Job Search and the Gender Wage Gap*

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Abstract

We use data from a survey on a broad range of job search behavior, including on-the-job search, to examine the contribution of differences in the job search and job offer process to the gender wage gap. We show that men and women have similar job-to-job transition rates overall, but women are more likely to seek out and transition to part-time work. Women exert more job search effort but are generally equally successful in generating job offers per unit of search. The offers women receive, however, tend to pay lower wages, offer fewer hours, and offer less benefits. Relatedly, women appear more likely to accept lower wages to avoid nonwage job disamenities. We find that women's search effort is less responsive to the wage than men's search effort, and they have lower reservation wages. At the same time, women are more likely to reject a job offer that requires relocation, a doubled, commute, or increased hours. Additional survey responses suggest the disproportionate burdens of child rearing on women drive the observed gender differences in job valuations. These results imply women are more likely to face a *multidimensional job ladder* when pursuing or accepting a job offer. We develop an equilibrium model of labor market search where individuals can search while employed or nonemployed and where they value both the wage and nonwage aspects of a job. We allow for gender differences in multiple aspects of the search and matching process, including valuation of job amenities. We evaluate how much gender differences in these factors contribute to the overall wage gap. Our model can account for a nontrivial fraction of the observed wage gap, with gender differences in amenity preferences and job turnover each accounting for roughly half the contribution.

Keywords: gender wage gap, job search, job amenities, wage offers, on-the-job search
JEL Classifications: J16, J60

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1 Introduction

Researchers have been studying the gap in earnings between men and women for decades. Despite a narrowing of the gap over this period, current estimates suggest that women earn about 78 percent of what men earn, on average. A large part of the gender wage gap is due to the occupational choices of men and women (see, for example, Groshen, 1991; Blau and Kahn, 2000; among others), but even after controlling for gender differences in occupational choices, a sizable wage gap remains. Moreover, the gap tends to widen during the working-age years of the life cycle, with differences in labor force interruptions identified as a primary factor for this widening (Bertrand, Goldin, and Katz, 2010; Goldin, 2014).

In this paper, we use the Job Search Supplement of the Survey of Consumer Expectations (SCE) to study how much gender differences in the job search process can account for the gender wage gap.[1] The survey contains extensive information on the job search behavior and labor market outcomes of its respondents. Notably, the survey has extensive data on *on-the-job search*—existing studies of job search behavior by gender typically focus on the unemployed. Regardless of employment status, several margins in the job search and job offer process can generate gender differences in wage outcomes. First, men and women can differ in their search intensity. Second, men and women can differ in the types of jobs that they search for—e.g., they may look for jobs within different occupations, with differing hours, benefits, or other job (dis)amenities. Third, men and women can differ in their search methods. These may include differences in the reliance on more formal, direct search methods vs. the use of social or professional networks. Fourth, men and women may differ in how successful they are in generating job offers. Fifth, men and women may differ in the quality of offers that they receive. Finally, men and women may differ in the offers that they are willing to accept, and in the factors that drive the acceptance decision. These differences may occur for a variety of reasons, including differences in search behavior and gender discrimination.

We document gender wage gaps in the Current Population Survey (CPS) and SCE data that are comparable to those found in the broad literature on the subject. As Table 1 shows, men earn an hourly wage that is 18 to 31 log points higher than women, unconditionally, and men have

[1] Bowlus (1997) is an earlier study that presents evidence that gender differences in the search process contribute to the gender wage gap, though she focuses on workers who report separating for personal reasons in the NLSY.

weekly earnings that are 30 to 44 log points higher than women, unconditionally, depending on the survey used. Accounting for differences in demographics, occupation, and household composition reduces the hourly wage gap to 16 to 21 log points and the weekly earnings gap to 24 to 31 log points, depending on the survey used.

Table 1: The Gender Wage Gap for the Currently Employed

	CPS Data					**SCE Data**	
	(1)	(2)	(3)	(4)	HH Heads	(1)	(3)
Dependent variable: log real hourly wage							
Female coefficient	−0.179	−0.224	−0.161	−0.159	−0.193	−0.308	−0.210
	(.001)	(.001)	(.001)	(.001)	(.001)	(.018)	(.018)
R^2	0.048	0.296	0.429	0.431	0.457	0.088	0.318
Dependent variable: log real weekly earnings							
Female coefficient	−0.301	−0.350	−0.245	−0.243	−0.296	−0.441	−0.312
	(.001)	(.001)	(.001)	(.002)	(.003)	(.021)	(.021)
R^2	0.059	0.259	0.399	0.400	0.432	0.097	0.333
Year, state controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age, educ., race controls		Yes	Yes	Yes	Yes		Yes
Occupation controls,			Yes	Yes	Yes		Yes
Marriage, children controls				Yes			
N	1,179,815				477,942	6,227	

Notes: The table reports the coefficient estimates on a female dummy in separate regressions that include the controls indicated within each column. The dependent variable is the log real hourly wage or the log real weekly earnings. The samples are all employed individuals, excluding the self-employed, age 25 to 64 pooled across months between July 2013 and December 2022 in the CPS (first five columns) or the in the October 2013-22 waves of the SCE Job Search Supplement (last two columns). Robust standard errors are in parentheses.

We find considerable gender differences throughout each stage of the job search process, particularly among the employed. Women tend to exert more search effort than men but also tend to be just as effective as men in the number of job offers they generate per unit of search effort. Women also tend to have similar job-to-job transition rates as men, a result that holds across several surveys. These patterns, however, mask considerable heterogeneity in the types of jobs men and women search for and are willing to accept.

While men and women have similar job-to-job transition rates overall, women are more likely to transition into part-time work and less likely to transition into full-time work. On the surface, gender differences in the earnings gains from job switching appear minimal, but once one controls for prior earnings (i.e., one's position on the job ladder) men achieve about 8 percent higher earnings from job switching. Related to this, we find that women receive job offers that tend to be lower wage, have fewer hours, and are less likely to offer any benefits. In fact, we find that

the gender gap in offered wages is similar to the gap in current wages observed in Table 1. We also find that women are more likely to have their offers come through a formal search process than be unsolicited.

Digging deeper into the job search process, we find more stark differences by gender. Women are much more likely to search for and accept part-time work, and more likely to cite child or family obligations as the reason for doing so. Women's search intensity is also substantially less responsive to wages than men's search intensity; and women exert considerably less search effort than men at the lower end of the job ladder. The gender differences we document for the *search-wage elasticity* are considerably larger than the differences we find for the *search-job satisfaction elasticity*—that is, women are only somewhat less likely than men to search hard for a new job when they are dissatisfied with their current job.

Our evidence on job preferences suggests the dichotomy in search behavior may stem from women trading off lower wages to avoid nonwage job disamenities. Among the employed, we find that women's reservation wages are 34 log points lower then men's reservation wages unconditionally, and 25 log points lower after applying the same controls as in Table 1. The differences among the nonemployed are large as well. At the same time, women prefer about 12 log points fewer work hours per week than men (regardless of controls) and a significantly higher fraction of them report that they would not accept any job that doubles their commute, forces them to relocate, or increases their work hours by 10 percent or more. In other words, while women may be more willing to accept a job paying lower wages, they are less willing to accept nonwage job disamenities. Put another way, women's labor market search and matching behavior more strongly favors a *multidimensional job ladder* where they are more likely than men to trade off wages for other aspects of job quality.

We develop an equilibrium model of labor market search that allows for endogenous search effort and search while employed and nonemployed. Workers value both the wage and nonwage aspects of a job. We build on the models of Bagger and Lentz (2019), and Christensen et al. (2005), with wage offers and bargaining as in Cahuc, Postel-Vinay, and Robin (2006). We introduce job disamenities within a job search framework along the lines of Hwang, Mortensen, and Reed (1998), and Bonhomme and Jolivet (2009). Finally, we allow job valuations, search behavior, and labor market outcomes to potentially vary by employment status (as in Faberman

et al., 2022) and by gender. We calibrate the model by targeting moments from our empirical evidence. Our calibration is able to match the data well.

We then calculate how much of the observed gender wage gap the model can produce. The model can account for about 25 percent of the observed residual wage gap. Gender differences in search costs and the value of non-market time account for little of the contribution. Instead, gender differences in the valuation of nonwage job disamenities and in job turnover rates each account for nearly all of the model-implied gender wage gap, and do so in roughly equal amounts. We find this evidence as suggestive of the importance of nonwage (dis)amenities and the types of jobs that provide these amenities. The relatively low overall share of the gap the model is able to explain suggests that factors outside the model, such as gender differences in bargaining, unobserved heterogeneity (such as a higher burden for child rearing for women), and pay discrimination likely account for the remainder of the observed wage gap.

Our study is one of several recent studies to focus on gender differences in job search behavior. It builds on early work by Bowlus (1997). Perhaps most related to our study is the work of Le Barbanchon, Rathelot, and Roulet (2021). They show how much gender differences in preferences for commuting contributes to the gender wage gap using a sample of unemployed job seekers in France. They find that a greater disutility of commuting among women accounts for about 14 percent of the wage gap. D'Angelis (2023) documents a similar tradeoff among early-career women, who trade off wages for a greater access to parental leave, while Wiswall and Zafar (2017) find similar evidence in an experimental setting of undergraduates. Lochner and Merkl (2023) show that women in Germany are more likely to apply for jobs that allow greater work flexibility, while Fluchtman et al. (2024) show that observationally equivalent unemployed men and women in Denmark have significantly different job application behavior, in terms of the types of jobs they apply to. Cortes et al. (2023) show that, among recent MBA graduates, women tend to be more risk averse in their job acceptance decisions, while Rousille (2024) shows that there exists a gender gap in the asking wages of men and women in online job offers that can fully explain the final offered wage gap. Our research also builds on previous work examining gender differences in occupational sorting (Blau and Khan, 2017; Cortes and Pan, 2017; Erosa et al., 2022) and sorting induced by the firm, e.g., though offering a compensating wage differential (Morchio and Moser, 2023). Finally, we build on work that highlights workers' value for flexible work arrangements

(Mas and Pallais, 2017; Hall and Mueller, 2018; Sorkin, 2018; Maestas et al., 2023).

The next section describes our survey data and measurement approach. The following section presents our evidence on estimated gender wage gaps, search behavior by gender, and search outcomes by gender. Section 4 presents an equilibrium model of on-the-job search with endogenous search effort, worker valuation of nonwage job amenities, and search behavior and outcomes that potentially vary by gender. It also describes the calibration and parametrization of our model, as well as our quantification of the model-implied sources of the gender wage gap. Section 5 concludes.

2 Data and Measurement

Our data come from a supplement to the Survey of Consumer Expectations (SCE), administered by the Federal Reserve Bank of New York. The SCE is a monthly, nationally-representative survey of roughly 1,100 individuals that asks respondents their expectations about various aspects of the economy. The supplement was designed by Faberman et al. (2022), who first administered it in October 2013, and have administered it annually each October since then. The supplement asks a broad range of questions on employment status, job search behavior, and job search outcomes. Demographic data are also available for respondents through the monthly portion of the SCE survey.[2]

The survey asks a variety of questions that are tailored to an individual's employment status and job search behavior. It asks the employed about their wages, hours, benefits, and the type of work that they do, including questions on the characteristics of their workplace. It asks the nonemployed a range of detailed questions on their most recent employment spell and their reasons for nonemployment. It also asks individuals about their work history over the prior five years, as well as detailed information about the preceding job of the currently employed.

Regardless of employment status, the survey asks all individuals if they searched for work within the last four weeks, and if they did not search, whether they would accept a job if one was offered to them. For individuals who searched or would at least be willing to accept a new job if offered, the survey asks a series of questions relating to their job search (if any),

[2] A more detailed description of the survey, including basic statistics and its comparability to the Current Population Survey, is in Faberman et al. (2022).

including the reasons for their decision to (not) search. It then asks an exhaustive set of questions search methods used (e.g., updating resumes, searching online, contacting employers directly) and whether and why the search was targeted in some way (e.g. towards part-time work, or work similar to one's previous job). It also asks about the number of job applications completed within the last four weeks and the number of employer contacts and job offers received. It also probes further to see how those contacts and offers came about, i.e., whether they were the result of traditional search methods or whether they came about through a referral or an unsolicited employer contact. For those who received an offer, including any offers within the last six months, the survey asks about a range of characteristics of the job offer, including the wage offered, the expected hours, its benefits, as well as the type of work to be done and the characteristics of the employer. It also asks what led, or may lead, the respondent to accept or reject the offer, and asks a range of questions about whether there was any bargaining with either the current or future employer. Finally, the survey elicits a reservation wage from individuals who either looked for work or stated that they would accept a job if a suitable one was offered. It follows up with questions on the desired weekly work hours and by how much the reservation wage would have to increase if the job involved various disamenities, such as a doubled commute or relocation.

Many of the survey questions, including the questions on basic demographics and household characteristics, follow a format similar to the Current Population Survey (CPS). The survey also identifies the labor force status of respondents at several different points in their employment history: at the time of the survey, at the time of their hiring (if currently employed), and at the time of their job offer (if they received an offer within the last six months). We also impute a labor force status for individuals four weeks prior to the survey.[3] Our ability to identify labor force status at these different points allows us to deal with time aggregation and related issues when comparing the search and job-finding behavior of the employed and nonemployed. In particular, our ability to impute a labor force status four weeks prior to the survey allows us to examine subsequent search behavior and search outcomes over the month as a function of their initial labor force status.

Our study uses a sample from the SCE supplement of individuals aged 25 to 64 pooled across

[3]Our methodology for determining one's labor force status four weeks earlier draws from responses to multiple questions. We detail our methodology for this determination in Faberman et al. (2022).

the October 2013-2022 surveys. This provides just over 7,900 individual observations. Individuals are only in the SCE for, at most, one year, so our sample is a panel of repeated cross sections rather than longitudinal. The survey does not ask the self-employed about job search, so the self-employed are generally excluded by construction throughout our analysis. We also focus on the subsample of individuals who received a job offer within the last six months. By construction, some of these offers will reflect the respondent's current job, which we identify through a separate question in the survey. After removing offers with only partial data, the offer sample has 1,836 observations. We use this sample to examine a range of job offer characteristics. Note that we first asked respondents whether they received any offer in the last month, and only if they did not, did we ask about offers received in the last six months. Thus, the data allow us to determine the monthly job offer arrival rate.

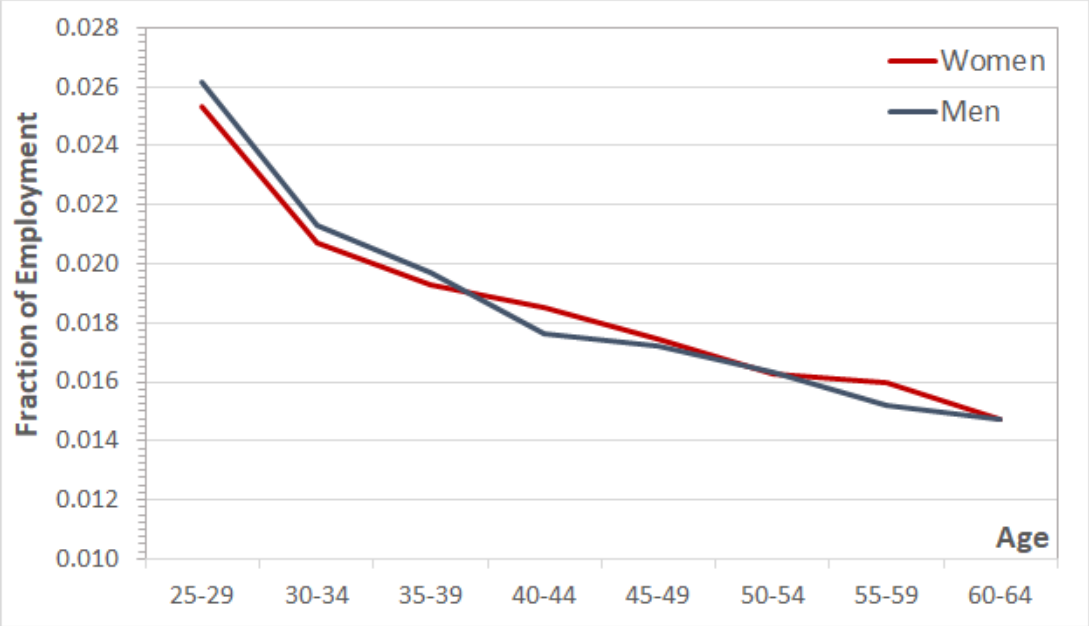
3 Evidence

We begin this section with evidence on gender differences in job switching. Next, we present evidence on search behavior and search outcomes by gender, including the characteristics of job offers received. We then move on to document gender differences in job search preferences over wages, job satisfaction, and nonwage job attributes.

3.1 Gender Differences in Employment Transitions

Figure 1 reports the job-to-job transition rate for men and women by broad age category. We measure the rates as the percent of the prior month's employed who change jobs over the month in the CPS. Job-to-job transition rates are very similar for men and women, with the rates of both falling from about 2.6 percent in their twenties to about 1.5 percent in their early sixties. Table 2 reports the estimated gender difference in job-to-job transition rates conditional on observable characteristics and across several surveys. Specifically, the table reports the coefficients on a female dummy variable from regressions run similarly to the Mincer-style wage regressions in Table 1, but with the monthly incidence of a job-to-job transition as the dependent variable. We find little differences in job-to-job transition rates between men and women. This is true regardless of our additional controls for demographics, occupation, and household composition, and regardless of the whether we estimate the gender difference using the CPS, SCE, or the

Figure 1: Job-to-Job Transition Rates by Gender and Age



Notes: Figure reports job-to-job transition rates by gender and age bin. Rates are measured as the fraction of the prior month's employment. Estimates are from two-month matched observations of all employed aged 25 to 64 in the CPS between July 2013 and December 2022.

Table 2: Gender Differences in Job-to-Job Transitions

	CPS Data				**SCE**	**SIPP**
	(1)	(2)	(3)	(4)	**Data**	**Data**
Dependent variable: E-to-E transition rate						
Female coefficient	−0.0002	0.0000	0.0001	0.0000	0.0052	−0.0011
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0041)	(0.0002)
Year, state controls	Yes	Yes	Yes	Yes	Yes	Yes
Age, educ., race controls		Yes	Yes	Yes	Yes	Yes
Occupation controls,			Yes	Yes	Yes	Yes
Marriage, children controls				Yes		Yes
R^2	0.000	0.001	0.002	0.003	0.042	0.003
N	2,925,438				6,161	2,823,691

Notes: Estimates from CPS, SCE, and SIPP data. CPS and SCE data are pooled over 2013-22, for all employed aged 25 to 64, excluding the self-employed. SIPP estimates are for pooled cohorts aged 25 to 64 employed between 1995 and 2012. E-to-E transitions in the SCE are the fraction of employed who accepted an offer in the last 4 weeks, excluding acceptances of secondary jobs. All regressions control for time period and state. Robust standard errors in parentheses.

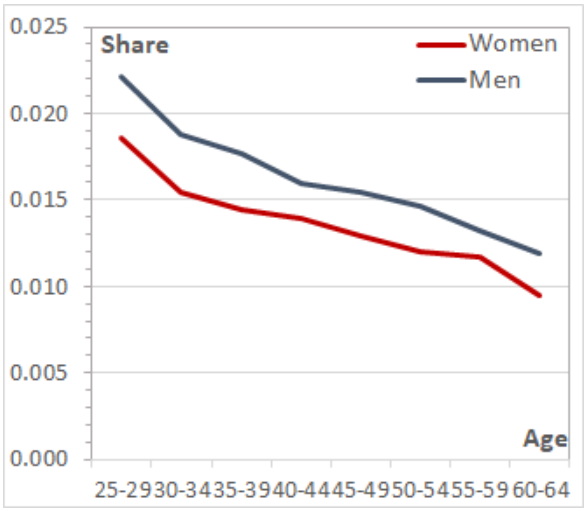
Survey of Income and Program Participation (SIPP).[4]

Figure 2, however, suggests that the similar patterns in overall transition rates for men and

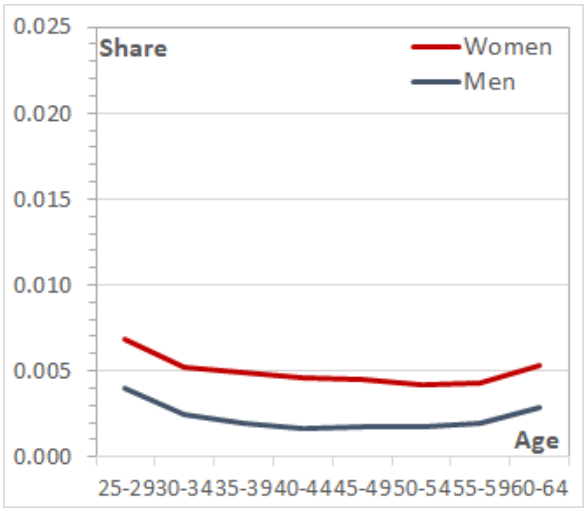
[4]In the CPS and SIPP, we have explicit survey questions that identify a job-to-job transition. The SCE data are not longitudinal, however, so we identify these transitions using those employed in the current and prior months who reported accepting a job within the last four weeks.

Figure 2: Job-to-Job Transition Rates to Full-Time or Part-Time Work by Gender and Age

(a) Job-to-Job Transition to Full-Time



(b) Job-to-Job Transition to Part-Time



Notes: Figure reports job-to-job transition rates to full-time work (left panel) or part-time work (right panel) by gender and age bin. Rates are measured as the fraction of the prior month's employment. Estimates are from two-month matched observations of all employed aged 25 to 64 in the CPS between July 2013 and December 2022.

women mask notable heterogeneity in the *types* of jobs men and women transition into. The figure shows that, conditional on job switching, men are considerably more likely to transition to full-time work, while women are considerably more likely to transition into part-time work. The gaps in transition rates by type of work are roughly constant by age.

Table 3 presents another aspect of job switching where the headline estimates mask significant gender differences. The table reports the year-over-year earnings gains of individuals who are currently employed and were employed in the CPS twelve-months prior, and reported transitioning into their current job within the prior three months (i.e., are recent hires).[5] If we only condition on the same observables we use in Tables 1 and 2 we find almost no gender gap in the growth rates of hourly wages or weekly earnings. If we additionally control for prior earnings, however, we find that men have wage growth that is 5.5 log points higher than women's wage growth and have weekly earnings growth that is 8.4 log points higher than women's earnings growth. Individuals at lower ends of the wage ladder tend to have higher earnings growth. Consequently,

[5]We measure earnings growth and identify job switchers in this way because of the nature of CPS interviews. Respondents are in the survey for four months, out for eight months, and in again for four more months, and are only asked about their earnings during their fourth and last months in the survey. Our approach estimates earnings gains among recent hires using the maximum amount of information on employment transitions following the initial earnings observation in the CPS.

Table 3: Gender Gaps in Earnings Growth Among Recent Hires

	(1)	(2)	(3)	(4)
Dependent variable: log real hourly wage				
Female coefficient	−0.003	−0.003	0.005	−0.055
	(0.006)	(0.006)	(0.006)	(0.006)
R^2	0.001	0.003	0.008	0.182
Dependent variable: log real weekly earnings				
Female coefficient	−0.000	0.001	0.006	−0.084
	(0.007)	(0.007)	(0.007)	(0.006)
R^2	0.001	0.006	0.010	0.303
Year, state controls	Yes	Yes	Yes	Yes
Age, education, race controls		Yes	Yes	Yes
Occupation controls			Yes	Yes
(log) year-ago weekly earnings				Yes
N		421,226		

Notes:Table reports the coefficient estimates on a female dummy (for all employed) interacted with a dummy for whether the individual was a recent hire in separate regressions that include the controls indicated within each column. The dependent variable is either the log real hourly wage or log real weekly earnings, and the sample used is all individuals age 25 to 64 who are employed in the current month and one year ago in the final outgoing rotation group of the CPS using pooled monthly data from July 2013 to December 2022.

the results suggest that we find essentially no gender gap in earnings growth among recent hires when we do not control for prior earnings because women occupy lower rungs of the wage ladder. Once we control for this (through the prior job's earnings), we find a significant gender gap in earnings growth.

3.2 Gender Differences in Search Effort and Outcomes

The similar job-to-job transition rates in Figure 1 and Table 2 also mask notable heterogeneity in job search behavior by gender. Table 4 reports job search effort by gender and employment status using several metrics. On average, women search more than men, regardless of whether we look at the extensive margin (the fraction who looked within the last month) or the intensive margin (the number of job applications sent in the last month or hours spent searching in the last week). Overall, about 25 percent of women report actively looking for work in the prior month, compared to 20 percent of men. The gender difference is slightly larger among the employed. Women also spend more hours searching per week and send more job applications per month than men. Across all individuals, women spend about 1.4 hours per week looking for work, while men spend 1.1 hours per week looking for work. Women also send 1.4 applications per month,

Table 4: Job Search Effort by Gender and Employment Status

	All		Employed		Nonemployed	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**
By Current Employment Status						
Pct. actively looking for work	19.7	24.5	19.2	25.2	21.5	24.2
	(0.6)	(0.7)	(0.7)	(0.8)	(1.5)	(1.4)
Pct. looking only for part-time	18.9	28.4	17.9	25.6	22.3	35.6
work, conditional on search	(1.4)	(1.4)	(1.5)	(1.6)	(3.3)	(3.1)
Hours spent searching, last	1.05	1.41	0.76	1.10	2.14	2.17
seven days	(0.07)	(0.07)	(0.06)	(0.07)	(0.22)	(0.21)
N	3,901	4,037	3,185	3,095	716	942
By Employment Status in Prior Month						
Applications sent in last four	0.98	1.37	0.80	1.04	1.66	2.28
weeks	(0.08)	(0.10)	(0.07)	(0.07)	(0.22)	(0.24)
Applications sent, excluding search	0.86	1.12	0.66	0.73	1.66	2.28
for additional work	(0.07)	(0.08)	(0.06)	(0.06)	(0.22)	(0.24)
N	3,901	4,037	3,196	3,155	705	882

Notes: Estimates come from authors' tabulations from the October 2013-22 waves of the SCE Job Search Supplement for all individuals aged 25-64 excluding the self employed. Standard errors are in parentheses.

compared to 1.0 applications per month for men.[6] Looking within employment states, much of the gender difference in search effort is due to differences in on-the-job search. A nontrivial amount is due to composition—that is, women are more likely to be nonemployed, and the nonemployed tend to search more intensely. Men and women also differ in the types of jobs they look for. For example, a good portion of the gender differences in on-the-job search reflects the fact that women are more likely to be searching for a job in addition to their current one.

Conditional on job search, women are also 9.5 percentage points, or about one-and-a-half times, more likely to only seek part-time work, consistent with their employment transitions observed in the CPS. Table 5 presents the reasons men and women state they are only looking for part-time work. Women are overwhelmingly more likely than men to cite child care duties as their primary reason, even more so when we restrict the sample to those with children. Men are more likely to cite a desire for additional income as their primary reason for seeking only part-time work.

Table 6 reports gender differences in job search outcomes, again for all individuals and by employment status. Women tend to receive more job offers than men, especially among the

[6]Note that we report applications sent, as well as all subsequent statistics measured over the prior four weeks, by respondents' employment status one month earlier. We do this to ensure the reported employment status matches a respondent's most likely employment status at the time they conducted the reported activity.

Table 5: Reasons for Only Looking for Part-Time Work by Gender

	All Job Seekers		All w/ Children	
Percent citing...	**Men**	**Women**	**Men**	**Women**
Child care duties	3.2	16.1	6.6	34.2
	(0.6)	(1.0)	(1.4)	(2.1)
Hours flexibility	9.5	9.6	4.1	8.2
	(1.0)	(0.8)	(1.2)	(1.2)
Already employed	19.9	16.6	27.1	16.5
	(1.3)	(1.0)	(2.6)	(1.6)
Additional income	56.5	42.9	53.4	31.7
	(1.7)	(1.4)	(2.9)	(2.0)
Other reason	10.9	14.3	8.8	9.5
	(1.1)	(1.0)	(1.6)	(1.3)
N	891	1,277	300	536

Notes: Estimates come from authors' tabulations from the October 2013-22 waves of the SCE Job Search Supplement for all individuals aged 25-64 that stated they are only looking for, or would accept a job offer of, part-time work. Standard errors are in parentheses.

employed, but this is almost entirely because women search more intensely than men. Men and women receive roughly the same amount of offers per application sent, especially among the employed. A notable difference is that men are somewhat more likely to receive an *unsolicited* job offer (i.e., an offer that was not the result of the respondent's search efforts), especially among the nonemployed. In contrast, men and women have significant differences in their offer acceptance rates, with women being much more likely to accept a job offer. Across all individuals, men accept 24 percent of their offers while women accept 44 percent of their offers. The difference in acceptance rates is slightly smaller among the employed, and about the same among the nonemployed.

The difference in offer acceptance rates is notable because, despite the fact that women receive more offers, they tend to receive relatively poorer offers, on average. Tables 7 and 8 document this finding. Table 7 reports the gender wage gap in the log offered hourly wage and log offered weekly earnings, applying the same controls as we had in Table 1, and additionally controlling for employment status (since both the employed and nonemployed receive job offers in our sample). The table shows that, on average, the gender gap in offered wages is about the same as the gender gap in the current wages of the employed. Unconditionally, men receive wage offers that are 28 log points higher than women's wage offers, and with all controls (including demographics, household composition, employment status, and occupation), men receive wage offers that are

Table 6: Job Offers and Acceptance Rates by Gender and Employment Status

	All		Employed		Nonemployed	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**
By Employment Status in Prior Month						
Fraction with a formal offer in last four weeks	0.071 (0.004)	0.101 (0.005)	0.074 (0.005)	0.099 (0.005)	0.100 (0.011)	0.105 (0.010)
Fraction with an unsolicited offer in last four weeks	0.027 (0.003)	0.021 (0.002)	0.025 (0.003)	0.023 (0.003)	0.034 (0.007)	0.015 (0.004)
Offers per application sent	0.081	0.073	0.092	0.095	0.061	0.046
Fraction of formal offers accepted in last four weeks	0.243 (0.028)	0.442 (0.026)	0.270 (0.031)	0.415 (0.029)	0.322 (0.059)	0.512 (0.052)
N	3,901	4,037	3,196	3,155	705	882

Notes: Estimates come from authors' tabulations from the October 2013-22 waves of the SCE Job Search Supplement for all individuals aged 25-64 excluding the self employed. Standard errors are in parentheses.

Table 7: Gender Gaps in Offered Wages and Earnings

	(1)	(2)	(3)	(4)	(5)
Dependent variable: log real offered wage					
Female coefficient	−0.279	−0.247	−0.182	−0.171	−0.167
	(0.034)	(0.032)	(0.034)	(0.034)	(0.034)
Adjusted R^2	0.104	0.248	0.410	0.422	0.426
N			1,836		
Dependent variable: log offered earnings					
Female coefficient	−0.494	−0.468	−0.353	−0.340	−0.336
	(0.047)	(0.045)	(0.047)	(0.047)	(0.047)
Adjusted R^2	0.114	0.216	0.399	0.409	0.410
N			1,836		
Year, state controls	Yes	Yes	Yes	Yes	Yes
Age, education, race controls		Yes	Yes	Yes	Yes
3-digit occupation controls			Yes	Yes	Yes
LFS at offer controls				Yes	Yes
HH children, marital status controls					Yes

Notes: The table reports the estimated coefficients on a dummy variables for female from OLS regressions of the listed dependent variables on the female variable and the listed control variables in each column. Household children and marital status controls are the number of household children and a dummy variable for those who are married, alone and interacted with female, while labor force status at offer controls are a dummy for whether the respondent was employed at the time of offer. Three-digit occupation controls are based on the current job for the employed and the most recent job of the nonemployed. Regressions use data on all individuals aged 25-64 who received a job offer with the last six months from the October 2013-22 waves of the SCE Job Search Supplement. Robust standard errors are in parentheses.

17 log points higher than women's wage offers. Furthermore, men receive job offers with 49 log points higher weekly earnings unconditionally, and 34 log points higher earnings after controls.

Table 8 reports the (unconditional) characteristics of the job offer and the job offer process by gender, along with the female–male gap for each characteristic, unconditionally and after applying

Table 8: Job Offer Characteristics by Gender

	All		Female − Male Gap	
	Men	**Women**	**Uncond.**	**w/ Controls**
log offer usual hours	3.52	3.32	-0.203	-0.169
	(0.02)	(0.02)	(0.029)	(0.032)
Pct. of offers with no benefits	35.6	46.7	11.12	8.09
	(1.7)	(1.6)	(2.29)	(2.46)
Pct. of offers with any bargaining	39.6	32.6	-6.92	-5.34
	(1.7)	(1.5)	(2.24)	(2.67)
Pct. of offers with any counteroffer	11.8	11.4	-0.40	-0.28
	(1.1)	(1.0)	(1.50)	(1.76)
Pct. of offers that were unsolicited	27.4	16.2	-11.27	-7.42
	(1.5)	(1.2)	(1.90)	(2.22)
N	836	1000		

Notes: Estimates come from authors' tabulations from the October 2013-22 waves of the SCE Job Search Supplement for all individuals who received an offer in the prior six months aged 25-64 excluding the self employed. Standard errors are in parentheses.

the same full set of controls as in column (4) of Table 7. Unconditionally, men receive offers with hours that are 20 log points higher than the hours in women's job offers, and after controls, their advantage in hours is 17 log points. The table also shows that women are significantly more likely to receive a job offer that provides no benefits.[7] Across all individuals, 36 percent of men's job offers come with no benefits, while 47 percent of women's job offers come with no benefits. Controlling for observables reduces the female–male gap by 3 percentage points.

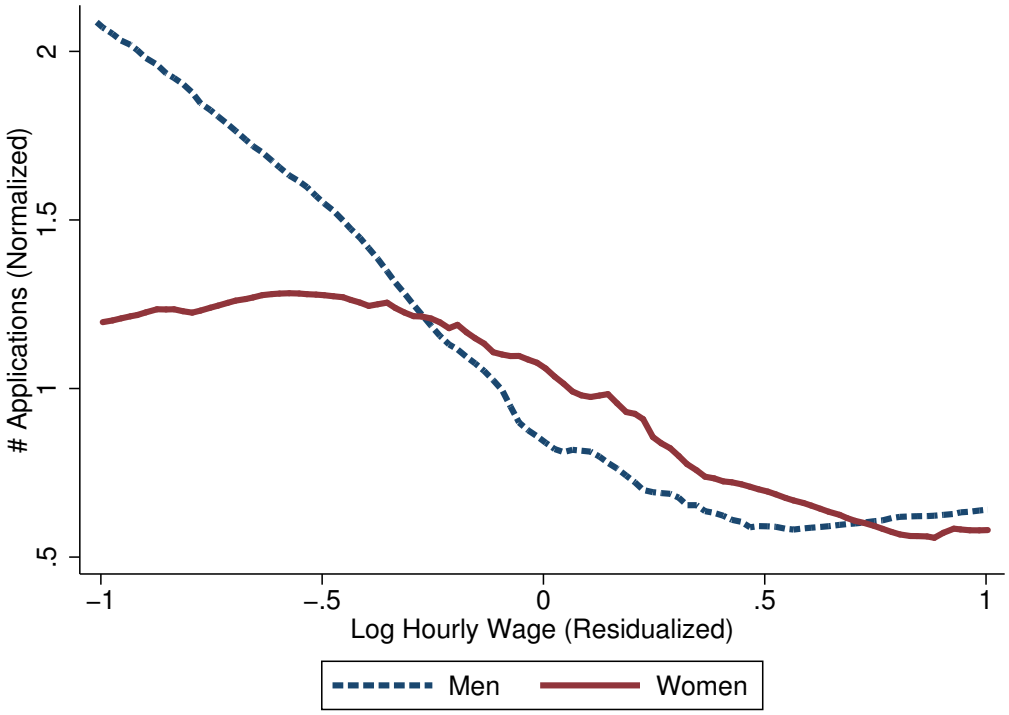
Table 8 shows that there are also notable differences in the job offer process. Consistent with previous studies, we find that men are more likely to bargain over a job offer than women, even after applying our controls. At the same time, we find no significant gender difference in the incidence of a counteroffer by their current employer. Men, however, are about 70 percent more likely to receive their offer from an unsolicited employer contact than women. Just over 27 percent of men's offers are unsolicited, while 16 percent of women's offers are unsolicited, and controlling for observables only reduces the gap by about 4 percentage points.

3.3 Gender Differences in Search-Job Value Elasticities

Next, we examine the link between search behavior, wages, and job satisfaction. We start by estimating the relationship between search intensity (measured as the number of applications

[7]These include health benefits, retirement benefits, quality-of-life benefits, stock options or other equity stakes, or any other nonwage form of compensation.

Figure 3: Applications Sent by Current Wage and Gender



Notes: Estimates are lowess smoothed plots of job applications sent in the last four weeks vs. the residualized log current wage for all employed age 25 to 64, excluding the self-employed. Wages condition on age, education, race, marital status, incidence of household children, and fixed effects for state, year, and 3-digit occupation. Sample is from the 2013-22 waves of the SCE.

sent in the prior four weeks) and an individual's (log) current wage. We do this by estimating a nonlinear relationship between applications sent and a residualized wage that controls for the same observables as in Table 1 for all employed individuals. We estimate the relationship separately by gender using a lowess smoother and report our results in Figure 3. The figure shows a negative relationship between search effort and wages for both men and women. This is consistent with a job ladder model of the labor market. In these models, workers search for new jobs to move up a job ladder (where jobs are generally ranked by their wage). Workers at the lower "rungs" of the job ladder have more to gain from a new job, probabilistically speaking, and therefore search harder. Workers near the top of the job ladder have only a small chance of finding a better job, and therefore search little. Notably, the figure shows that the relationship between search effort and wages is generally steeper for men than for women, particularly for wages at the lower end of the distribution.

Table 9: Estimated Search-Wage Elasticities by Gender

Dependent variable:	**Applications Sent**			**Pr(Applied)**	**Search Hours**
	All Employed	**F-T Employed**	**All w/ Children**	**All Employed**	**All Employed**
log current real wage, men	−0.841	−0.725	−0.800	−0.395	−0.416
	(0.179)	(0.126)	(0.245)	(0.069)	(0.145)
log current real wage, women	−0.207	−0.155	−0.145	−0.065	−0.161
	(0.114)	(0.121)	(0.183)	(0.053)	(0.098)
Dependent var. mean, men	0.79	0.65	0.78	0.157	0.77
Dependent var. mean, women	1.05	0.91	1.26	0.218	1.10

Notes: Estimates are from the SCE Job Search Supplement pooled over October 2013 to October 2022, for all employed aged 25 to 64, excluding the self-employed. Regressions are run separately for men and women and control for age, education, race, 3-digit occupation, and year and state effects (N equals 3,160 and 3,067 for men and women, respectively). Dependent variables are the number of applications sent in the last four weeks, the incidence of any application sent in the last four weeks, and the hours spent searching for work in the last seven days. Each dependent variable is divided by its gender-specific mean. Robust standard errors in parentheses.

Next, we estimate the relationship between search effort and the (log) hourly wage for all employed individuals separately by gender via OLS regressions, applying the same controls as before. We normalize the dependent variables by dividing them by their gender-specific means so that our one can interpret our coefficients as elasticities. We use the number of applications sent in the last four weeks, the probability an individual sends any application in the last four weeks, and the hours spent searching in the last seven days as our search effort measures. We also replicate the analysis on applications sent restricting the sample to the full-time employed and to all employed with children. We report our estimates in Table 9. Again, there is a consistently negative relationship between search effort and the wage across our specifications and across our subsamples, and the relationship is consistently more negative for men than for women. We find that the search-wage elasticity is -0.84 for men and -0.21 for women for all employed individuals and using applications sent as our search effort measure, implying that the search intensity of men is about four times more responsive to their current wage than the search intensity of women. The gender difference in elasticities is about the same if we restrict the sample to full-time employed or those with children. The elasticities are smaller overall for our other measures of search effort, but a substantial gender difference in their values remains, with men's search effort being more responsive to the wage in each case.

One reason women's search effort may be less responsive to the wage is that it is more responsive to other, nonwage aspects of the job. We explore this with specific measures of job

disamenities in the next subsection. Here, though, we can reestimate our search elasticity with respect to an ordinal measure of job satisfaction rather than log wages. This produces search-job satisfaction elasticities by gender that capture how the search efforts of men and women respond to their overall satisfaction with their job. Job satisfaction includes their values for both the wage and nonwage aspects of the job. If women value nonwage aspects more than men, we should at least see a smaller gap in the search-job satisfaction elasticities than in the search-wage elasticities, if not an equating of the two for men and women.

Table 10 reports our results. We use the (normalized) number of applications sent in the last four weeks as our dependent variable. Our measure of job satisfaction is a 1 to 5 ranking of each respondent's satisfaction with their current job (where 5 represents "extremely satisfied"). The SCE Job Search Supplement began asking the job satisfaction question in 2014. We estimate the elasticity using the raw ordinal ranking and using a dummy variable equal to one if the respondent had a job satisfaction ranking of 4 or 5. We re-run our regressions for all employed, the full-time employed, and the employed with children separately by gender, and use the same controls as in Table 9. For all employed individuals, the search-job satisfaction elasticities by gender are much closer to each other than the search-wage elasticities. The elasticity estimate for men is -0.90 and the elasticity estimate for women is -0.64. The two elasticities are even closer and are not statistically different from each other in the other subsamples or for the discrete measure of job satisfaction. Thus, while women's search effort appears not very responsive to the wage, it is much more responsive to their overall job satisfaction. This is consistent with the notion that women place a higher value on nonwage aspects of their job.

3.4 Gender Differences in Job Valuations

Thus far, our evidence presents a somewhat contradictory picture of gender differences in job search. Women search harder and tend to receive more offers as a result, but these offers tend to be low-quality in terms of wages, hours, and benefits. Nevertheless, women are more likely to accept these offers. Women are less likely to search more intensely when they are in a low-wage job, relative to men, but their search effort is more responsive to their overall job satisfaction. To better understand this behavior, we next examine gender differences in the self-reported reasons for how individuals value particular jobs.

Table 10: Estimated Search-Job Satisfaction Elasticities by Gender

Dependent variable:	**Applications Sent**			
Job Satisfaction Measure:	**Satisfaction Ranking (1 to 5)**			**Pr(Satisfaction ≥ 4)**
	All Employed	**F-T Employed**	**All w/ Children**	**All Employed**
Job satisfaction	−0.900	−0.665	−0.885	−1.457
coefficient, men	(0.108)	(0.098)	(0.166)	(0.254)
Job satisfaction	−0.636	−0.586	−0.822	−1.201
coefficient, women	(0.071)	(0.078)	(0.120)	(0.173)
Dependent var. mean, men	0.78	0.63	0.74	0.78
Dependent var. mean, women	1.08	0.95	1.25	1.08

Notes: Estimates are from the SCE Job Search Supplement pooled over October 2014 to October 2022, for all employed aged 25 to 64, excluding the self-employed. Regressions are run separately for men and women and control for demographics (age, education, race, marital status, number of household children), 3-digit occupation, and year and state effects (N equals 2,755 and 2,708 and the mean job satisfaction rankings are 3.86 and 3.76 for men and women, respectively). Dependent variables are the number of applications sent in the last four weeks, the incidence of any application sent in the last four weeks, and the hours spent searching for work in the last seven days. Robust standard errors in parentheses.

The SCE Job Search Supplement collects survey responses on individuals' reservation wages, desired work hours, and several hypotheticals about how a respondent's reservation wage would need to change to accept certain job disamenities. It asks these of all individuals who looked for work or stated they "might" take a job if offered (regardless of labor force status). We estimate the gender gaps in the log reservation wage and log desired work hours, and report these in Table 11, applying the same controls as in earlier exercises. We depart from the earlier exercises in that we estimate the gender gap separately for the employed and nonemployed. We find a somewhat larger gender gap in the reservation wage than we found for offered wages or the current wages of the employed. Among the employed, women have a reservation wage that is 34 log points lower than men's reservation wage unconditionally, and the gap only falls to 25 log points when we apply all of our controls. Among the nonemployed, the gender gap in the reservation wage is 23 log points unconditionally and 15 log points after applying all controls. Women also prefer fewer work hours than men. Among the employed, the gap is about 12 log points, and among the nonemployed, the gap is about 7 log points. Adding additional controls does little to affect the results.

In Table 12, we report the fraction of individuals who would not take a job (at any wage) if the listed job characteristic changed to become a greater disamenity. Among those who would still accept a job with the listed job disamenity, we also report how much their reservation wage

Table 11: Gender Gaps in Reservation Wages and Desired Work Hours

	(1)	(2)	(3)	(4)
Dependent variable: log real hourly reservation wage				
Female × employed	−0.343	−0.308	−0.260	−0.248
	(0.017)	(0.016)	(0.016)	(0.016)
Female × nonemployed	−0.225	−0.180	−0.144	−0.146
	(0.034)	(0.031)	(0.032)	(0.032)
Adjusted R^2	0.195	0.347	0.438	0.449
Dependent variable: log desired weekly work hours				
Female × employed	−0.117	−0.120	−0.099	−0.115
	(0.016)	(0.016)	(0.017)	(0.026)
Female × nonemployed	−0.071	−0.099	−0.066	−0.068
	(0.031)	(0.031)	(0.034)	(0.039)
Adjusted R^2	0.056	0.065	0.102	0.105
Year, state controls	Yes	Yes	Yes	Yes
Age, education, race controls		Yes	Yes	Yes
Occupation controls			Yes	Yes
Marriage, children controls,				Yes
N		6,095		

Notes: The table reports the estimated coefficients on the interaction between a dummy variable for female and employment status from OLS regressions of the listed dependent variables on these interactions, dummy variables for employment status, and the listed control variables in each column. Household children and marital status controls are the number of household children and a dummy variable for those who are married. Three-digit occupation controls are based on the current job for the employed and the most recent job of the nonemployed. Regressions use data on all individuals aged 25-64 who either looked for work or stated they might take a job if offered to them from the October 2013-22 waves of the SCE Job Search Supplement. Robust standard errors are in parentheses.

would have to change to accept the disamenity, on average, by gender. We report the female–male difference in these statistics unconditionally and conditional on the same controls as in earlier analyses. The disamenities we focus on are a hypothetical need to relocate, a doubling of one's commute, and a 10 percent increase in required work hours.

In contrast to the findings in Table 11 that showed women had lower reservation wages, Table 12 shows that women have much stronger preferences on the nonwage characteristics of the job. Women are 11 percentage points more likely to state they would not accept a job that requires them to relocate at any wage. Women are also 10 percentage points more likely to refuse a job at any wage that doubles their commute, and 7 percentage points more likely to refuse a job that required 10 percent higher hours than their desired hours. In all three cases, adding our controls does little to alter the estimates.

The bottom panel of Table 12 shows that, conditional on being willing to accept the hypothetical job disamenities, men and women require roughly similar increases in their reservation wages

Table 12: Gender Gaps in Job Disamenity Valuations

	Unconditional Means		Female − Male Gap	
	Men	**Women**	**Uncond.**	**w/ Controls**
Percentages who refuse the disamenity				
Percent that would not	43.9	55.0	11.03	10.92
relocate at any wage	(0.9)	(0.9)	(1.28)	(1.40)
Percent that would not double	26.4	36.7	10.35	10.86
commute at any wage	(0.8)	(0.9)	(1.19)	(1.84)
Percent that would not increase	15.9	23.2	7.31	6.30
hours 10% at any wage	(0.7)	(0.8)	(1.02)	(1.17)
Increase in reservation wage needed to accept disamenity (conditional on acceptance)				
Percent increase in wage	31.9	33.4	1.53	1.18
needed to relocate	(0.9)	(1.0)	(1.34)	(1.55)
Percent increase in wage double	22.2	23.1	0.87	0.14
needed to double commute	(0.7)	(0.8)	(1.00)	(1.17)
Percent increase in wage	8.4	9.2	0.85	0.93
needed to increase hours 10%	(0.4)	(0.5)	(0.55)	(0.65)
N	2,946	3,149		

Notes: Estimates from all individuals aged 25-64 who either looked for work or stated they might take a job if offered to them from the October 2013-22 waves of the SCE Job Search Supplement. Controls include state, year, age, race, education, 3-digit occupation of current/most recent job, and employment status. Standard errors in parentheses.

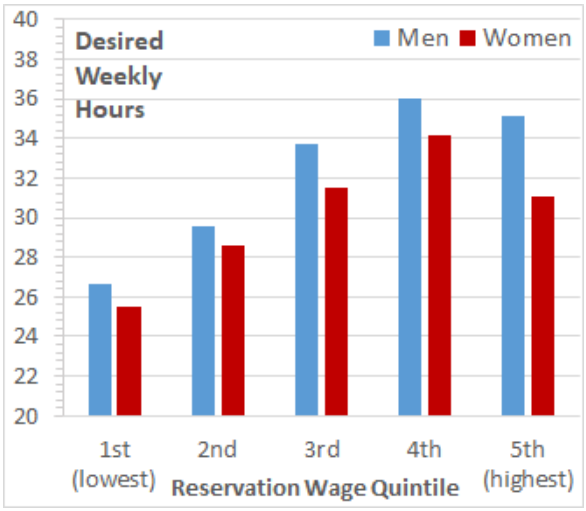
to do so. This is true after applying our controls as well. Thus, most of the gender differences in what individuals would be willing to accept to take a job with these disamenities are along the extensive margin—i.e., in whether they would accept such a job at all and not in how much of a compensating differential they would need to accept such a job.

Figure 4 illustrates the relationship between nonwage aspects of the job and individuals' reservation wages. The left panel of the figure reports desired weekly work hours by gender and quintile of the reservation wage distribution. The right panel reports the percentage of individuals who would reject a doubling of their commute at any wage by gender and reservation wage quintile. The figure shows that women prefer fewer work hours across the reservation wage distribution, though the gender gap is somewhat higher for higher reservation wages. The figure also shows that women are more likely to reject a doubled commute across the reservation wage distribution, and again, the gender gap is larger for higher reservation wages. Thus, the gender differences in valuations of nonwage job characteristics are pervasive throughout the wage distribution.

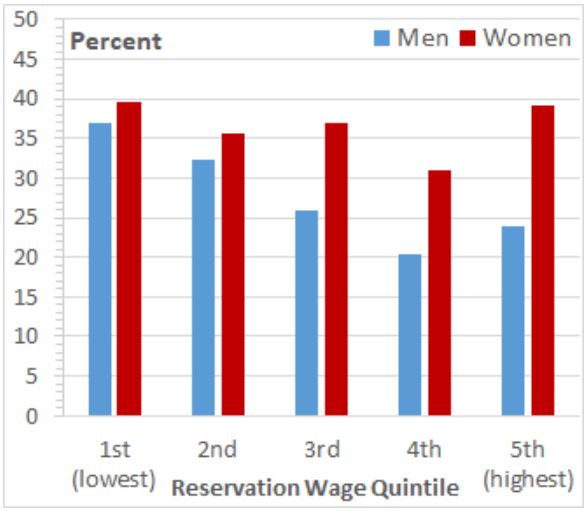
Taken together, the evidence on reservation wages and nonwage job preferences suggest that

Figure 4: Gender Differences in Hours and Commuting Valuations by Reservation Wages

(a) Desired Work Hours



(b) Fraction Rejecting a Doubled Commute



Notes: Figure reports respondents' desired weekly work hours (left panel) and the fraction who would not accept a doubled commute at any wage by quintiles of their reported reservation wage. Sample is all individuals in the SCE age 25 to 64 who report looking for work or who might take a job if offered, across the SCE Job Search Supplement from October 2013 to October 2022.

women may prefer lower wages because they have a stronger disutility of certain job disamenities than men. With respect to our elasticity estimates from the previous subsection, the evidence suggests that women's job search is less responsive to their wage because they have relatively stronger preferences on the nonwage aspects of a job. In this sense, women are more likely than men to face a *multidimensional job ladder* when deciding whether to pursue or accept a job. The evidence is consistent with recent work by Le Barbanchon, Rathelot, and Roulet (2021), who find that women are willing to accept a lower wage to avoid a longer commute; D'Angelis (2023) who finds that early-career women are willing to accept lower wages in order to obtain greater parental leave; and Wiswall and Zafar (2017), who find that women are more likely to trade off wages for job flexibility in an experimental setting. Our evidence from Table 5, which showed that women were more likely to choose part-time work because of child-care reasons, suggests that the burdens of child rearing on women may drive these preferences. The tradeoff between wages and job (dis)amenities is a key feature of the model we develop in the next section.

4 An Equilibrium Model with On-the-Job Search and Amenities

We set up an equilibrium search model with on-the-job search and endogenous search effort, where men and women differ along five dimesions: Preferences for non-wage amenities, preferences about non-market work/leisure, frequency of labor force interruptions, job search costs and efficiency and differences in bargaining power. Our model is based on Cahuc, Postel-Vinay and Robin (2006) and Bagger and Lentz (2019), but with two main extensions: First, we follow Faberman et al. (2022), and allow for differences in search costs and efficiency by employment status. Second, we introduce a match-specific disamenity, similar to Hwang, Mortensen, and Reed (1998) and Bonhomme and Jolivet (2009). The main goal of our modeling exercise is to quantify the different sources of the gender wage gap as well as to perform counterfactual simulations with different disamenity distributions.

4.1 Model Setup

Time is discrete and its discount rate is r. Firms are ex ante homogeneous and post vacancies, v, to recruit workers. The labor market consists of male and female workers, denoted by $g \in \{m, f\}$. Workers can be either employed or unemployed, with $j \in \{e, u\}$ denoting their employment status.[8]

Job Search and Production. When employed, workers may separate from their job via layoff at a rate δ_g, via a reallocation shock at a rate ρ_g, or via an endogenous quit to a new job. Reallocation shocks result in an offer for the worker but with the outside option of unemployment. Workers search for work both on and off the job, exerting an endogenous level of search effort, s, to generate job offers. Offer arrival rates potentially differ by gender and employment status. Offers arrive at a rate $\lambda_g^j(s)$, where s is search effort and where workers incur search costs of $c_g^j(s)$, which are increasing and convex in s.

Importantly, workers value both their wage earned, w, less a job disamenity, a, while employed. Their flow utility of employment is defined as $u_g(w, a) = w - \nu_g a$ and therefore depends on their gender through differential preferences on nonwage job disamenities, where ν_g represents the

[8] While we refer to those without jobs as unemployed, we calibrate them to all nonemployed individuals in our quantitative exercise.

disutility the worker receives per unit of disamenity, a. Unemployed workers receive flow utility b_g, which also potentially differs by gender. Output net of disamenity costs is py, where p is an aggregate productivity shifter and y is match-specific productivity. Let F_y be the distribution of match-specific productivity and F_a be the distribution of job disamenities. The flow value of the job match can be written as

$$\omega = py - \nu_g a. \tag{1}$$

Joint Match Value. We assume that firms' and workers' search and separations decisions are jointly optimal, which makes the problem tractable in general equilibrium as in Bagger and Lentz (2019). One can show that the flow value of the match, ω, is the only state variable for the employed worker to keep track of. [9] The joint value of a match, $K_g(\omega)$, thus satisfies:

$$\begin{aligned} K_g(\omega) = \max_{s,R^\delta,R^e} \Bigg\{ & \omega - c_g^e(s) + \frac{1}{1+r}\Bigg[K_g(\omega) - \delta_g[K_g(\omega) - U_g - V] \\ & + \tilde{\rho}_g(\theta) \int_{R^\delta} [W_g(\omega', 0) + V - K_g(\omega)] dF_g(\omega') - \tilde{\rho}_g(\theta) F_g(R^\delta)[K_g(\omega) - U_g - V] \\ & + \tilde{\lambda}_g^e(s,\theta) \int_{R_g^e} [W_g(\omega', \omega) + V - K_g(\omega)] dF_g(\omega') \Bigg] \Bigg\}, \end{aligned} \tag{2}$$

where $F_g(\omega) = \int F_y(\omega + \nu_g \hat{a}) dF_a(\hat{a})$ and $dF_g(\omega) = \int dF_y(\omega + \nu_g \hat{a}) dF_a(\hat{a})$, $\tilde{\rho}_g(\theta) = (1-\delta_g)\rho_g \lambda(\theta)$ and $\tilde{\lambda}_g^e(s,\theta) = (1-\delta_g)(1-\rho_g)\lambda_g^e(s)\lambda(\theta)$.[10] A worker who receives an exogenous separation shock flows into unemployment. If a worker receives a reallocation shock ρ_g, they sample an outside offer and accept it if the offered match value is above the optimal reservation match value R_g^δ. In the absence of separation or reallocation shocks, the worker samples an outside offer with probability $\tilde{\lambda}_g^e(s,\theta)$ from the distribution $F_g(\cdot)$ and accepts the offer if its flow value is above the optimal reservation flow value, $R_g^e(\omega)$.

Value of Unemployment. The value of unemployment, U_g, satisfies:

$$U_g = \max_{s,R^u} \Big\{ b_g - c_g^u(s) + \frac{1}{1+r}\Big[U_g + \lambda_g^u(s,\theta) \int_{R^u} [W_g(\omega', 0) - U_g] dF_g(\omega') \Big] \Big\}, \tag{3}$$

[9] Intuitively, this follows from random matching, which implies that the probability of getting an outside offer with a particular combination of y' and a' is independent of the particular combination of y and a in the current match.

[10] Search effort is bounded above at $\bar{s}_i$ such that the probability of an offer does not exceed one.

where b_g is the type-specific flow value of unemployment, $\lambda_g^u(s,\theta) = \lambda_g^u(s)\lambda(\theta)$ is the probability of matching with a firm, and R_u^g is the unemployed worker's optimal reservation match output.

Vacancy Posting. Firms pay a per-period vacancy posting cost, c, and vacancies are filled with probability $q(\theta)$. Let $J_g(\omega',\omega)$ be the value of the firm in a match with flow value ω' when the outside option of the worker is a match with flow value ω, and with $\omega = 0$ if the worker's outside option is unemployment. The value of a vacancy, V, satisfies:

$$\begin{aligned} V &= -c + \frac{1}{1+r}\Bigg[V + q(\theta)\sum_g \pi_g \Bigg(\frac{u_g}{S}\lambda_g^u(s_g^u)\int_{R_g^u}(J_g(\omega',0)-V)dF_g(\omega') \\ &+ \frac{1-u_g}{S}\tilde{\rho}_g\int_{R_g^\delta}(J_g(\omega',0)-V)dF_g(\omega') \\ &+ \frac{1-u_g}{S}\int \tilde{\lambda}_g^e(s_g^e(\hat{\omega}))\int_{R_g^e(\hat{\omega})}(J_g(\omega',\hat{\omega})-V)dF_g(\omega')G_g(\hat{\omega})d\hat{\omega}\Bigg)\Bigg], \end{aligned} \tag{4}$$

where $\tilde{\rho}_g = (1-\delta_g)\rho_g$ and $\tilde{\lambda}_g^e(s) = (1-\delta_g)(1-\rho_g)\lambda_g^e(s)$. Aggregate effective search effort is $S = \sum \pi_g S_g$, where the effective number of searchers is $S_g = u_g\lambda(s_g^u) + (1-u_g)[\tilde{\rho}_g + \int \tilde{\lambda}_g^e(s_g^e(\hat{\omega}))G_g(\hat{\omega})]d\hat{\omega}$ and where $G_g(\omega)$ is the cumulative distribution function of match value ω for workers of gender g.

Wage Contracts. Wage contracts are negotiated at the beginning of the match and renegotiated in the presence of an outside offer as in Cahuc et al. (2006). The value of a job offer with output ω' for workers in a match with output ω satisfies the Nash-Bargaining solution:

$$W_g(\omega',\omega) = \tau_g(K_g(\omega') - V) + (1-\tau_g)K_g(\omega). \tag{5}$$

Similarly, the value of a job offer with productivity y for unemployed workers satisfies:

$$W_g(\omega',0) = \tau_g(K_g(\omega') - V) + (1-\tau_g)U_g. \tag{6}$$

where the workers' bargaining share is τ_g, which potentially varies by gender. The value of the match for firms, $J_g(\omega',\omega)$, is the remainder of the joint value $K_g(\omega')$.

While the worker values only depend on the joint flow value ω, the wage itself will depend on both the joint flow value as well as the amenity of the match, $w_g^{NB}(\omega,a)$. In fact, we can define a Nash-Bargain transfer $t_g^{NB}(\omega)$ such that $t_g^{NB}(\omega) = w_g^{NB}(\omega,a) - \nu_g a$ and $\omega - t_g^{NB}(\omega) = py - w_g^{NB}(\omega,a)$. One can easily prove that t_g^{NB} only depends on ω and not its components.

Using the Nash-bargaining solutions, one can simplify the value functions for the joint match value and the value of unemployment. To simplify the presentation, we impose the equilibrium zero profit condition $V = 0$. The joint value of a match then can be rewritten as:

$$\begin{aligned} K_g(\omega) \quad &= \max_{s,R^\delta,R^e} \Bigg\{ \omega - c_g^e(s) + \frac{1}{1+r} \Bigg[K_g(\omega) - [\delta_g + \tilde{\rho}_g(\theta)](K_g(\omega) - U_g) \\ &\quad + \tilde{\rho}_g(\theta) \int_{R^\delta} \tau_g(K_g(\omega') - U_g) dF_g(\omega') + \tilde{\lambda}_g^e(s,\theta) \int_{R^e} \tau_g(K_g(\omega') - K_g(\omega)) dF_g(\omega')) \Bigg] \Bigg\} \end{aligned} \tag{7}$$

The value of unemployment can be rewritten as:

$$U_g \quad = \quad \max_{s,R^u} \left\{ b_g - c_g^u(s) + \frac{1}{1+r} \Big[U_g + \lambda_g^u(s,\theta) \int_{R^u} \tau_g(K_g(\omega) - U_g) dF_g(\omega) \Big] \right\}. \tag{8}$$

Using the Nash-bargaining solutions, one can also simplify the value functions for vacancy posting as follows:

$$\begin{aligned} V \quad &= \quad -c + \frac{1}{1+r} \Bigg[V + q(\theta) \sum_g \Bigg(\frac{u_g}{S} \lambda_g^u(s_g^u) \int_{R_g^u} (1-\tau_g)(K_g(\omega') - U_g - V) dF_g(\omega') \\ &+ \quad \frac{1-u_g}{S} \tilde{\rho}_g \int_{R_g^\delta} (1-\tau_g)(K_g(\omega') - U_g - V) dF_g(\omega') \\ &+ \quad \frac{1-u_g}{S} \int \tilde{\lambda}_g^e(s_g^e(\hat{\omega})) \int_{R_g^e(\hat{\omega})} (1-\tau_g)(K_g(\omega') - K_g(\hat{\omega}) - V) dF_g(\omega') dG_g(\hat{\omega}) \Bigg) \Bigg]. \end{aligned} \tag{9}$$

First Order Optimality Conditions. Given these simplified value functions, the first order condition with respect to s for employed and unemployed individuals, respectively, are:

$$(1+r) c_g^e(_s')(s_g^e(\omega)) = \tilde{\lambda}_g^e(_s')(s_g^e(\omega), \theta) \int_{R_g^e(\omega)} [\tau_g(K(\omega') - K(\omega))] dF_g(\omega') \tag{10}$$

$$(1+r) c_g^u(_s')(s_g^u) = \lambda_g^u(_s')(s_g^u, \theta) \int_{R_g^u} \tau_g[K(\omega') - U_g] dF_g(\omega'), \tag{11}$$

where $(_s')$ is our short form for the derivative with respect to s. The first order conditions for the reservation productivities are:

$$K_g(R_g^\delta) = U_g \tag{12}$$

$$K_g(R_g^u) = U_g \tag{13}$$

$$K_g(R_g^e(\omega)) = K_g(\omega), \tag{14}$$

which implies that $R_g^e(\omega) = \omega$ and $R_g^\delta = R_g^u$.

Stationary Distribution and Equilibrium. The steady-state unemployment rate, u_g, is pinned down by equalizing the inflow and outflows as follows:

$$u_g \lambda_g^u(s_g^u, \theta)[1 - F_g(R_g^u)] = (1 - u_g)[\delta_g + \tilde{\rho}_g(\theta) F_g(R_g^\delta)]. \tag{15}$$

The steady-state distribution of workers across ω, $G_g(\omega)$, is pinned down by equating employment inflows and outflows as follows:

$$\begin{aligned} &u_g \lambda_g^u(s_g^u, \theta)[F_g(\omega) - F_g(R_g^u)] + (1 - u_g)\tilde{\rho}_g(\theta)[F_g(\omega) - F_g(R_g^\delta)] = \\ &(1 - u_g)[\delta_g + \tilde{\rho}_g(\theta)]G_g(\omega) + (1 - u_g) \int^{\omega} [1 - F_g(\max\{R_g^e(\hat{\omega}), \omega\})] \tilde{\lambda}_g^e(s_g^e(\hat{\omega}), \theta) dG_g(\hat{\omega}), \end{aligned} \tag{16}$$

which shows the mass of workers who get an acceptable job offer equal to ω or lower on the left-hand side and the mass of workers who either lose the job due to a separation shock or leave the job because they accept a better offer that is above ω.

Definition 1 *A stationary equilibrium is defined as the search efforts s_g^u and $s_g^e(\omega)$, the reservation outputs R_g^u, R_g^δ, and $R_g^e(\omega)$, the unemployment rates u_g, the distributions $G_g(\omega)$, the labor market tightness θ, and the value functions $K_g(\omega)$, U_g, and V, that for all ω and g satisfy equations (7)-(9), the first-order conditions (10)-(14), the steady-state conditions (15) and (16), and the zero-profit condition $V = 0$.*

The stationary equilibrium is independent of the offered values $W_g(\omega', \omega)$ and $J_g(\omega', \omega)$ and thus does not require us to solve for the wage contracts. This considerably simplifies the equilibrium solution. Given the Nash-Bargaining solution, it is easy to solve for the offered values. In the Appendix, we derive the wage functions, $w_g^{NB}(\omega, a)$, implied by these offered values and amenities.

4.2 Model Calibration

Our model builds on Faberman et al. (2022) by introducing the concept of a job disamenity and potential variation in key moments and parameters by gender.[11] While part of our calibration strategy follows their approach, we incorporate job disamenities and variation by gender to capture the key moments we identify in our empirical analysis.

[11] The model here also assumes that worker bargaining shares do not differ by employment status and abstracts from censoring of offers and unobserved worker heterogeneity.

Table 13: Model Parameterization

A. Externally Calibrated Parameters

Parameter	Value	Source/Target
r	0.9966	Annual 4% discount rate
p	1.00	Normalization
c	0.80	$\theta = 1$
μ	1.00	Normalization
η	0.50	Petrongolo and Pissarides (2001)
τ	0.50	Hosios condition
γ	3.60	Faberman et al. (2022)
μ_y	1.00	Normalization
σ_y	0.27	Faberman et al. (2022)
μ_a	0.00	Normalization
σ_a	0.20	Normalization
σ_{ε_w}	0.31	Faberman et al. (2022)

B. Internally Calibrated Parameters

Parameter	Value	Target
κ_m^u , κ_f^u	0.039, 0.043	Search effort of U
κ_m^e , κ_f^e	0.004, 0.013	Search effort of E
α_m^u , α_f^u	0.045, 0.020	Unsolicited offer rate of U
α_m^e , α_f^e	0.033, 0.032	Unsolicited offer rate of E
β_m^u , β_f^u	0.044, 0.052	Offer rate of U
β_m^e , β_f^e	0.007, 0.026	Offer rate of E
b_m , b_f	1.053, 1.013	Acceptance rate of U
ν_m , ν_f	0.250, 1.000	Search-wage gradient
ρ_m , ρ_f	0.054, 0.068	Acceptance rate of E
δ_m , δ_f	0.000, 0.002	Non-employment rate

We assume a functional form for the search cost function identical to Faberman et al. (2022), but allow the scaling parameters to vary by gender, since our empirical results strongly suggest this is the case:

$$c_g^j(s) = \frac{\kappa_g^j}{1+\gamma} s^{1+\gamma} \text{ for } g \in \{m, f\} \text{ and } j \in \{e, u\}.$$

In our baseline calibration, we use $\gamma = 3.6$ based on the estimates from Faberman et al. (2022). As in the model, we assume that offers arrive at a rate $\lambda_g^j(s) = \alpha_g^j + \beta_g^j s$, and obtain our estimates for α_g^j through unsolicited offer rates and β_g^j using the search effort and offer arrival rates observed in the data.

We calibrate the flow value of unemployment, b_g, to match the gender-specific offer acceptance rates of the nonemployed. Similarly, we calibrate the job reallocation rate, ρ_g, to the gender-specific acceptance rates of the employed and the job destruction rate, δ_g to match the gender-

specific nonemployment rates. In our baseline parameterization, we assume that the bargaining shares of men and women are equal and satisfy the Hosios condition, $\tau_m = \tau_f = 0.5$.

As in Faberman et al. (2022), we assume that the distribution of productivity y is normal with mean $\mu_y = 1$ and standard deviation $\sigma_y = 0.27$. We also assume that wages are measured with error, and allow for a log-normal distribution of measurement error that has mean zero and standard deviation $\sigma_{\epsilon_w} = 0.31$. We must also make assumptions on the distribution of and valuation of disamenities offered by firms. In our baseline case, we normalize the mean level of disamenities to zero ($\mu_a = 0$) and assume a standard deviation of $\sigma_a = 0.2$. We then set the gender-specific disamenity valuations, ν_g, to match the gender-specific search-wage gradients we observe in the data.

We calibrate the remaining parameters of the model using standard approaches in the labor search literature. Specifically, we set the interest rate r to target a 4 percent annual discount rate, and set the flow cost of vacancies c to be consistent with a steady-state ratio of vacancies to job seekers equal to 1. We summarize our externally-calibrated parameters in Panel A of Table 13.

Panel B of Table 13 reports the estimates for our internally-calibrated parameters. The parameterization implies that women tend to face higher search costs, and more so when employed. Men and women tend to have similar effectiveness in job search (measured by offer arrival rates per unit of search effort) and, perhaps surprisingly, have similar flow values of unemployment. Women have somewhat higher separation rates—reflecting their higher job turnover in the data—and a notably higher value of nonwage job amenities.

Finally, Table 14 reports how well the model matches the target data moments for men and women. In short, the model does an excellent job of matching all moments.

4.3 Quantifying the Contributions to the Gender Wage Gap

For our final exercise, we use our model to see how much of the observed gender wage gap we can explain from the gender differences in job search costs and job search behavior identified in the model. We then perform several counterfactuals where we shut down various gender differences in search behavior to see how much of the gap is explained by those differences.

We summarize our exercise in Table 15. We target the residualized gender wage gap from

Table 14: Target Moments and Model Values

	Men		Women	
Moment	Target	Model	Target	Model
Search effort of U	1.67	1.67	2.07	2.06
Search effort of E	0.77	0.77	1.07	1.07
Unsolicited offer rate of U	0.04	0.04	0.02	0.02
Unsolicited offer rate of E	0.03	0.03	0.03	0.03
Offer rate of U	0.12	0.12	0.13	0.13
Offer rate of E	0.09	0.09	0.12	0.12
Acceptance rate of U	0.46	0.46	0.61	0.61
Acceptance rate of E	0.29	0.29	0.39	0.39
Search-wage gradient	-0.80	-0.82	-0.54	-0.52
Non-employment rate	0.21	0.21	0.27	0.27

Table 15: The Gender Wage Gap in the Data and Model

	Gender wage gap:	
	(logs)	(% of obs.)
Observed gap (SCE data)	0.161	—
Calibrated model	0.040	24.8%
Model counterfactuals:		
- Same search costs and efficiency	0.048	29.8%
- Same value of non-market time	0.032	19.9%
- Same re-allocation/separation rates	0.018	11.2%
- Same preferences for amenities	0.022	13.7%

the CPS that controls for state, year, demographics, and occupation. Overall, the model can account for a nontrivial 25 percent of the 16 log point difference between men's and women's wages. If we impose that men and women have identical search costs and effectiveness in search, the model actually increases the share of the gap explained, to 30 percent. This is because women are slightly more effective in generating job offers, which helps to dampen the gender wage gap. If we give men and women the same value of nonmarket time, we can explain just under 20 percent of the gender wage gap, suggesting a relatively small role for this factor. Conversely, if we impose the same job separation rates on men and women, or impose the same disutility from job disamenities, we can account for roughly half of the model's ability to explain the gender wage gap in each case. In other words, the fact that women have a stronger disutility of job disamenities than men, and tend to experience higher job separation rates, accounts for most of the model's ability to explain the gender wage gap.

The exercise also leaves a substantial amount of the gender wage gap unaccounted for. This

suggests that factors outside of the model, such as gender differences in bargaining, unobserved heterogeneity (such as a higher burden for child rearing for women), and wage discrimination likely account for the remainder of the observed wage gap.

5 Conclusion

In this paper, we explore how much gender differences in job search behavior and job search outcomes can explain the observed gender wage gap. Women disproportionately bear the burdens of child rearing, and as a result experience greater labor market interruptions. Our earlier research (Faberman et al., 2022) suggests this could lead to slower moves up the job ladder for women through the job search channel.

We document several new facts on gender differences in job search behavior. First, women tend to search harder than men for new work, and this is true regardless of their employment status. Men and women are roughly equally effective in generating job offers through their search efforts. The two facts combine to lead to greater offer arrival rates for women. Nevertheless, women tend to receive offers that pay lower wages, offer fewer hours, and have fewer benefits than men's job offers. The offer wage gaps are similar in magnitude to the estimated wage gaps for all currently-employed men and women. Further analysis suggests that the differences in offer characteristics comes from gender differences in job valuations. Women have lower reservation wages, on average, but have stronger preferences on the nonwage aspects of their job (e.g., commuting, work hours). Consistent with these results, we find that women's search behavior is also relatively less elastic with respect to their current wage but more elastic with respect to overall job satisfaction. In this sense, women are more likely than men to face a *multidimensional job ladder* when deciding whether to pursue or accept a job. Survey responses suggest that a disproportionate burden of child rearing falling on women drives their preferences on wages and job amenities.

To evaluate how much our documented patterns of job search behavior account for the observed gender wage gap, we develop an equilibrium model of labor market search where individuals endogenously exert search effort to find new work and can search on and off the job. Importantly, we allow workers to value a nonwage job disamenity in addition to their wage. Search costs, search

effectiveness (in terms of job offer arrival rates), and the value of disamenities potentially differ by gender. We solve the model by targeting the key moments from our empirical analysis. Our baseline model suggests that the gender differences captured by the model can explain a notable part of the residual gender wage gap, with gender differences in valuations of disamenities and job turnover as the main contributors.

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