percent of women); and commuting distance (22 percent of women compared to 11 percent of men).

3.1 Search frequency

Drawing on the Job Search Supplement, I document differences in job search behavior between men and women. Table 2 documents the extensive margin of search, reflected in those who reported active search across different time horizons or sent an application in the last four weeks. Women are more likely have actively searched across all time horizons. In the last four weeks, 29 percent of women report looking for work compared to 20 percent of men, and 26 percent of women sent at least one application compared to 17 percent of men. Across all extensive margin measures, women search at least seven percentage points more than men. The first differences column shows the raw means, while the second shows the differences after controlling for demographic and worker controls, and state and year fixed effects. The raw mean differences between men and women are statistically significant, and remain so after including controls.

Appendix Table 16 breaks down the differences further 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 XX.

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***	3.51***
			(1.29)	(1.20)
Actively searched, last 4 weeks	20.25	28.82	8.57***	2.68**
			(1.42)	(1.28)
Actively searched, last 12 months	33.60	45.52	11.91***	5.62***
			(1.58)	(1.50)
Sent application(s), last 4 weeks	16.94	25.63	8.69***	2.89**
			(1.35)	(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. 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. Differences in hours spent searching and applications sent remain significant even after including controls. Appendix Figure 3 shows the same 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.

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***	0.24*
			(0.12)	(0.13)
Applications sent, past 4 weeks	1.03	1.73	0.69***	0.32*
			(0.16)	(0.17)
Applications for new job, past 4 weeks	0.83	1.40	0.57***	0.28**
			(0.13)	(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. Although women search more than men on extensive and intensive margins, the receive a similar number of offers in the last four weeks. When comparing raw means, the share of women with a formal is statistically larger than men. However after including controls, the difference is no longer significant. The share who receive an unsolicited offer does not differ by gender. Appendix Table 20 shows a similar table for outcomes, except including offers for additional work. The results in this table are unchanged. Men and women have a similar number of offers if looking over a longer horizon of six months. Moreover they receive a similar number of interviews in the last four weeks.

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	-0.01
			(0.03)	(0.03)
Percent with:				
Formal offer for new job	6.68	9.06	2.38***	0.69
			(0.67)	(0.90)
Unsolicited offer for new job	2.42	2.10	-0.32	-0.18
			(0.37)	(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 the yield of job search efforts using two measures of inputs and outputs. The two measures of inputs are hours spent searching and applications sent. The two measures of outputs are the number of job offers and share with at least one offer. In Panel A, women are on average 22.5% less efficient in generating job offers compared to men. Women with children are less efficient when limiting the sample to men and women with children. In this case, women are 40.5% less efficient in generating job offers. Panel C compares men and women without children. Amongst this sample, men and women are only 6% less efficient than men. The role of children in impacting and directing the job search process motivates the inclusion of a parental leave in the model.

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

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.

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

Notes: Table shows the offer yield separately for men and women, and the ratio of yields. Two search inputs are considered as well as two job search outcomes.

The wage estimates reveal significant gender disparities in both offered and accepted wages. Without controls, women receive lower offered wages than men by 0.30 log points, and lower accepted wages by 0.27 log points. Even after adjusting for various demographic and job-related factors, the wage gap remains significant, with women earning approximately 0.09–0.17 log points less than men across different wage measures.

Table 6. Wage estimates

		Men	Women	Difference
Previous wage	Raw means	3.00	2.77	-0.23***
N=6,612		(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=6,612		(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=6,612		(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)
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)
Accepted wage	Raw means	2.98	2.77	-0.22***
N=574		(0.03)	(0.03)	(0.05)
	Residualized	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.

Table 7. 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	3.39	3.34	-0.05
		(0.02)	(0.02)	(0.03)
	Including recent hours	3.41	3.39	-0.02
		(0.02)	(0.02)	(0.03)
Offered hours	Raw means	3.53	3.35	-0.18***
N=1,281		(0.02)	(0.02)	(0.03)
	Residualized	3.41	3.39	-0.02
		(0.02)	(0.02)	(0.03)
	Including recent hours	3.41	3.39	-0.02
		(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	3.29	3.26	-0.03
		(0.03)	(0.03)	(0.04)
	Including recent hours	3.41	3.39	-0.02
		(0.02)	(0.02)	(0.03)

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, home ownership, 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 1. Kernel density of log real weekly offered wage

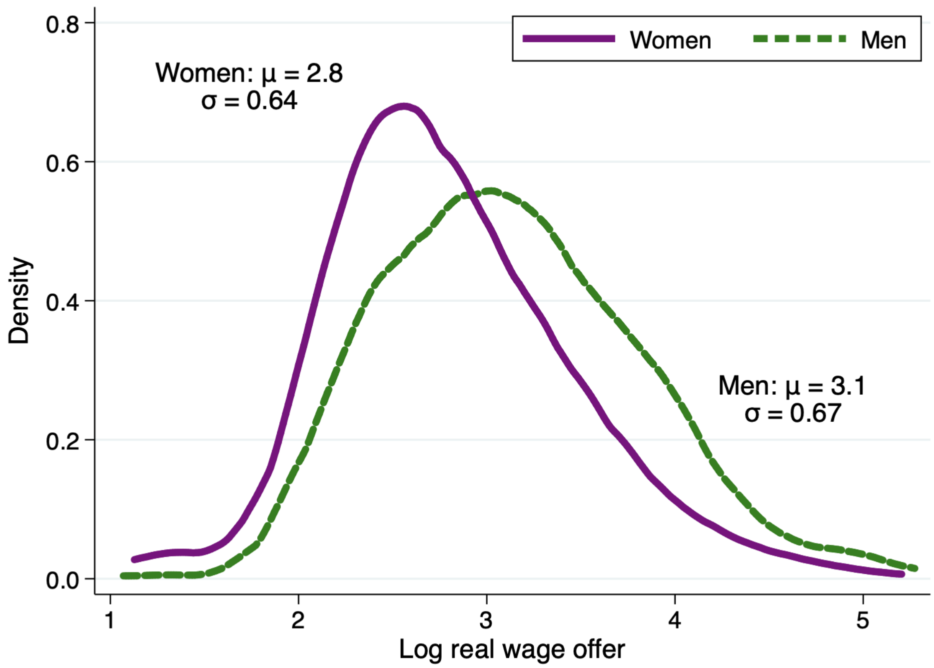


Table 8 provides insights into the methods through which men and women received their best job offers. The most notable gender difference is that women are far less likely than men to report unsolicited offers (15.62% of women vs. 26.13% of men, $p < 0.01$), but more likely to have been referred by former coworkers.

Table 8. Job search method

	Men	Women	Coefficient on women indicator from separate OLS regressions	
			Difference	Difference
Method of best offer (percent):				
Unsolicited	26.13	15.62	-10.51***	-8.66***
			(2.06)	(2.14)
Referred by friend	20.01	23.35	3.34	3.39
			(2.13)	(2.19)
Online search	17.17	16.64	-0.52	-2.09
			(1.93)	(1.99)
Employer's website	16.17	16.44	0.27	-1.70
			(1.91)	(1.98)
Referred by former co-worker	11.68	14.41	2.72	4.13**
			(1.74)	(1.81)
Referred by current employee	9.94	9.45	-0.49	-0.57
			(1.53)	(1.61)
Enquired with employer directly	8.36	6.61	-1.76	-1.59
			(1.35)	(1.39)
Previously worked for employer	8.30	9.14	0.84	0.48
			(1.87)	(1.98)
Employment agency	4.84	4.78	-0.07	-0.85
			(1.10)	(1.15)
Union	1.44	0.72	-0.72	-0.61
			(0.53)	(0.56)
Temporary job became permanent	0.75	0.96	0.22	-0.02
			(0.48)	(0.51)
Other means	2.71	4.14	1.43	1.50
			(0.95)	(0.99)
Observations	698	815	1,513	1,513
Workers controls			no	yes
State and year fixed effects			no	yes

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

The benefits associated with job offers show large disparities between men and women. Women are less likely than men to receive benefits such as dental insurance, stock options, and retirement contributions as part of their job offers. Notably, 45.27% of women reported receiving no benefits, compared to only 33.67% of men, a significant difference of 11.60 percentage points (p < 0.01).

Table 9. Job offer features

	Men	Women	Difference	Difference
Percent with offer:				
Received while employed full-time	67.30	55.48	-11.83***	-7.75***
			(3.29)	(2.98)
Unsolicited	26.13	15.64	-10.49***	-8.66***
			(2.54)	(2.60)
Involving bargaining	40.54	32.83	-7.71**	-6.60**
			(3.19)	(3.07)
Not offering benefits	33.60	46.32	12.72***	10.00***
			(3.33)	(3.10)
Received through a referral	34.68	40.99	6.30*	7.76**
			(3.27)	(3.15)
Involving counter-offer	12.46	12.82	0.36	1.15
			(2.25)	(2.10)
From large firm (1k+ employees)	41.37	38.81	-2.56	-3.21
			(2.48)	(3.14)
In a different occupation	47.29	50.01	2.72	2.57
			(2.76)	(3.55)
Observations	698	815	1,513	1,513
Worker controls			no	yes
State and year fixed effects			no	yes

Notes: This is analogous to Table 10 except with and without controls. Worker controls include: age, age-squared, three education categories, four race categories, employment status, home ownership, marital status, and number of children under six. 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 10. Job offer benefits

	Men	Women	Coefficient on women indicator from separate OLS regressions	
			Difference	Difference
Benefit included in best offer (percent):				
Health insurance	60.83	48.30	-12.53***	-10.52***
			(2.77)	(3.36)
Dental insurance	54.80	43.37	-11.43***	-9.15***
			(2.78)	(3.36)
Retirement contribution	47.02	33.58	-13.44***	-11.16***
			(2.71)	(3.23)
Life insurance	32.53	28.97	-3.56	-2.42
			(2.58)	(3.10)
Flex. Spending Accounts	24.48	18.65	-5.83**	-3.29
			(2.29)	(2.58)
Pension plan	15.76	14.01	-1.75	-0.90
			(1.99)	(2.37)
Stock options	13.78	7.50	-6.29***	-5.77***
			(1.69)	(2.09)
Quality of life benefits	10.80	10.28	-0.52	-0.19
			(1.72)	(1.78)
Commuter benefits	9.08	5.50	-3.58**	-2.98**
			(1.44)	(1.45)
Childcare assistance	2.76	3.47	0.70	1.20
			(0.98)	(1.11)
Housing subsidy	1.71	0.83	-0.88	-0.71
			(0.61)	(0.70)
No benefits	33.67	45.27	11.60***	9.29***
			(2.73)	(3.36)
Observations	585	706	1,291	1,291
Worker controls			no	yes
State and year fixed effects			no	yes

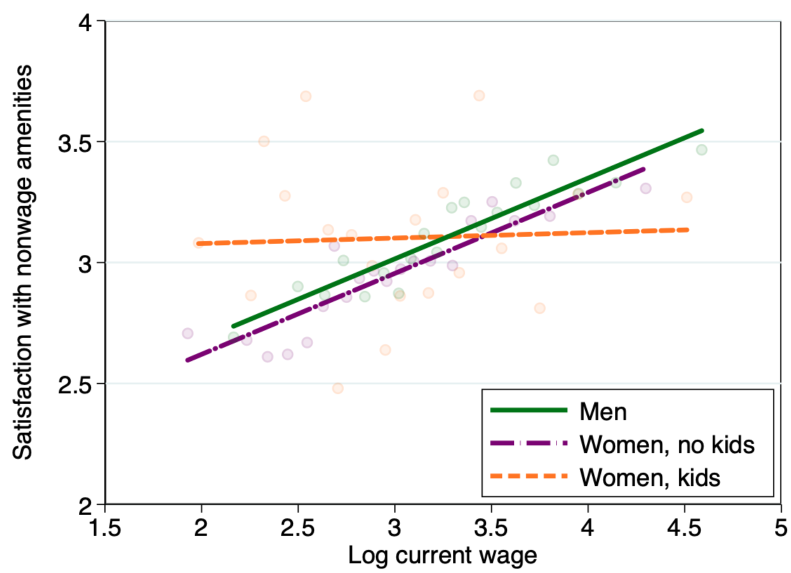
Notes: Table shows features of job offers. $^{***}p < 0.01$, $^{**}p < 0.05$,$^{*}p < 0.1$. *Source:* Estimates are calculated using the October 2013–2021 waves of the SCE Job Search Supplement.

3.3 Non-wage amenities

Table 11. Acceptance rates of hypothetical job offer

	Men	Women	Coefficient on women indicator from separate OLS regressions: Difference	Difference
Percent who would accept offer if required to:				
Work 10% more hours	60.52	56.55	-3.97***	-7.06***
			(1.33)	(1.37)
Double daily commute	34.98	29.50	-5.48***	-7.55***
			(1.26)	(1.29)
Relocate	17.97	14.67	-3.30***	-4.49***
			(1.00)	(1.02)
Observations	2,681	2,817	5,498	5,498
Worker controls			no	yes
State and year fixed effects			no	yes

Figure 2. Current wage versus satisfaction with nonwage amenities



The third fact is that men and women have differing preferences for non-wage amenities of a job. To show this, I first estimate the elasticity of search effort to wages. Given the lack of information about the search behavior of the employed prior to the SCE Job Search Supplement, the only two papers to previously measure empirically the relationship between search intensity and wages are Faberman et al. (2022) and Mueller (2010).

Faberman et al. (2022) focus on all those employed, and do not differentiate between men and women. Meanwhile Mueller (2010) uses ATUS data, which is a survey that asks persons the amount of time spent on job search in the prior day. There are measurement concerns in the ATUS job search measure and reasons to believe it is understated. For example, since respondents are asked to recall activities and time spent in the prior day, it is likely that short periods of job search are either omitted or understated.

Table 12 estimates the relationship between search effort and the current real wage in a linear regression. I consider three different measures of search – two capturing incidence in Panel A and one intensity in Panel B. The job ladder model postulate a negative relationship between wages and search. This is because as wages increases, search effort declines as the gains from search diminish. The negative and statistically significant coefficients in Table 12 show this job ladder motive is present for both men and women.

The job ladder motive is stronger for men than women, reflected in the smaller point estimates for men. Together with the mean of the dependent variable, I construct elasticities by dividing the point estimate by the mean. In Panel B, the search effort-wage elasticity for men is 2.6 times greater than the elasticity for women, -0.58 compared to -0.22.

The elasticity of search effort with respect to the current wage is negative for both men and women, indicating that higher wages reduce the intensity of job search. However, women exhibit a lower elasticity (-0.394) compared to men (-0.775), suggesting that women's search effort is less sensitive to wage changes.

Econometric specification for individual i in state s at year t:

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

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 an OLS regression of three different search measures regressed on the log real current wage. Panel A includes two binary measures of incidence of search. The active search measure is equal to one for any type of search in the last four weeks. The application measure is equal to one if the respondent sent any application in the last four weeks. Panel B includes one measure of the intensity of search, namely the number of applications sent in the last four weeks. Worker controls include: age, age-squared, three education categories, four race categories, an indicator for whether the respondent owns their house, marital status, and the number of children under six years old. 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. The number of applications sent is winsorized at the 0.1 percentile. The self-employed are excluded. 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.

3.4 Labor force attachment

The fourth fact is that women have a weaker attachment to the labor market and are more likely to restart their job search after time out of the labor force. Table 13 shows the mean number of months spent without a job in the last five years. This includes both those who are unemployed and out of the labor force. Women are statistically more likely to not have had a job in the last five years due to family obligations, other reasons, and are slightly more likely to be enrolled in school compared to men. Women spent 4 months without a job due to family obligations, compared to 1 month for men. Barring those who are disabled or retired, family obligations is the chief reason women did not have a job.

This table examines the total months without a job over the past 5 years, finding that family obligations play a much larger role in explaining women's labor force non-participation compared to men. Women report an average of 4.70 months without work due to family obligations, compared to only 1.01 months for men (p < 0.01).

Table 13. Months without a job in last 5 years and reasons

	Men	Women	Coefficient on women indicator from separate OLS regressions	
			Difference	Difference
Reasons for not having a job in last 5 years (months):				
Looking for work	2.32	2.49	0.17	-0.06
			(0.21)	(0.22)
Disabled or retired	2.28	2.73	0.46	-0.90**
			(0.39)	(0.38)
Enrolled in school	1.32	1.29	-0.03	-0.59***
			(0.20)	(0.22)
Family obligations	1.01	4.70	3.70***	2.58***
			(0.40)	(0.39)
Discouraged	0.21	0.33	0.12	0.01
			(0.09)	(0.10)
Other reasons	0.78	1.31	0.54**	0.32
			(0.22)	(0.24)
Observations	1,421	1,710	3,131	3,131
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.

Table 14 shows the percent of people who search for either part-time work or an additional job (Panel A) as well as the reasons for searching for part-time work (Panel B). Women are significantly more like to search for part time work as well as an additional job. As for reasons, women are more likely to look for part-time work due to issues relating to child care. Men are more likely to seek part-time work for additional income.

The final table highlights gender differences in part-time work. Women are significantly more likely to search for part-time work (26.67% of women compared to 18.86% of men, $p < 0.01$) and are far more likely to cite childcare availability as a reason for seeking part-time employment (11.98% of women vs. 1.22% of men, $p < 0.01$).

Table 14. Part-time work

	Men	Women	Coefficient on women indicator from separate OLS regressions	
			Difference	Difference
Reasons for seeking part-time work (percent):				
Just want additional income	49.88	40.30	-9.59***	-7.47**
			(3.50)	(3.55)
Hours flexibility	7.20	7.28	0.09	0.19
			(1.76)	(1.81)
Limited retirement income	6.84	6.68	-0.17	0.95
			(2.13)	(2.10)
Child care availability	1.22	11.98	10.76***	8.55***
			(1.67)	(1.41)
Other	5.91	7.82	1.91	-0.43
			(1.85)	(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.

3.5 Children

Table 15. Extensive and intensive margins of job search for women by children status

	No children	Children	Coefficient on children indicator from separate OLS regressions	
			Difference	Difference
Panel A: Extensive margin				
Percent who:				
Actively searched, last 7 days	19.91	24.92	4.12*	4.87**
			(2.25)	(2.45)
Actively searched, last 4 weeks	23.90	28.51	4.79**	5.21**
			(2.37)	(2.58)
Sent application, last 4 weeks	20.73	25.48	4.95**	4.62*
			(2.27)	(2.46)
Panel B: Intensive margin				
Number of:				
Hours searching, past 7 days	1.16	1.79	0.63*	0.69**
			(0.35)	(0.29)
Applications sent, past 4 weeks	1.28	2.23	0.95**	0.82*
			(0.46)	(0.44)
Applications for new job, past 4 weeks	0.93	1.96	1.03**	0.99**
			(0.45)	(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.

4 Model

4.1 Environment

The labor market is populated by unit mass of individuals. Time is continuous and individuals differ in their gender and children status. Individuals can either be female ($g = F$) or male ($g = M$). And individuals can either have kids ($k = 1$), or not have kids ($k = 0$). If individuals have children, their status permanently changes from $k = 0$ to $k = 1$.

Workers in the labor market can either be employed, in which case $e = E$, or unemployed, in which case $e = U$. Job matches are subject to exogenous separation shocks, denoted by $\delta_{g,k}$. In addition to being employed or unemployed, individuals can either be on parental leave or not. Individuals enter parental leave following an exogenous shock, denoted by δ_g^p. To ensure that the population distribution of people with and without kids remains balanced, workers permanently leave labor force and new workers enter at constant rates. There is an inflow of mass δ_g^r of new workers of each gender without kids ($k = 0$) into unemployed pool. Below I describe each of the value functions in turn.

4.2 Employment

Workers receive utility $u(w, a) = w + \eta a$ from a job with wage w and amenity a. They choose search effort s that results in a job offer arrival rate $\lambda^E(s) = \alpha^E + \beta^E s$ from employment and at rate $\lambda^U(s) = \alpha^U + \beta^U s$ from unemployment at a flow utility cost $c(s) = \kappa s^{1+(1/\gamma)}$. Jobs are destroyed at rate δ. Employed workers enter parental leave at rate δ^p. Workers permanently leave the labor force at rate δ^r. The discount rate is r.

The value of employment at utility u is $V(u)$ and satisfies the following HJB equation:

$$rV(u) = \max_s \left\{ \begin{array}{c} u - c(s) + \lambda^E(s) \int_{u'} \max\{V(u') - V(u), 0\} dF(u') + \delta[U - V(u)] \\ +\delta^p \left[P^E(u) - V(u)\right] - \delta^r V(u) \end{array} \right\},$$

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

$$rV(u) = \max_s \left\{ \begin{array}{c} u - c(s) + \lambda^E(s) \int_{u' \geq u} [V(u') - V(u)] dF(u') + \delta[U - V(u)] \\ +\delta^p \left[P^E(u) - V(u)\right] - \delta^r V(u) \end{array} \right\},$$

For simplicitly, for the remainder of this subsection, we write $\lambda(s)$ as a short-hand for $\lambda^E(s)$, and similarly we write (α, β) instead of $\left(\alpha^E, \beta^E\right)$.

The optimal policy choice s^* must satisfy the following FOC w.r.t. s:

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

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

Using integration by parts, we have

$$
\begin{aligned}
\int_{u' \geq u} \left[V\left(u'\right) - V\left(u\right)\right] dF\left(u'\right) &= \int_{u' \geq u} V\left(u'\right) dF\left(u'\right) - V\left(u\right) \bar{F}\left(u\right) \\
&= \left[V\left(u'\right) F\left(u'\right)\right]_{u'=u}^{u_{max}} - \int_{u' \geq u} V'\left(u'\right) F\left(u'\right) du' - V\left(u\right) \bar{F}\left(u\right) \\
&= V\left(u_{max}\right) - V\left(u\right) F\left(u\right) - \int_{u' \geq u} V'\left(u'\right) F\left(u'\right) du' - V\left(u\right) \bar{F}\left(u\right) \\
&= V\left(u_{max}\right) - V\left(u\right) - \int_{u' \geq u} V'\left(u'\right) F\left(u'\right) du' \\
&= \int_{u' \geq u} V'\left(u'\right) du' - \int_{u' \geq u} V'\left(u'\right) F\left(u'\right) du' \\
&= \int_{u' \geq u} V'\left(u'\right) \bar{F}\left(u'\right) du'
\end{aligned}
$$

Using this and the functional form for the job offer arrival rate $\lambda\left(s\right)$, we can write the FOC w.r.t. search effort as

$$
c'\left(s\right) = \beta \int_{u' \geq u} V'\left(u'\right) \bar{F}\left(u'\right) du'
$$

Implicitly, this equation defines the employed workers' optimal search effort s^* as a function of current utility u:

$$
s^*\left(u\right) = \left(c'\right)^{-1} \left(\beta \int_{u' \geq u} V'\left(u'\right) \bar{F}\left(u'\right) du'\right)
$$

Starting with the value for employment, we rearrange to get

$$
\left[r + \delta + \delta^p + \delta^r\right] V\left(u\right) = \max_s \left\{ u - c\left(s\right) + \lambda\left(s\right) \underbrace{\int_{u' \geq u} \left[V\left(u'\right) - V\left(u\right)\right] dF\left(u'\right)}_{\text{this part will be simplified using Int. by Parts}} + \delta U + \delta^p P^E\left(u\right) \right\}
$$

Integration by parts for the value of employment:

$$
\left[r + \delta + \delta^p + \delta^r\right] V\left(u\right) = \max_s \left\{ u - c\left(s\right) + \lambda\left(s\right) \underbrace{\int_{u' \geq u} V'\left(u'\right) \bar{F}\left(u'\right) du'}_{\text{this is obtained using Int. by Parts}} + \delta U + \delta^p P^E\left(u\right) \right\}
$$

where $\bar{F}(u') = 1 - F(u')$ is the survivor function.

Now finding the derivative of $V(u)$ w.r.t. u by the envelope condition for u:

$$
\begin{aligned}
\left[r + \delta + \delta^p + \delta^r\right] V'(u) = 1 & \\
& - \left[\frac{\partial c\left(s^*(u)\right)}{\partial s}\frac{\partial s^*(u)}{\partial u}\right] \\
& + \frac{\partial \lambda\left(s^*(u)\right)}{\partial s}\frac{\partial s^*(u)}{\partial u}\int_{u' \geq u} V'(u')\,\bar{F}(u')\,du' \\
& - \lambda\left(s^*(u)\right) V'(u)\,\bar{F}(u) \\
& + \delta^p \left(P^E\right)'(u) \\
= 1 - \lambda(s^*)\, V'(u)\,\bar{F}(u) + \delta^p \left(P^E\right)'(u) &
\end{aligned}
$$

Rearranging, we get

$$
V'(u) = \frac{1 + \delta^p \left(P^E\right)'(u)}{r + \delta + \delta^p + \delta^r + \lambda(s^*)\,\bar{F}(u)}
$$

To summarize, we start with an initial guess for $V'(u)$ and then iterate on two equations from above:

$$
\begin{aligned}
s^*(u) &= \left(c'\right)^{-1}\left(\beta \int_{u' \geq u} V'(u')\,\bar{F}(u')\,du'\right) \\
V'(u) &= \frac{1 + \delta^p \left(P^E\right)'(u)}{r + \delta + \delta^p + \delta^r + \lambda(s^*)\,\bar{F}(u)}
\end{aligned}
$$

After finding $V'(u)$ in this fashion, we obtain $V(u)$ as

$$
V(u) = \int V'(u)\,du
$$

with the assumed normalization $V(u_{min}) = 0$.

4.3 Unemployment

The value of unemployment is:

$$
rU = \max_s \left\{ b - c(s) + \lambda^U(s) \int_{u'} \max\left\{V(u') - U, 0\right\} dF(u') + \delta^p \left(P^U - U\right) - \delta^r U \right\},
$$

where 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

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

For simplicitly, for the remainder of this subsection, we write $\lambda(s)$ as a short-hand for $\lambda^{U}(s)$, and similarly we write (α, β) instead of $\left(\alpha^{U}, \beta^{U}\right)$.

The optimal policy choice s^{*} must satisfy the following FOC w.r.t. s:

$$c'(s^{*}) = \lambda'(s^{*}) \int_{u' \geq \phi} \left[V(u') - U \right] dF(u')$$

Using integration by parts and making use of the fact that $U = V(\phi)$, by definition of the reservation utility level ϕ, we have:

$$\begin{aligned}
\int_{u' \geq \phi} \left[V(u') - U \right] dF(u') &= \int_{u' \geq \phi} V(u') \, dF(u') - U \bar{F}(u) \\
&= \left[V(u') F(u') \right]_{u'=\phi}^{u_{max}} - \int_{u' \geq \phi} V'(u') F(u') \, du' - U \bar{F}(u) \\
&= V(u_{max}) - V(\phi) F(\phi) - \int_{u' \geq \phi} V'(u') F(u') \, du' - U \bar{F}(u) \\
&= V(u_{max}) - V(\phi) - \int_{u' \geq \phi} V'(u') F(u') \, du' \\
&= \int_{u' \geq \phi} V'(u') \, du' - \int_{u' \geq \phi} V'(u') F(u') \, du' \\
&= \int_{u' \geq \phi} V'(u') \bar{F}(u') \, du'
\end{aligned}$$

Using this and the functional form for the job offer arrival rate $\lambda(s)$, we can write the FOC w.r.t. search effort as

$$c'(s^{*}) = \beta \int_{u' \geq \phi} V'(u') \bar{F}(u') \, du'$$

Implicitly, this equation defines the unemployed workers' optimal search effort s^{*}:

$$s^{*} = (c')^{-1} \left(\beta \int_{u' \geq \phi} V'(u') \bar{F}(u') \, du' \right)$$

Moving the value for unemployment, we rearrange to get

$$[r+\delta^p+\delta^r]\,U=\max_s\left\{b-c\left(s\right)+\lambda\left(s\right)\underbrace{\int_{u'\geq\phi}\left[V\left(u'\right)-U\right]dF\left(u'\right)}_{\text{this part will be simplified using Int. by Parts}}+\delta^pP^U\right\}$$

Integration by parts for the value of unemployment:

$$[r+\delta^p+\delta^r]\,U=\max_s\left\{b-c\left(s\right)+\lambda\left(s\right)\underbrace{\int_{u'\geq\phi}V'\left(u'\right)\bar{F}\left(u'\right)du'}_{\text{this is obtained using Int. by Parts}}+\delta^pP^U\right\}$$

Rearranging, we get

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

To summarize, we start with an initial guess for U and an (updated) initial guess for $V'\left(u\right)$ and thus $V\left(u\right)$ from before, then iterate on three equations from above:

$$\begin{aligned}V\left(\phi\right)&=U\\ s^*&=\left(c'\right)^{-1}\left(\beta\int_{u'\geq\phi}V'\left(u'\right)\bar{F}\left(u'\right)du'\right)\\ U&=\frac{b-c\left(s^*\right)+\lambda\left(s^*\right)\int_{u'\geq\phi}V'\left(u'\right)\bar{F}\left(u'\right)du'+\delta^pP^U}{r+\delta^p+\delta^r}\end{aligned}$$

4.4 Parental Leave from employment

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

$$rP^E\left(u\right)=b^p+0.6\left(u\right)+\lambda^{p,U}\left(U-P^E\left(u\right)\right)+\lambda^{p,E}\left(V\left(u\right)-P^E\left(u\right)\right)-\delta^rP^E\left(u\right)$$

Rearranging to put like terms together:

$$\left[r+\lambda^{p,U}+\lambda^{p,E}+\delta^r\right]P^E\left(u\right)=b^p+0.6\times u+\lambda^{p,U}U+\lambda^{p,E}V\left(u\right)$$

Now finding the derivative of $P^E(u)$ w.r.t. u:

$$\left[r+\lambda^{p,U}+\lambda^{p,E}+\delta^r\right]\left(P^E\right)'(u) = 0.6+\lambda^{p,E}V'(u)$$
$$\left(P^E\right)'(u) = \frac{0.6+\lambda^{p,E}V'(u)}{r+\lambda^{p,U}+\lambda^{p,E}+\delta^r}$$

4.5 Parental Leave from employment

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

$$rP^U = b^p + \lambda^{p,U}\left(U - P^U\right) - \delta^r P^U$$

Putting like terms together:

$$P^U = \frac{b^p + \lambda^{p,U}U}{r+\lambda^{p,U}+\delta^r}$$

5 Model

5.1 Employment

Workers receive utility $u(w,a) = w + \eta a$ from a job with wage w and amenity a. They choose search effort s that results in a job offer arrival rate $\lambda^E(s) = \alpha^E + \beta^E s$ from employment and at rate $\lambda^U(s) = \alpha^U + \beta^U s$ from unemployment at a flow utility cost $c(s) = \kappa s^{1+(1/\gamma)}$. Jobs are destroyed at rate δ. Employed workers enter parental leave at rate δ^p. Workers permanently leave the labor force at rate δ^r. The discount rate is r.

The value of employment at utility u is $V(u)$ and satisfies the following HJB equation:

$$rV(u) = \max_s \left\{ \begin{array}{c} u - c(s) + \lambda^E(s)\int_{u'} \max\{V(u') - V(u), 0\}\, dF(u') + \delta\left[U - V(u)\right] \\ +\delta^p\left[P^E(u) - V(u)\right] - \delta^r V(u) \end{array} \right\},$$

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

$$rV\left(u\right)=\max_{s}\left\{\begin{array}{c}u-c\left(s\right)+\lambda^{E}\left(s\right)\int_{u'\geq u}\left[V\left(u'\right)-V\left(u\right)\right]dF\left(u'\right)+\delta\left[U-V\left(u\right)\right]\\+\delta^{p}\left[P^{E}\left(u\right)-V\left(u\right)\right]-\delta^{r}V\left(u\right)\end{array}\right\},$$

For simplicitly, for the remainder of this subsection, we write $\lambda\left(s\right)$ as a short-hand for $\lambda^{E}\left(s\right)$, and similarly we write $\left(\alpha,\beta\right)$ instead of $\left(\alpha^{E},\beta^{E}\right)$.

The optimal policy choice s^{*} must satisfy the following FOC w.r.t. s:

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

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

Using integration by parts, we have

$$\begin{aligned}\int_{u'\geq u}\left[V\left(u'\right)-V\left(u\right)\right]dF\left(u'\right)&=\int_{u'\geq u}V\left(u'\right)dF\left(u'\right)-V\left(u\right)\bar{F}\left(u\right)\\&=\left[V\left(u'\right)F\left(u'\right)\right]_{u'=u}^{u_{max}}-\int_{u'\geq u}V'\left(u'\right)F\left(u'\right)du'-V\left(u\right)\bar{F}\left(u\right)\\&=V\left(u_{max}\right)-V\left(u\right)F\left(u\right)-\int_{u'\geq u}V'\left(u'\right)F\left(u'\right)du'-V\left(u\right)\bar{F}\left(u\right)\\&=V\left(u_{max}\right)-V\left(u\right)-\int_{u'\geq u}V'\left(u'\right)F\left(u'\right)du'\\&=\int_{u'\geq u}V'\left(u'\right)du'-\int_{u'\geq u}V'\left(u'\right)F\left(u'\right)du'\\&=\int_{u'\geq u}V'\left(u'\right)\bar{F}\left(u'\right)du'\end{aligned}$$

Using this and the functional form for the job offer arrival rate $\lambda\left(s\right)$, we can write the FOC w.r.t. search effort as

$$c'\left(s\right)=\beta\int_{u'\geq u}V'\left(u'\right)\bar{F}\left(u'\right)du'$$

Implicitly, this equation defines the employed workers' optimal search effort s^{*} as a function of current utility u:

$$s^{*}\left(u\right)=\left(c'\right)^{-1}\left(\beta\int_{u'\geq u}V'\left(u'\right)\bar{F}\left(u'\right)du'\right)$$

Starting with the value for employment, we rearrange to get

$$[r+\delta+\delta^p+\delta^r]\,V(u)=\max_s\left\{u-c(s)+\lambda(s)\underbrace{\int_{u'\geq u}\left[V(u')-V(u)\right]dF(u')}_{\text{this part will be simplified using Int. by Parts}}+\delta U+\delta^p P^E(u)\right\}$$

Integration by parts for the value of employment:

$$[r+\delta+\delta^p+\delta^r]\,V(u)=\max_s\left\{u-c(s)+\lambda(s)\underbrace{\int_{u'\geq u}V'(u')\,\bar{F}(u')\,du'}_{\text{this is obtained using Int. by Parts}}+\delta U+\delta^p P^E(u)\right\}$$

where $\bar{F}(u')=1-F(u')$ is the survivor function.

Now finding the derivative of $V(u)$ w.r.t. u by the envelope condition for u:

$$\begin{aligned}
[r+\delta+\delta^p+\delta^r]\,V'(u)&=1\\
&\quad-\left[\frac{\partial c(s^*(u))}{\partial s}\frac{\partial s^*(u)}{\partial u}\right]\\
&\quad+\frac{\partial\lambda(s^*(u))}{\partial s}\frac{\partial s^*(u)}{\partial u}\int_{u'\geq u}V'(u')\,\bar{F}(u')\,du'\\
&\quad-\lambda(s^*(u))\,V'(u)\,\bar{F}(u)\\
&\quad+\delta^p\left(P^E\right)'(u)\\
&=1-\lambda(s^*)\,V'(u)\,\bar{F}(u)+\delta^p\left(P^E\right)'(u)
\end{aligned}$$

Rearranging, we get

$$V'(u)=\frac{1+\delta^p\left(P^E\right)'(u)}{r+\delta+\delta^p+\delta^r+\lambda(s^*)\,\bar{F}(u)}$$

To summarize, we start with an initial guess for $V'(u)$ and then iterate on two equations from above:

$$\begin{aligned}
s^*(u)&=\left(c'\right)^{-1}\left(\beta\int_{u'\geq u}V'(u')\,\bar{F}(u')\,du'\right)\\
V'(u)&=\frac{1+\delta^p\left(P^E\right)'(u)}{r+\delta+\delta^p+\delta^r+\lambda(s^*)\,\bar{F}(u)}
\end{aligned}$$

After finding $V'(u)$ in this fashion, we obtain $V(u)$ as

$$V(u) = \int V'(u)\, du$$

with the assumed normalization $V(u_{min}) = 0$.

5.2 Unemployment

The value of unemployment is:

$$rU = \max_s \left\{ b - c(s) + \lambda^U(s) \int_{u'} \max\{V(u') - U, 0\}\, dF(u') + \delta^p \left(P^U - U\right) - \delta^r U \right\},$$

where 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

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

For simplicitly, for the remainder of this subsection, we write $\lambda(s)$ as a short-hand for $\lambda^U(s)$, and similarly we write (α, β) instead of $\left(\alpha^U, \beta^U\right)$.

The optimal policy choice s^* must satisfy the following FOC w.r.t. s:

$$c'(s^*) = \lambda'(s^*) \int_{u' \geq \phi} \left[V(u') - U\right] dF(u')$$

Using integration by parts and making use of the fact that $U = V(\phi)$, by definition of the reservation utility level ϕ, we have:

$$\begin{aligned}
\int_{u'\geq\phi}\left[V\left(u'\right)-U\right]dF\left(u'\right) &= \int_{u'\geq\phi}V\left(u'\right)dF\left(u'\right)-U\bar{F}\left(u\right)\\
&= \left[V\left(u'\right)F\left(u'\right)\right]_{u'=\phi}^{u_{max}}-\int_{u'\geq\phi}V'\left(u'\right)F\left(u'\right)du'-U\bar{F}\left(u\right)\\
&= V\left(u_{max}\right)-V\left(\phi\right)F\left(\phi\right)-\int_{u'\geq\phi}V'\left(u'\right)F\left(u'\right)du'-U\bar{F}\left(u\right)\\
&= V\left(u_{max}\right)-V\left(\phi\right)-\int_{u'\geq\phi}V'\left(u'\right)F\left(u'\right)du'\\
&= \int_{u'\geq\phi}V'\left(u'\right)du'-\int_{u'\geq\phi}V'\left(u'\right)F\left(u'\right)du'\\
&= \int_{u'\geq\phi}V'\left(u'\right)\bar{F}\left(u'\right)du'
\end{aligned}$$

Using this and the functional form for the job offer arrival rate $\lambda\left(s\right)$, we can write the FOC w.r.t. search effort as

$$c'\left(s^*\right)=\beta\int_{u'\geq\phi}V'\left(u'\right)\bar{F}\left(u'\right)du'$$

Implicitly, this equation defines the unemployed workers' optimal search effort s^*:

$$s^*=\left(c'\right)^{-1}\left(\beta\int_{u'\geq\phi}V'\left(u'\right)\bar{F}\left(u'\right)du'\right)$$

Moving the value for unemployment, we rearrange to get

$$\left[r+\delta^p+\delta^r\right]U=\max_s\left\{b-c\left(s\right)+\lambda\left(s\right)\underbrace{\int_{u'\geq\phi}\left[V\left(u'\right)-U\right]dF\left(u'\right)}_{\text{this part will be simplified using Int. by Parts}}+\delta^pP^U\right\}$$

Integration by parts for the value of unemployment:

$$\left[r+\delta^p+\delta^r\right]U=\max_s\left\{b-c\left(s\right)+\lambda\left(s\right)\underbrace{\int_{u'\geq\phi}V'\left(u'\right)\bar{F}\left(u'\right)du'}_{\text{this is obtained using Int. by Parts}}+\delta^pP^U\right\}$$

Rearranging, we get

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

To summarize, we start with an initial guess for U and an (updated) initial guess for $V'\left(u\right)$ and thus $V\left(u\right)$ from before, then iterate on three equations from above:

$$\begin{aligned}
V\left(\phi\right) &= U \\
s^* &= \left(c'\right)^{-1}\left(\beta\int_{u' \geq \phi} V'\left(u'\right)\bar{F}\left(u'\right)du'\right) \\
U &= \frac{b - c\left(s^*\right) + \lambda\left(s^*\right)\int_{u' \geq \phi} V'\left(u'\right)\bar{F}\left(u'\right)du' + \delta^p P^U}{r + \delta^p + \delta^r}
\end{aligned}$$

5.3 Parental Leave from employment

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

$$rP^E\left(u\right) = b^p + 0.6\left(u\right) + \lambda^{p,U}\left(U - P^E\left(u\right)\right) + \lambda^{p,E}\left(V\left(u\right) - P^E\left(u\right)\right) - \delta^r P^E\left(u\right)$$

Rearranging to put like terms together:

$$\left[r + \lambda^{p,U} + \lambda^{p,E} + \delta^r\right] P^E\left(u\right) = b^p + 0.6 \times u + \lambda^{p,U}U + \lambda^{p,E}V\left(u\right)$$

Now finding the derivative of $P^E\left(u\right)$ w.r.t. u:

$$\begin{aligned}
\left[r + \lambda^{p,U} + \lambda^{p,E} + \delta^r\right]\left(P^E\right)'\left(u\right) &= 0.6 + \lambda^{p,E}V'\left(u\right) \\
\left(P^E\right)'\left(u\right) &= \frac{0.6 + \lambda^{p,E}V'\left(u\right)}{r + \lambda^{p,U} + \lambda^{p,E} + \delta^r}
\end{aligned}$$

5.4 Parental Leave from employment

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

$$rP^U = b^p + \lambda^{p,U}\left(U - P^U\right) - \delta^r P^U$$

Putting like terms together:

$$P^U = \frac{b^p + \lambda^{p,U} U}{r + \lambda^{p,U} + \delta^r}$$

6 Calibration

7 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 in terms of incidence of search as well as intensity. 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. These differences are driven primarily by the presence of children. When comparing the efficiency of men and women without children, there is no statistical differences. 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 an accounting decomposition of the wage distribution, unemployment, and match quality into differences in the cost of job search, payoffs to job search, and other factors.

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Appendix

Table 16. Extensive margin of search, by employment status

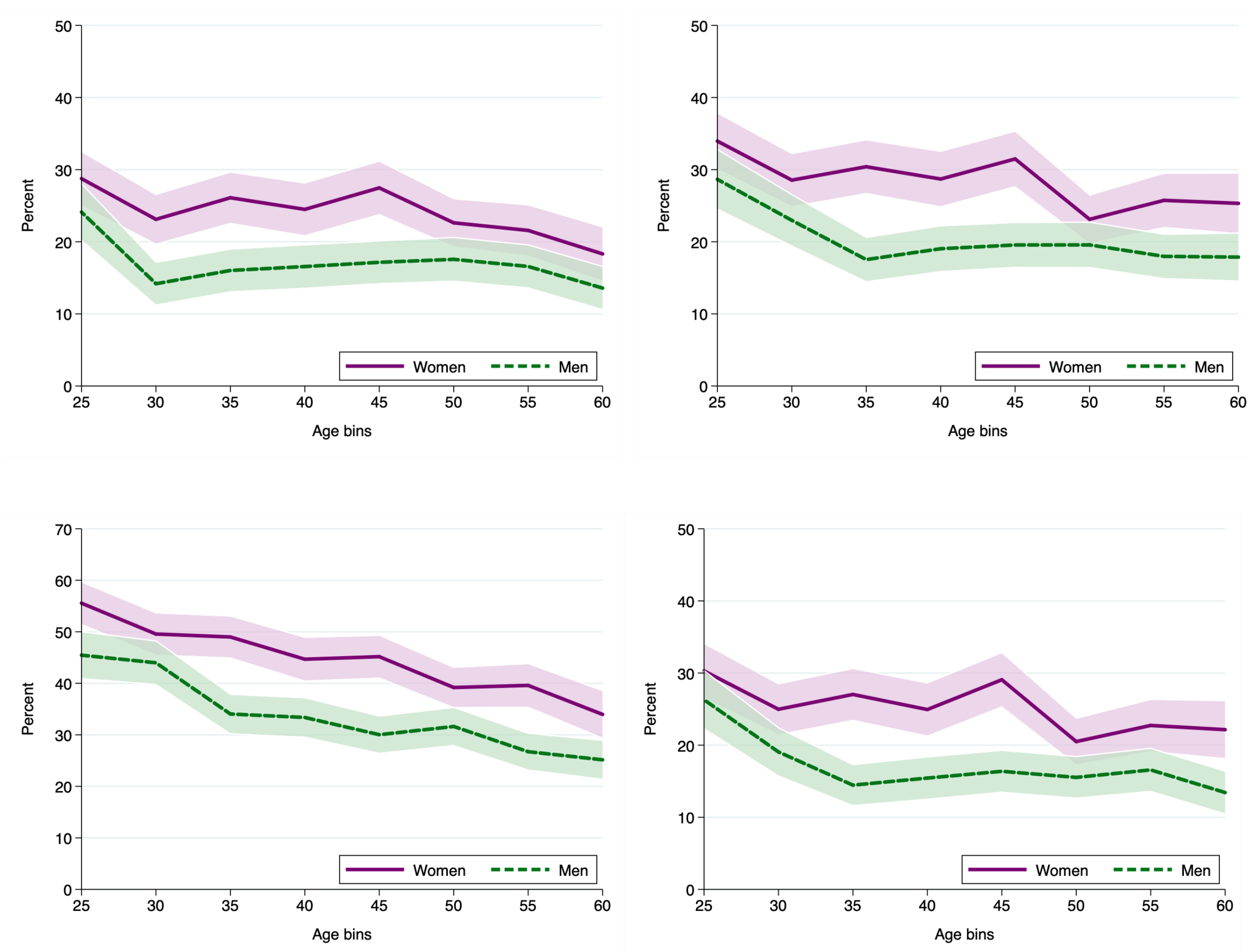
	Men		Women		Difference	
	Emp.	Unemp.	Emp.	Unemp.	(1) v. (3)	(2) v. (4)
Percent who:						
Actively searched, last 7 days	13.87	91.20	20.06	84.64	6.19***	-6.56*
	(0.60)	(2.37)	(0.72)	(2.51)	(0.93)	(3.72)
Actively searched, last 4 weeks	17.03	100.00	24.02	100.00	6.99***	0.00
	(0.65)	(0.00)	(0.76)	(0.00)	(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 3. 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 17. 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 18. Incidence conditional on active search

	Men	Women	Difference
Percent who searched for:			
An additional job	20.06	29.06	9.00***
			(2.17)
Part-time work	18.86	26.67	7.81***
			(2.15)
Work similar to current job	24.67	19.64	-5.03**
			(2.23)
Observations	716	933	1,415

Notes: Table reports desired job features, conditional on active search. 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 19. Incidence conditional on active search, by employment status

	Men		Women		Difference	
	Emp.	Unemp.	Emp.	Unemp.	(1) v. (3)	(2) v. (4)
Percent who searched for:						
An additional job	25.46	0.00	39.27	0.00	13.81***	0.00
	(1.82)	(0.00)	(1.81)	(0.00)	(2.62)	(0.00)
Part-time work	18.34	20.64	26.20	27.95	7.86***	7.31
	(1.65)	(3.38)	(1.67)	(3.12)	(2.40)	(4.82)
Work similar to current job	29.25	10.39	22.84	11.52	-6.41**	1.13
	(2.09)	(2.61)	(1.70)	(2.32)	(2.68)	(3.60)
Observations	572	144	725	208	1,086	329

Notes: This is analogous to Table 18 except broken down by employment status. 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 20. 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.

Figure 4. Kernel density of log current wage

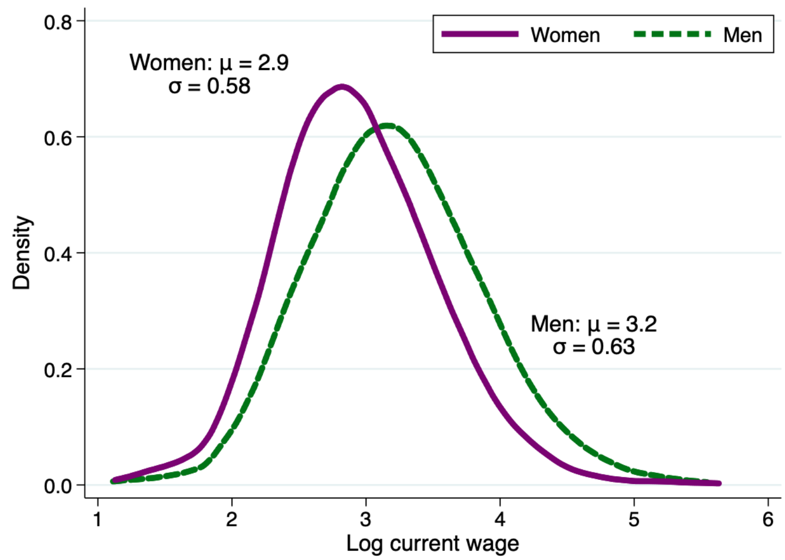


Figure 5. Kernel density of log reservation wage

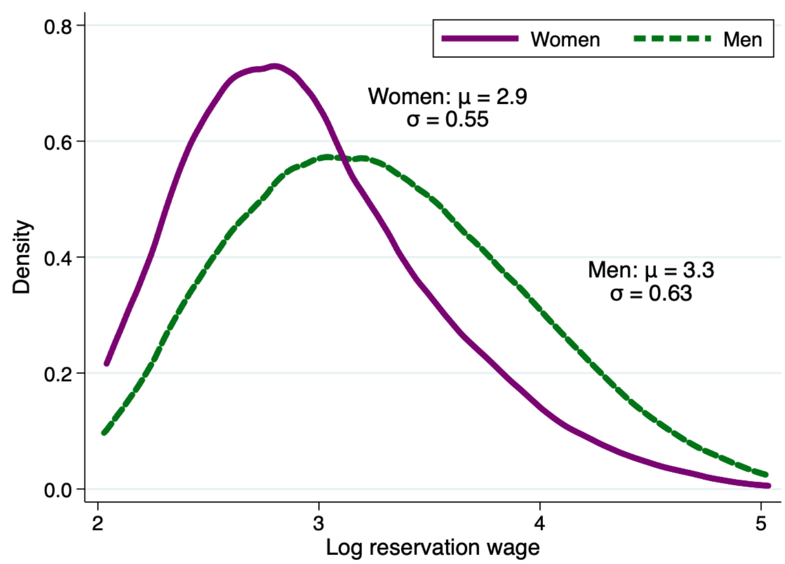


Figure 6. Kernel density of log previous wage

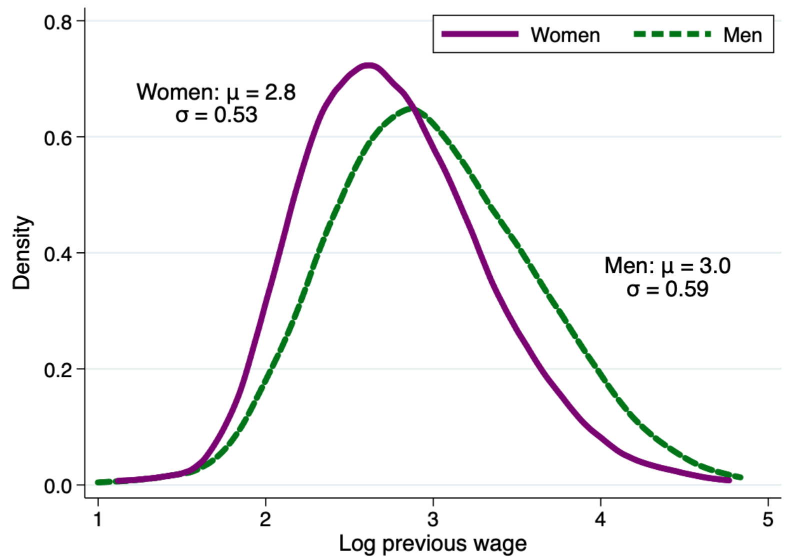


Table 21. Elasticity of job search, ATUS

	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 7. Months without a job