Job Search and the Gender Wage Gap*

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Abstract

We analyze a broad range of job search behavior, with an emphasis on on-the-job search, and examine the contribution of the job search process to the gender wage gap. We show that men and women have similar job-to-job transition rates, but women's search effort is less responsive to their wages than men's search effort. Women exert more search effort but are equally successful in generating job offers per unit of search. While women have lower reservation wages, they are more likely to reject a job offer that requires relocation, a longer commute, or increased hours. We develop an equilibrium model of on-the-job search where workers value both the wage and nonwage aspects of a job, climbing a multi-dimensional job ladder. We allow for gender differences in willingness to pay for job amenities and various aspects of the job search process and calibrate them based to match our empirical evidence. Our model can account for the observed wage gap, with gender differences in amenity preferences and value of nonmarket time accounting for the majority of the gender wage gap.

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

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1 Introduction

The gender wage gap remains significant and negative, with recent estimates indicating that women earn, on average, approximately 78% of men's earnings. 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) and the Current Population Survey (CPS) over the 2013-2022 period to study how much gender differences in the job search process can account for the gender wage gap. The SCE 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. The CPS is the official source of U.S. labor market statistics. It is a relatively large household sample with a broad range of labor market information, including wages, and allows one to follow individuals as they transition to and from jobs. We combine information from both sources to document several margins in the job search and job offer process that can generate gender differences in wage outcomes.

We first document gender wage gaps in the data and show that men earn an hourly wage that is 16 to 21 log points higher than women, even after controlling for detailed demographic and job characteristics. Surprisingly, we find no significant difference in job-to-job transition rates between men and women. Given the extensive literature on role of job-to-job transitions in wage growth, this absence of a gender differences in transitions is particularly relevant in analyzing the sources of the remaining gender wage gap.

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. Our evidence also suggests that men and women search for different types of jobs. Notably, women are more likely to seek out part-time work, and gender differences in job-to-job transitions become evident when we differentiate them between part-time and full-time work.

We show that women's search intensity is less responsive to wages than men's search intensity; women exert considerably less search effort than men at the lower end of the wage distribution. This has implications for how men and women move up the job ladder. When we move to examining job search outcomes, we find that women receive job offers that tend to be lower wage and have fewer hours. In fact, we find that the gender gap in offered wages is similar to the observed gap in current wages. Despite men and women having similar job-to-job transition rates, men achieve about 8 percent higher earnings growth from job switching once we control for prior earnings (i.e., one's position on the job ladder).

Our evidence on job preferences suggests the dichotomy in search behavior may stem from women trading off lower wages for nonwage job amenities (or to avoid nonwage disamenities). Among the employed, we find that women's reservation wages are 24 log points lower than men's reservation wages, conditional on demographics and job characteristics. At the same time, women prefer about 10 log points fewer work hours per week than men 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. The evidence is consistent with the recent literature documenting a higher willingness to pay for job amenities among women (see, for example, Wiswall and Zafar, 2017; Le Barbanchon, Rathelot, and Roulet, 2021; and Maestas et al., 2023).

We next develop an equilibrium model of on-the-job search where workers value both the wage and nonwage aspects of a job, and therefore climb *a multi-dimensional job ladder* throughout their career. 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

amenities 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 account for. Gender differences in search costs and job separation rates account for little of the contribution. Instead, gender differences in the valuation of nonwage job amenities and in the value of non-market time each account for nearly all of the model-implied gender wage gap. Differences in the willingness to pay for job amenities is the biggest contributor, accounting for two thirds of the gender wage gap.

Related Literature. Our paper contributes to two strands of literature. The first one is the extensive literature on gender differences in labor market outcomes building on Claudia Goldin's extensive work. Bowlus (1997) is an earlier study that presents evidence that gender differences in the search process contribute to the gender wage gap, focusing on workers who report separating for personal reasons in the NLSY. Le Barbanchon, Rathelot, and Roulet (2021) show how gender differences in preferences for commuting contribute 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 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).

We also contribute to the literature on the role of on-the-job search in shaping labor market outcomes. This includes early work by Parsons (1973) and Burdett (1978), and more recent work by Christensen et al. (2005), Cahuc, Postel-Vinay, and Robin (2006), and Bagger and Lentz (2019). These studies document the importance of on-the-job search and its related job-ladder dynamics. There is also a natural connection between our paper and the literature emphasizing the importance of amenities in on-the-job search models such as Hwang, Mortensen, and Reed (1998), and Bonhomme and Jolivet (2009).

The next section describes our survey data and measurement approach and presents our evidence on estimated gender wage gaps, search behavior by gender, and search outcomes by gender. Section 3 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 4 concludes.

2 Empirical Evidence

We document several facts on gender differences in job search behavior and outcomes using the Job Search Supplement to the Survey of Consumer Expectations (SCE), administered by the Federal Reserve Bank of New York, and the Current Population Survey (CPS).

2.1 Data and Measurement

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.[1] The survey asks a variety of questions that are comparable to the questions on work and labor force status included in the CPS. It asks additional questions tailored to an individual's employment status and job search behavior, including a range of questions on work history.

Regardless of employment status, the SCE 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), including the reasons for their decision to (not) search. It then asks an exhaustive set of questions search methods used 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 job offers received. It probes further to see how those offers came about. For those who received an offer within the last six months, the survey asks about a range of characteristics of the job offer, including the wage offered, the expected hours, and any benefits offered. It also asks several questions related to bargaining and whether the respondent will accept or reject the offer (if they had not already done so). 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

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

disamenities, such as a doubled commute or relocation.

Many of the questions in the SCE, including the questions on basic demographics and household characteristics, follow a format similar to the Current Population Survey (CPS). This allows us to produce comparable estimates of the gender wage gap, as well as other results, across both surveys. While the SCE provides us with a broad range of information on job search, job offers, and job preferences, the CPS provides us with a larger and higher-frequency data source to produce robust estimates of labor market transitions. The SCE survey also identifies the labor force status of respondents at several different points in their employment history; notably, at the time of the survey, 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.[2] 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, it 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 samples from the SCE supplement and from the CPS of individuals aged 25 to 64 pooled across the October 2013-2022 surveys for the SCE, and pooled across July 2013 to December 2022 for the CPS. This provides just over 7,900 individual observations in the SCE, and over 1.84 million observations in the CPS. Individuals are only in the SCE for, at most, one year, so our SCE sample is a panel of repeated cross sections rather than longitudinal. The CPS has a limited longituding dimension, as respondents are in the survey for four consecutive months, out for eight months, and then in again for four more months. We exclude the self-employed from our analysis, partly because the SCE survey does not ask them. The SCE also provides us with a 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 SCE offer sample has

[2]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).

1,836 observations. Note that the SCE first asks whether respondents received any offer in the last month, and only if they did not, does it ask about offers received in the last six months. Thus, the data allow us to determine the monthly job offer arrival rate.

2.2 The Gender Wage Gap

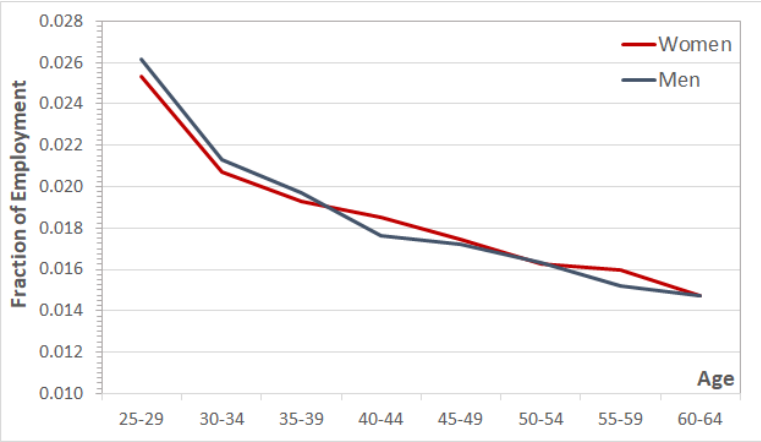
We document gender wage gaps in the CPS and SCE data that are comparable to those found in the broad literature on the subject. As Table 1 shows, men earn an hourly wage that is 18 to 30 log points higher than women, unconditionally, and men have weekly earnings that are 30 to 44 log points higher than 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	−0.304	−0.205
	(.001)	(.001)	(.001)	(.001)	(.001)	(.016)	(.015)
R^2	0.048	0.296	0.429	0.431	0.457	0.107	0.381
Dependent variable: log real weekly earnings							
Female coefficient	−0.301	−0.350	−0.245	−0.243	−0.296	−0.436	−0.307
	(.001)	(.001)	(.001)	(.002)	(.003)	(.019)	(.019)
R^2	0.059	0.259	0.399	0.400	0.432	0.112	0.373
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.

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.

2.3 Gender Differences in Employment Transitions

While gender differences in labor market flows have been well documented, the literature has typically abstracted from gender differences in job-to-job transitions. We present evidence from three data sources to show that men and women transition to new jobs at very similar rates.

Figure 1 reports the job-to-job transition rate for men and women by broad age category for all workers in our CPS sample. We measure the rates as the percent of the prior month's employed who change jobs over the month. Job-to-job transition rates are very similar for men and women, with the rates for 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 no significant 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

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.

CPS, SCE, or the Survey of Income and Program Participation (SIPP).[3]

Table 3 presents an important aspect of job switching: earnings growth among those who recently transitioned to a new job. It shows a notable gender difference in earnings growth. 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).[4] 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, we find essentially

[3]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.

[4]We measure earnings growth and identify job switchers in this way because of the nature of CPS interviews. Respondents 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.

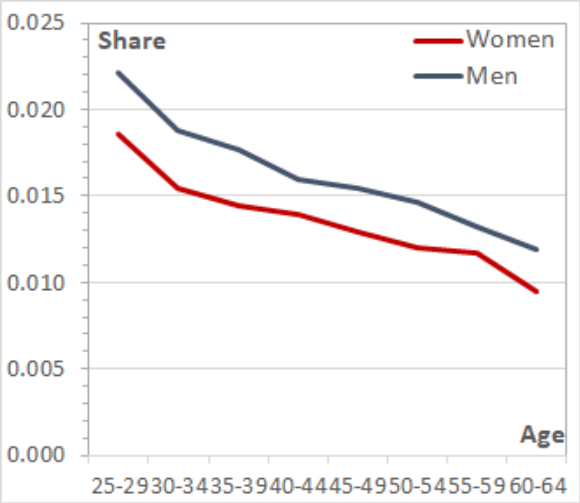
no gender gap in earnings growth among recent hires when we do not control for prior earnings because women occupy lower rungs of the wage ladder. Once we control for this (through the prior job's earnings), we find a significant gender gap in earnings growth.

Figure 2 suggests that the similar patterns in overall transition rates for men and women mask notable heterogeneity in the *types* of jobs men and women transition into, consistent with the earnings growth differentials we find once controlling for one's prior job. 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.[5]

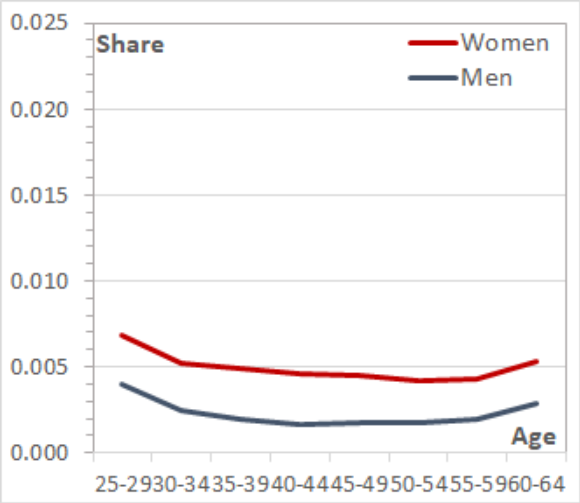
[5]In the online appendix, we estimate the wage penalty for part-time workers controlling for demographics, occupation, and household characteristics from the CPS and find that part-time workers have hourly wages that 18.5 log points lower than full-time workers. Since part-time work has a well-known wage penalty, so the disproportionate sorting of women into part-time work can at least partially account for the gender gap in earnings growth.

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.

2.4 Gender Differences in Search Effort

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, compared to 1.0 applications per month for men.[6] Looking within employment states, much of 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

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.

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.

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.

2.5 Gender Differences in Search Outcomes

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 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 differ considerably in their offer acceptance rates, with women being 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.

Despite the fact that women receive more offers and are more likely to accept them, they tend to receive relatively poorer offers, on average, as evidenced in Tables 7 and 8. 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

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.

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 16 log points higher than women's wage offers. Furthermore, men receive job offers with 49 log points higher weekly earnings unconditionally, and 33 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 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.

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

Table 7: Gender Gaps in Offered Wages and Earnings

	(1)	(2)	(3)	(4)	(5)
Dependent variable: log real offered wage					
Female coefficient	−0.275	−0.242	−0.175	−0.166	−0.162
	(0.031)	(0.029)	(0.030)	(0.030)	(0.030)
Adjusted R^2	0.114	0.287	0.453	0.464	0.468
N			1,836		
Dependent variable: log offered earnings					
Female coefficient	−0.489	−0.463	−0.347	−0.335	−0.331
	(0.045)	(0.043)	(0.045)	(0.044)	(0.045)
Adjusted R^2	0.123	0.233	0.419	0.427	0.429
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.

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.

2.6 Gender Differences in Search Elasticities

A key relationship in search models with endogenous search is the elasticity of search effort with respect to wages. Workers higher up on job ladder have fewer opportunities for better offers and

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.

therefore search less intensely.[8] The data on applications and search time support this implication for on-the-job search (see Faberman et al., 2022). We estimate the relationship between search effort (measured as the number of applications sent in the prior four weeks) and an individual's (log) current wage for men and women separately. We estimate a nonlinear relationship between applications sent and a residualized wage that controls for the same observables as in Table 1 for all employed. We estimate the relationship 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, consistent with a job-ladder model of the labor market. However, 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.

We explore the gender difference in their search-wage relationship via OLS regressions of search effort on wages estimated separately by gender. Specifically, we estimate the relationship between several measures of search effort and the (log) hourly wage for all employed individuals

[8] In these models, workers move up a job ladder (where jobs are generally ranked by their wage) by searching for new work. Workers at the lower "rungs" of the job ladder have more to gain from a new job and therefore search more intensely. Workers near the top of the job ladder have only a small chance of improving their position, and therefore search little.

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.

as well as subsets of the employed, applying the same controls as before. We normalize the dependent variables by dividing them by their gender-specific means so that 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 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 -0.89 for men and -0.36 for women for all employed individuals and using applications sent as

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	−0.886	−0.703	−1.050	−0.443	−0.574
	(0.176)	(0.168)	(0.297)	(0.078)	(0.151)
log current real wage, women	−0.361	−0.323	−0.363	−0.151	−0.303
	(0.130)	(0.141)	(0.243)	(0.065)	(0.116)
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.

our search effort measure, implying that the search intensity of men is nearly 2.5 times more responsive to their current wage than the search intensity of women, though standard errors are sizable for both estimates. There is a smaller gender difference in elasticities if we restrict the sample to full-time employed, but the gender difference in elasticities increases somewhat if we restrict the sample to those with children. The elasticities are smaller overall for our other measures of search effort, but a sizable 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, suggesting one might obtain comparable search elasticities for men and women if one were to take into account their overall job satisfaction.The SCE has asked the employed to rank their overall job satisfaction as part of the survey since 2014. We re-estimate our search elasticity with respect to this ordinal measure of job satisfaction rather than the log hourly wage. This produces search-job satisfaction elasticities by gender that capture how the search intensity of men and women varies with their overall job satisfaction, which should reflect their valuation of both 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. Job satisfaction is a 1 to 5 ranking of each respondent's satisfaction with their current job (where 5 represents "extremely satisfied"). We estimate the elasticity using the raw ordinal ranking and log of the ranking (consistent with the literal interpretation of an elasticity). 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 -0.88, roughly the same as their search-wage elasticity. The elasticity estimate for women is -0.61, nearly double their search-wage elasticity. The two elasticities are closer when we restrict the sample to full-time employed and are essentially equal when we restrict to those with children. The elasticities are larger but the gender difference is qualitatively similar (about 1.5 times larger for men) when we use the log of the job satisfaction ranking. Thus, while women's search effort appears not very responsive to the wage, it appears considerably 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.

2.7 Gender Differences in Job Valuations

Our findings thus far indicate that men and women evaluate various job characteristics differently. 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). These responses provide useful information to evaluate this hypothesis.

We estimate the gender gaps in the log reservation wage and log desired work hours, and

Table 10: Estimated Search-Job Satisfaction Elasticities by Gender

Dependent variable:	**Applications Sent**			
Job Satisfaction Measure:	**Satisfaction Ranking (1 to 5)**			**ln(Satisfaction Rank)**
	All Employed	**F-T Employed**	**All w/ Children**	**All Employed**
Job satisfaction	−0.873	−0.676	−0.807	−3.061
coefficient, men	(0.095)	(0.087)	(0.150)	(0.279)
Job satisfaction	−0.613	−0.553	−0.834	−1.942
coefficient, women	(0.066)	(0.070)	(0.115)	(0.188)
Dependent var. mean, men	0.74	0.60	0.70	0.74
Dependent var. mean, women	1.07	0.92	1.24	1.07

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 values are 3.87 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.

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 24 log points when we apply all of our controls. Among the nonemployed, the gender gap in the reservation wage is 21 log points unconditionally and 14 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 only slightly reduces these gaps.

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 separately by gender. Among those who would still accept a job with the listed job disamenity, we also report how much their reservation wage would have to change to accept it. We report the female–male difference in these statistics unconditionally and conditional on the same controls as in earlier analyses. The

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

	(1)	(2)	(3)	(4)
Dependent variable: log real hourly reservation wage				
Female × employed	−0.340	−0.305	−0.254	−0.243
	(0.017)	(0.015)	(0.016)	(0.016)
Female × nonemployed	−0.213	−0.168	−0.137	−0.139
	(0.033)	(0.030)	(0.032)	(0.031)
Adjusted R^2	0.197	0.355	0.450	0.454
Dependent variable: log desired weekly work hours				
Female × employed	−0.117	−0.120	−0.099	−0.100
	(0.016)	(0.016)	(0.017)	(0.017)
Female × nonemployed	−0.071	−0.093	−0.066	−0.059
	(0.031)	(0.031)	(0.034)	(0.034)
Adjusted R^2	0.056	0.065	0.102	0.104
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		5,968	

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.

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 hypothet-

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		

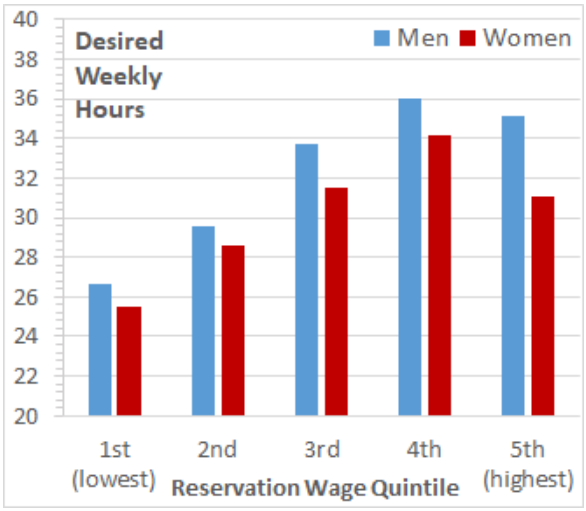
Notes: Estimates from all individuals aged 25-64 who either looked for work or stated they might take a job if offered to them from the October 2013-22 waves of the SCE Job Search Supplement. Controls include state, year, age, race, education, 3-digit occupation of current/most recent job, and employment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

ical job disamenities, men and women require roughly similar increases in their reservation wages 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.

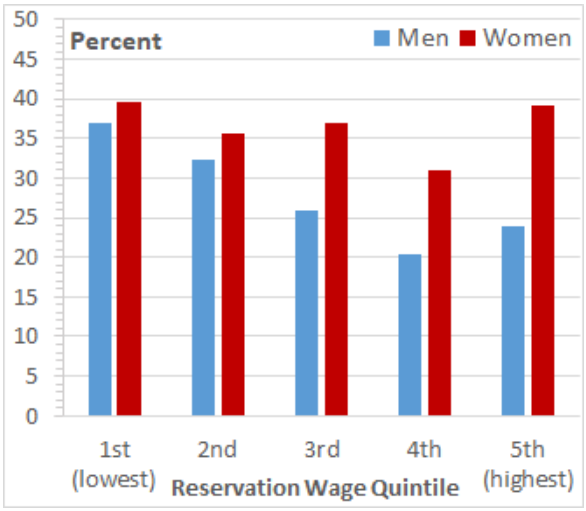
Figure 4 illustrates the relationship between nonwage aspects of the job and individuals' reservation wages. The left panel of the figure reports desired weekly work hours by gender and quintile of the reservation wage distribution. The right panel reports the percentage of individuals who would reject 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

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.

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 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 *multi-dimensional job ladder* when deciding whether to pursue or accept a job. The evidence is consistent with recent work by Maestas (2023), who find that women are more willing to trade off monetary compensation for job amenities than men; 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 (2018), who find that undergraduate women were willing to give up 7 percent of their pay to have a job that includes the option of part-time

hours, while men were willing to give up only 1 percent of pay. 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 next.

3 An Equilibrium On-the-Job Search Model with Amenities

We set up an equilibrium search model with on-the-job search and endogenous search effort, where men and women differ along five dimensions: preferences for nonwage amenities, values for nonmarket work/leisure, the frequency of market transitions, job search costs and search effectiveness, and differences in bargaining power. Our model is based on Cahuc, Postel-Vinay, and Robin (2006) and Bagger and Lentz (2019) with two main extensions. First, we follow Faberman et al. (2022) and allow for differences in search costs and search effectiveness 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 exercise is to quantify the contributions of the gender wage gap through a series of counterfactual simulations.

3.1 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.[9]

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,

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

s, to generate job offers. Offer arrival rates potentially differ by gender and employment status. Offers arrive at a rate $\lambda_g^j(s)$ and workers incur search costs of $c_g^j(s)$, which are increasing and convex in s.

Importantly, workers value both their wage earned, w, and a job amenity, a, while employed. Their flow utility of employment is defined as $u_g(w, a) = w + \nu_g(a - \bar{a})$, where ν_g represents the utility the worker receives per unit of amenity, a, and captures gender differences in preferences for nonwage job amenities. There is a reference level of the amenity, $\bar{a}$, so the overall valuation of the amenity can be either positive or negative. Amenities are produced by firms, which face a convex cost $\zeta c_a(a)$ and where ζ is a cost shifter that differs across firms and leads to dispersion in the provision of job amenities. We assume that firms provide a level of amenities that maximize the joint match surplus of the worker and the firm as follows: $\max_a \nu_g(a-\bar{a}) - \zeta c_a(a)$. Therefore, the optimal amenity production satisfies

$$c_a'(a_g(\zeta)) = \frac{\nu_g}{\zeta}, \tag{1}$$

which implies that the amenity production is increasing in the worker's marginal amenity valuation, ν_g, and decreasing in the firm's amenity cost shifter, ζ.

The market output of the match is py, where p is an aggregate productivity shifter and y is match-specific productivity. The flow value of the job match can be written as

$$\omega = py - \zeta c_a(a_g(\zeta)) + \nu_g(a_g(\zeta) - \bar{a}). \tag{2}$$

We let F_y be the distribution of match-specific productivity and F_ζ be the distribution of amenity cost shifters. Unemployed workers receive flow utility b_g, which also potentially differs by gender.

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 joint flow value of the match, ω, is the only state variable for the

employed worker to keep track of. [10] The joint value of a match, $K_g(\omega)$, thus satisfies:

$$K_g(\omega) = \max_{s,R^\delta,R^e} \Big\{ \omega - c_g^e(s) + \frac{1}{1+r} \Big[K_g(\omega) - \delta_g[K_g(\omega) - U_g - V] \\ + \tilde{\rho}_g(\theta) \int_{R_g^\delta} [W_g(\omega', 0) + V - K_g(\omega)] dF_g(\omega') - \tilde{\rho}_g(\theta) F_g(R^\delta)[K_g(\omega) - U_g - V] \\ + \tilde{\lambda}_g^e(s,\theta) \int_{R_g^e(\omega)} [W_g(\omega', \omega) + V - K_g(\omega)] dF_g(\omega') \Big] \Big\}, \tag{3}$$

where $W_g(\omega', \omega)$ is the value of the worker in a match with flow value ω' when their outside option is a match with flow value ω, $W_g(\omega', 0)$ is the value of the match when the worker's outside option is unemployment, U_g is the value of unemployment, and V is the value of a job vacancy. Furthermore, $F_g(\omega) = \int F_y(\frac{1}{p}[\omega + \hat{\zeta} c_a(a^*(\hat{\zeta})) - \nu_g(a^*(\hat{\zeta}) - \bar{a})]) dF_\zeta(\hat{\zeta})$, and $dF_g(\omega) = \frac{1}{p} \int dF_y(\frac{1}{p}[\omega + \hat{\zeta} c_a(a^*(\hat{\zeta})) - \nu_g(a^*(\hat{\zeta}) - \bar{a})]) dF_\zeta(\hat{\zeta})$. Workers face a reallocation probability $\tilde{\rho}_g(\theta) = (1 - \delta_g)\rho_g \lambda(\theta)$ and offer arrival rate $\tilde{\lambda}_g^e(s,\theta) = (1 - \delta_g)(1 - \rho_g)\lambda_g^e(s)\lambda(\theta)$, where $\lambda(\theta)$ is a common factor to offer arrival rates that depends only on labor market tightness θ.[11] 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 satisfies:

$$U_g = \max_{s,R^u} \Big\{ b_g - c_g^u(s) + \frac{1}{1+r} \Big[U_g + \lambda_g^u(s,\theta) \int_{R_g^u} [W_g(\omega', 0) - U_g] dF_g(\omega') \Big] \Big\}, \tag{4}$$

where b_g is the gender-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_g^u is the unemployed worker's optimal reservation match output.

[10] 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.

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

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 satisfies:

$$\begin{aligned} V &= -c + \frac{1}{1+r}\Bigg[V + q(\theta)\sum_g \pi_g \Bigg(\frac{u_g}{S}\lambda_g^u(s_g^u,\theta)\int_{R_g^u}(J_g(\omega',0)-V)dF_g(\omega') \\ &+ \frac{1-u_g}{S}\tilde{\rho}_g(\theta)\int_{R_g^\delta}(J_g(\omega',0)-V)dF_g(\omega') \\ &+ \frac{1-u_g}{S}\int \tilde{\lambda}_g^e(s_g^e(\hat{\omega}),\theta)\int_{R_g^e(\hat{\omega})}(J_g(\omega',\hat{\omega})-V)dF_g(\omega')G_g(\hat{\omega})d\hat{\omega}\Bigg)\Bigg]. \end{aligned} \tag{5}$$

Aggregate effective search effort is $S = \sum \pi_g S_g$, where the effective number of searchers is $S_g = u_g\lambda(s_g^u,\theta) + (1-u_g)[\tilde{\rho}_g(\theta) + \int \tilde{\lambda}_g^e(s_g^e(\hat{\omega}),\theta)G_g(\hat{\omega})]d\hat{\omega}$ and where $G_g(\omega)$ is the cumulative distribution function of realized match values 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 joint match value ω' for workers currently in a match with joint value ω satisfies the Nash-Bargaining solution:

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

Similarly, the value of a job offer with joint match value ω' for unemployed workers satisfies:

$$W_g(\omega', 0) = \tau_g(K_g(\omega') - V) + (1-\tau_g)U_g. \tag{7}$$

where the workers' gender-specific bargaining share is τ_g. 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 $t_g^{NB}(\omega) = w_g^{NB}(\omega, a^*) - \nu_g(a^* - \bar{a})$ and $\omega - t_g^{NB}(\omega) =$

$py - w_g^{NB}(\omega, a^*) - \zeta c_a(a^*)$. 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 $V = 0$. We can rewrite the value of a match as:

$$\begin{aligned} K_g(\omega) \quad &= \max_{s,R^\delta,R^e} \Bigg\{ \omega - c_g^e(s) + \frac{1}{1+r}\Big[K_g(\omega) - [\delta_g + \tilde{\rho}_g(\theta)](K_g(\omega) - U_g) \\ &\quad + \tilde{\rho}_g(\theta) \int_{R_g^\delta} \tau_g (K_g(\omega') - U_g) dF_g(\omega') + \tilde{\lambda}_g^e(s,\theta) \int_{R_g^e(\omega)} \tau_g (K_g(\omega') - K_g(\omega)) dF_g(\omega')) \Big] \Bigg\} \end{aligned} \tag{8}$$

The value of unemployment is now:

$$U_g \quad = \quad \max_{s,R^u} \left\{ b_g - c_g^u(s) + \frac{1}{1+r}\Big[U_g + \lambda_g^u(s,\theta) \int_{R_g^u} \tau_g (K_g(\omega) - U_g) dF_g(\omega) \Big] \right\}. \tag{9}$$

Using the Nash-bargaining solutions, we can also simplify the value functions for vacancy postings:

$$\begin{aligned} V \quad &= \quad -c + \frac{1}{1+r}\Bigg[V + q(\theta) \sum_g \Bigg(\frac{u_g}{S} \lambda_g^u(s_g^u, \theta) \int_{R_g^u} (1-\tau_g)(K_g(\omega') - U_g - V) dF_g(\omega') \\ &+ \quad \frac{1-u_g}{S} \tilde{\rho}_g(\theta) \int_{R_g^\delta} (1-\tau_g)(K_g(\omega') - U_g - V) dF_g(\omega') \\ &+ \quad \frac{1-u_g}{S} \int \tilde{\lambda}_g^e(s_g^e(\hat{\omega}), \theta) \int_{R_g^e(\hat{\omega})} (1-\tau_g)(K_g(\omega') - K_g(\hat{\omega}) - V) dF_g(\omega') dG_g(\hat{\omega}) \Bigg) \Bigg]. \end{aligned} \tag{10}$$

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

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

$$(1+r) c_g^u(_s')(s_g^u) = \lambda_g^u(_s')(s_g^u, \theta) \int_{R_g^u} \tau_g [K(\omega') - U_g] dF_g(\omega'), \tag{12}$$

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

reservation productivities are:

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

$$K_g(R_g^u) = U_g \tag{14}$$

$$K_g(R_g^e(\omega)) = K_g(\omega), \tag{15}$$

which imply 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 identified by equalizing the inflow and outflows as follows:

$$u_g \lambda_g^u(s_g^u, \theta)[1 - F_g(R_g^u)] = (1 - u_g)[\delta_g + \tilde{\rho}_g(\theta) F_g(R_g^\delta)]. \tag{16}$$

The steady-state distribution of workers across ω, $G_g(\omega)$, is identified by equating employment inflows and outflows between jobs with joint match value less than or equal to ω:

$$\begin{aligned} &u_g \lambda_g^u(s_g^u, \theta)[F_g(\omega) - F_g(R_g^u)] + (1 - u_g)\tilde{\rho}_g(\theta)[F_g(\omega) - F_g(R_g^\delta)] = \\ &(1 - u_g)[\delta_g + \tilde{\rho}_g(\theta) F_g(R_g^\delta)] G_g(\omega) + (1 - u_g) \int^{\omega} [1 - F_g(\max\{R_g^e(\hat{\omega}), \omega\})] \tilde{\lambda}_g^e(s_g^e(\hat{\omega}), \theta) dG_g(\hat{\omega}), \end{aligned} \tag{17}$$

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 $s_g^e(\omega)$, amenities $a_g(\zeta)$, 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 (8)-(10), the first-order conditions (1) and (11)-(15), the steady-state conditions (16) and (17), 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, $w_g^{NB}(\omega, a_g(\zeta))$, implied by these offered values and amenities.

3.2 Model Calibration

Our model builds on Faberman et al. (2022) by introducing the concept of a job amenity and potential variation in key moments and parameters by gender.[12] While part of our calibration strategy follows their approach, we incorporate job amenities and variation by gender to capture the key moments we identify in our empirical analysis.

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

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

In our baseline calibration, we use $\gamma_m = 3.6$ based on the estimates from Faberman et al. (2022). We choose γ_f to match the search-wage gradient for women, and we choose κ_g^j to match the average search effort by gender and employment status. 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. Note that we define labor market states as employed (E) and non-employed (N) and do not distinguish between the unemployed and those out of the labor force among the non-employed. We believe that it is important to account for all transitions between E and N, as women have frequent labor force interruptions, which could potentially affect their ability to climb the job ladder.

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-

[12]The model here also assumes that worker bargaining shares do not differ by employment status and abstracts 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	0.32	$\theta = 1$
μ	1.00	Normalization
η	0.50	Petrongolo and Pissarides (2001)
τ	0.50	Hosios condition
μ_y	0.35	Normalization
μ_a	1.00	Normalization
σ_a	0.34	Hall and Mueller (2018)
γ	3.60	Faberman et al. (2022)
ν_f, ν_m	1.00, 0.88	Maestas et al. (2023)
σ_{ε_w}	0.21	Bound and Krueger (1991)

B. Internally Calibrated Parameters

Parameter	Value	Target
σ_y	0.19	Search-wage gradient of men
κ_f^u , κ_m^u	0.018 , 0.020	Search effort, N
κ_f^e , κ_m^e	0.002 , 0.002	Search effort, E
α_f^u , α_m^u	0.015 , 0.034	Unsollicited offers, N
α_f^e , α_m^e	0.021 , 0.023	Unsollicited offers, E
β_f^u , β_m^u	0.052 , 0.053	Offers, N
β_f^e , β_m^e	0.048 , 0.063	Offers, E
z_f , z_m	0.283 , 0.307	Acceptance rate, N
ρ_f , ρ_m	0.060 , 0.047	Acceptance rate, E

specific nonemployment rates.[13] In our baseline parameterization, we assume that the bargaining shares of men and women are equal and satisfy the Hosios condition, $\tau_m = \tau_f = 0.5$.

We assume that the distribution of productivity y is log-normal with mean $\mu_y = 0.35$ and standard deviation $\sigma_y = 0.19$. For the former, we choose a positive value so that the average productivity net of amenity production costs is 0, and for the latter we choose to match the search-wage gradient for men. 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 $\sigma_{\epsilon_w} = 0.21$, which corresponds to the 13 percent of the variance of the raw log hourly wage.

[13] Note that our estimate of δ_g is zero for both men and women as the re-allocation shocks also lead to separations into non-employment and it turns out that they account for all E-to-N transitions in the data.

We must also make assumptions on the distribution of the amenity cost shifters and the valuation of amenities offered by firms. We assume that the cost of producing amenities is quadratic as follows: $\zeta c_a(a) = \frac{\zeta}{2}a^2$, which implies that optimal amenity production is $a_g(\zeta) = \frac{\nu_g}{\zeta}$. This further implies that the net value of the amenity production at the match level is $\nu_g(a_g(\zeta) - \bar{a}) - \zeta c_a(a_g(\zeta)) = \frac{\nu_g^2}{2}\frac{1}{\zeta} - \nu_g\bar{a}$. We normalize $\nu_f = 1$ and assume that the cost shifters are distributed such that the optimal amenities for women, $a_f(\zeta) = \frac{1}{\zeta}$, are distributed uniformly with mean 1. We set the standard deviation of $a_f(\zeta) = \frac{1}{\zeta}$ to 0.34 as in Hall and Mueller (2018). We set the reference level of the amenity to the average of the distribution of women (i.e., 1). For the amenity valuation of men, we refer to Maestes et al. (2023), who estimate the willingness to pay for various job amenities and find that a switch from the worst job to the best job is equivalent to a 58.8 percent wage increase for women and a 51.7 percent wage increase for men. The willingness to pay in our model is ν_g and thus the evidence in Maestas et al. pins down the relative willingness to pay $\frac{\nu_m}{\nu_f} = 0.517/0.588 = 0.88$.

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 used for the internal calibration.[14]

[14]The only moment reported in the table that we do not target in this calibration is the search-wage gradient for women. In the Appendix B, we report the results of a calibration, where we choose $\gamma_f = 0.8$ to match the

Table 14: Target Moments and Model Values

	Women		Men	
Moment	Target	Model	Target	Model
Search effort N	2.278	2.277	1.653	1.646
Search effort E	0.728	0.726	0.664	0.666
Unsol. offer rate N	0.015	0.015	0.034	0.034
Unsol. offer rate E	0.021	0.019	0.023	0.022
Censored offer rate N	0.028	0.028	0.021	0.021
Censored offer rate E	0.039	0.039	0.050	0.050
Formal offer rate N	0.105	0.105	0.100	0.100
Formal offer rate E	0.073	0.072	0.061	0.061
Acceptance rate N	0.645	0.649	0.499	0.499
Acceptance rate E	0.498	0.503	0.396	0.396
Non-employment rate	0.285	0.285	0.207	0.207

3.3 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. Overall, the model accounts for a gender wage gap of about 21.3 log points, which is very close to than the one we measure in the data as reported in Table 1. 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 slightly. This is because women are slightly less effective in generating job offers on-the-job, and increasing their effectiveness of on-the-job search to the same level as for men reduces the reservation wage and thus the average wage for women. If we additionally impose the same job separation and reallocation rates on men and women, then the wage gap remains nearly unaffected. This result may be surprising, given that women do not fall off the ladder as often as men. This effect is small in the model because there is also a counter-veiling effect: With lower job separation risk, women also set a lower reservation wage, which tends to lower the average wage for women. If additionally we

search-wage gradient of women.

Table 15: The Gender Wage and Value Gaps in the Model

	Gender wage gap:		Gender job value gap:	
	(logs)	(% change)	(logs)	(% change)
Calibrated model	0.213		0.042	
Model counterfactuals:				
+ Same seach costs and efficiency	0.218	2.3%	0.046	9.5%
+ Same re-allocation/separation rates	0.214	0.5%	0.042	0.0%
+ Same value of non-market time	0.172	-19.2%	0.002	-95.2%
+ Same preferences for amenities	0.000	-100%	0.000	-100%

Notes: The table reports the estimates of the gender wage and value gap in the model. The model counterfactuals report results of the model where the parameters of women are set to the same value as for men. In this table the model counterfactuals are *cumulative* such that in the last row all parameters for women are the same as for men. Table B1 in the Appendix reports results where we change the parameters for women one at a time.

give men and women the same value of nonmarket time, the wage gap drops further to 0.172. Finally, if we impose additionally that women and men have the same preference over nonwage amenities, then the gap drops to zero. Therefore, the preference for nonwage amenities accounts for a large difference in the wage gap between men and women.

We can also compute and decompose the gap in the value derived by workers from jobs, which we define as $w + \nu_g(a - \bar{a})$. The right two columns of Table 15 shows that this gap is also positive, i.e., women derive less utility from their jobs, even after controlling for amenity differences. The decomposition shows, however, that the sources of the value gap are different from the wage gap. For the job value gap, the preference over amenities is nearly inconsequential; what matters a lot is the difference in the valuation of nonmarket time.

4 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. 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.

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 amenity in addition to their wage. Search costs, search effectiveness (in terms of job offer arrival rates), and the value of amenities 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 account for a sizeable gender wage gap, with gender differences in valuations of amenities as the main contributor.

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ONLINE APPENDIX

A Additional Empirical Results

A.1 Additional Wage Estimates

Table A1: Gender Gap Estimates, SIPP Data

	(1)	(2)	(3)	(4)
Dependent variable: log real offered hourly wage				
Female coefficient	−0.238	−0.252	−0.225	−0.215
	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.085	0.232	0.307	0.313
Dependent variable: log real offered weekly earnings				
Female coefficient	−0.409	−0.428	−0.376	−0.369
	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.094	0.212	0.286	0.287
Year, state controls	Yes	Yes	Yes	Yes
Age, education, race controls		Yes	Yes	Yes
Occupation controls			Yes	Yes
Marriage, children controls				Yes
N		2,672,830		

Notes: Estimates from SIPP data pooled over 1995 to 2012. Sample is all employed age 25 to 64. Robust standard errors in parentheses.

Table A2: Gender Gap Estimates Among Part-Time Workers

	(1)	(2)	(3)	(4)
Dependent variable: log real hourly wage				
Female coefficient	−0.008	−0.028	−0.038	−0.021
	(0.006)	(0.006)	(0.006)	(0.008)
Adjusted R^2	0.029	0.218	0.408	0.410
Year, state controls	Yes	Yes	Yes	Yes
Female, age, education, race controls		Yes	Yes	Yes
Occupation controls			Yes	Yes
Marriage, children controls				Yes
N		55,884		

Notes: Estimates from CPS data pooled over July 2013-December 22, for all employed aged 25 to 64, excluding the self-employed. All regressions control for time period and state. Robust standard errors in parentheses.

Table A3: Part-Time Wage Penalty Estimates

	(1)	(2)	(3)	(4)
Dependent variable: log real hourly wage				
Part-time coefficient	−0.410	−0.303	−0.300	−0.185
	(0.002)	(0.002)	(0.002)	(0.002)
Adjusted R^2	0.081	0.332	0.338	0.445
Year, state controls	Yes	Yes	Yes	Yes
Female, age, education, race controls		Yes	Yes	Yes
Occupation controls			Yes	Yes
Marriage, children controls				Yes
N		832,776		

Notes: Estimates from CPS data pooled over July 2013-December 2022, for all employed aged 25 to 64, excluding the self-employed. All regressions control for time period and state. Robust standard errors in parentheses.

A.2 Additional Search Effort and Outcome Estimates

Table A4: Nonemployment-to-Employment Transition Rates by Gender

	CPS Data				**SCE**	**SIPP**
	(1)	(2)	(3)	(4)	**Data**	**Data**
Dependent variable: NE-to-E transition rate						
Female coefficient	−0.0335	−0.0386	0.0057	0.0048	0.024	
	(.0008)	(.0008)	(.0006)	(.0009)	(.021)	
Adjusted R^2	0.007	0.022	0.421	0.421	0.210	
N		836,766			1,438	
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	Yes

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 and employed between 1995 and 2012. NE-to-E transitions in the SCE are the fraction of the nonemployed 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.

Table A5: Reasons for PT Search by Gender and Employment Status

	All Employed		All Nonemployed	
	Men	**Women**	**Men**	**Women**
Primary reason one wants part-time work (Percent responding)				
Child care duties	0.6	11.4	8.5	24.0
	(0.3)	(1.1)	(1.7)	(2.1)
Hours flexibility	8.2	7.8	12.3	12.5
	(1.1)	(0.9)	(2.0)	(1.6)
Already employed	29.5	26.3	—	—
	(1.8)	(1.5)		
Additional income	56.7	47.3	56.1	35.3
	(2.0)	(1.7)	(3.0)	(2.4)
Other reason	5.0	6.4	23.2	27.8
	(0.9)	(0.8)	(2.6)	(2.2)
N	616	862	275	415

Notes: Estimates from SCE Job Search Supplement pooled over 2013-22, for all aged 25 to 64, excluding the self-employed. Labor force status refers to status in prior month. Standard errors in parentheses.

Table A6: Reasons for On-the-Job Search by Gender

	Men	Women
Lack of job stability	17.0	14.4
	(1.8)	(1.7)
Dissatisfaction with pay or benefits	49.2	56.8
	(2.4)	(2.3)
Commute too long	10.8	17.2
	(1.5)	(1.8)
Poor career advancement opportunities	23.2	17.4
	(2.0)	(1.8)
Poor skill fit or job duties	60.9	53.7
	(2.3)	(2.4)
Poor work hours	18.0	11.9
	(1.8)	(1.5)
Poor quality of work life	28.3	29.9
	(2.1)	(2.2)
Personal reasons ("just wanting a change")	48.2	41.4
	(2.4)	(2.3)
N	443	443

Notes: Estimates from SCE Job Search Supplement pooled over 2013-22, for all employed aged 25 to 64 who actively searched in the prior four weeks, excluding the self-employed.

Table A7: Job Offers and Acceptance Rates, Excluding Search for an Additional Job

	All		Employed		Nonemployed	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**
By Employment Status in Prior Month						
Fraction with a formal offer in last four weeks	0.069 (0.004)	0.081 (0.001)	0.061 (0.004)	0.075 (0.005)	0.100 (0.011)	0.105 (0.010)
Fraction with an unsolicited offer in last four weeks	0.025 (0.003)	0.019 (0.002)	0.023 (0.003)	0.021 (0.003)	0.034 (0.007)	0.015 (0.004)
Offers per application sent	0.080	0.073	0.092	0.102	0.061	0.046
Fraction of formal offers accepted in last four weeks	0.276 (0.030)	0.424 (0.028)	0.262 (0.034)	0.391 (0.033)	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 A8: Job Offer Characteristics by Gender and Employment Status

	Employed		Nonemployed	
	Men	**Women**	**Men**	**Women**
By Current Employment Status				
log offer usual hours	3.56 (0.02)	3.33 (0.02)	3.30 (0.06)	3.27 (0.05)
Pct. of offers with no benefits	30.2 (1.7)	42.3 (1.7)	64.7 (4.4)	62.9 (3.7)
Pct. of offers with any bargaining	40.5 (1.8)	34.4 (1.6)	34.3 (4.4)	25.8 (3.4)
Pct. of offers with any counteroffer	13.9 (1.3)	13.3 (1.2)	—	—
Pct. of offers that were unsolicited	27.3 (1.7)	17.1 (1.3)	28.1 (4.2)	12.8 (2.6)
N	718	831	118	169

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 to 64, excluding the self employed. Standard errors are in parentheses.

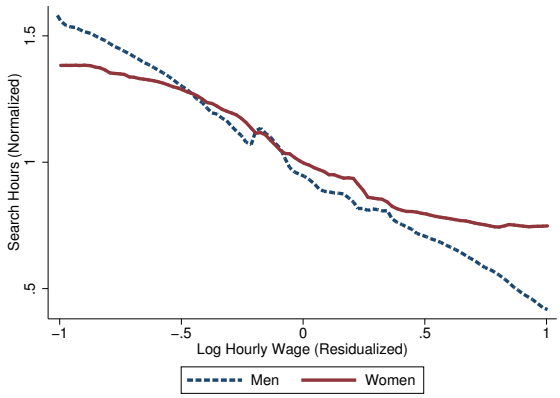
A.3 Additional Results on the Search-Wage Gradient

Figure A1: Search-Wage Gradient, Alternate Measures of Search

(a) Panel A: Applications, excl. search for additional work



(b) Panel B: Hours spent searching, last 7 days



Notes: Estimates are lowess smoothed plots of applications sent in the last four weeks, excluding search for an additional job (left panel) or hours spent searching for work in the last week (right panel) versus the current wage for all employed age 25 to 64, excluding the self-employed. Sample is from the 2013-22 waves of the SCE.

B Model Appendix

In this Appendix, we describe in more detail all the details of the model. For completeness, the Appendix will repeat some of the information in the main text.

B.1 Value Functions

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). Let $W_g(n, \xi, y, \zeta)$ be the value of the worker of type $g = [m, f]$ in a match with productivity y' and amenity cost shifter ζ', when the outside option is a match with productivity y and amenity cost shifter ζ, with $y = 0$ and $\zeta = 0$ if the worker's outside option is unemployment. The joint value of a match, $K_g(y, \zeta)$, then satisfies:

$$
\begin{aligned}
K_g(y,\zeta) = \max_{\bar{s}_e \geq s \geq 0, R_\delta(\zeta'), R_e(\zeta'), a} \Bigg\{ & (py + \nu_g(a - \bar{a}) - \zeta c_a(a) - c_e^g(s) \\
& + \frac{1}{1+r} \Bigg[K_g(y,\zeta) - \delta_g [K_g(y,\zeta) - U_g - V] \\
& + \tilde{\rho}_g(\theta) \int \int_{R_\delta(\zeta')} [W(y', \zeta', 0, 0) + V - K_g(y,\zeta)] dF_y(y') dF_\zeta(\zeta') \\
& - \tilde{\rho}_g(\theta) \int F(R_\delta(\zeta')) [K_g(y,\zeta,x) - U_g(x) - V] dF_\zeta(\zeta') \\
& + \tilde{\lambda}_g^e(s,\theta) \int \int_{R_e(\zeta')} [W_g(y', \zeta', y, \zeta) + V - K_g(y,\zeta)] dF_y(y') dF_\zeta(\zeta') \Bigg] \Bigg\},
\end{aligned}
\tag{B1}
$$

where $\tilde{\rho}_g(\theta) = (1 - \delta_g)\rho_g \lambda(\theta)$ and $\tilde{\lambda}_g^e(s, \theta) = (1 - \delta_g)(1 - \rho_g)\lambda_g^e(s)\lambda(\theta)$.[2] A worker who receives an exogenous separation shock flows into unemployment. If a worker receives a reallocation shock ρ_g, she samples an outside offer and accepts it if the offered wage is above the optimal reservation productivity $R_\delta^g(\zeta)$. 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 $F(\cdot)$ and accepts the offer if its match-specific productivity is above the optimal reservation productivity, $R_e^g(y, \zeta)$. Amenities are produced to maximize the match surplus and the FOC satisfies:

$$
c_a'(a_g(\zeta)) = \frac{\nu_g}{\zeta}, \tag{B2}
$$

which implies that (1) for the same ζ firms produce more a for the gender with a higher marginal utility for the amenity and (2) because of differences in ζ there is dispersion in the production of a for a given gender.

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

One can show that $K_g(y,\zeta) = K_g(py + \nu_g(a_g(\zeta) - \bar{a}) - \zeta c_a(a_g(\zeta)))$. For this reason, let's denote $\omega = py + \nu_g(a_g(\zeta) - \bar{a}) - \zeta c_a(a_g(\zeta))$, where $a_g(\zeta) = \arg\max(\nu_g(a - \bar{a}) - \zeta a)$, then we can write the joint match value as follows. Let $W_g(\omega, \omega')$ be the value of the worker of type $g = [m, f]$ in a match with joint output ω, when the outside option is a match with joint output ω', with $\omega = 0$ if the worker's outside option is unemployment. The joint value of a match, $K_g(\omega)$, then satisfies:

$$\begin{aligned} K_g(\omega) = \max_{\bar{s}_e \geq s \geq 0, R_\delta, R_e} \Bigg\{ & \omega - c_e^g(s) \\ & + \frac{1}{1+r} \Bigg[K_g(\omega) - \delta_g [K_g(\omega) - U_g - V] \\ & + \tilde{\rho}_g(\theta) \int_{R_\delta} [W(\omega', 0) + V - K_g(\omega)] dF_g(\omega') \\ & - \tilde{\rho}_g(\theta) F_g(R_\delta) [K_g(\omega) - U_g - V] \\ & + \tilde{\lambda}_g^e(s, \theta) \int_{R_e} [W_g(\omega', u) + V - K_g(\omega)] dF_g(\omega') \Bigg] \Bigg\}, \end{aligned} \tag{B3}$$

where $F_g(\omega) = \int F_y(\omega - \nu_g(a_g(\zeta) - \bar{a}) + \zeta c_a(a_g(\zeta))) dF_\zeta(\zeta)$ and $dF_g(\omega) = \int dF_y(\omega - \nu_g(a_g(\zeta) - \bar{a}) + \zeta c_a(a_g(\zeta))) dF_\zeta(\zeta)$. If we abstract from reallocation shocks, this simplifies to:

$$\begin{aligned} K_g(\omega) = \max_{\bar{s}_e \geq s \geq 0, R_\delta, R_e} \Bigg\{ & \omega - c_e^g(s) \\ & + \frac{1}{1+r} \Bigg[K_g(\omega) - \delta_g [K_g(\omega) - U_g - V] \\ & + \tilde{\lambda}_g^e(s, \theta) \int_{R_e} [W_g(\omega', \omega) + V - K_g(\omega)] dF_g(u') \Bigg] \Bigg\}. \end{aligned} \tag{B4}$$

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

$$U_g = \max_{\bar{s}_u \geq s \geq 0, R_u} \Big\{ b_g - c_u^g(s) + \frac{1}{1+r} \Big[U_g + \lambda_g^u(s, \theta) \int_{R_u} [W_g(\omega', 0) - U_g] dF_\omega^g(\omega') \Big] \Big\}, \tag{B5}$$

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 output ω when the outside option of the worker is a match with output ω', and with $\omega = 0$ if the worker's outside option is

unemployment. The value of a vacancy, V, satisfies:

$$\begin{aligned} V &= -c + \frac{1}{1+r}\Bigg[V + q(\theta)\sum_g \pi_g \Bigg(\frac{u_g}{S}\lambda_g^u(s_u^g)\int_{R_u^g}(J_g(\omega',0)-V)dF_g(\omega') \\ &+ \frac{1-u_g}{S}\tilde{\rho}_g\int_{R_\delta^g}(J_g(\omega',0)-V)dF_g(\omega') \\ &+ \frac{1-u_g}{S}\int \tilde{\lambda}_g^e(s_e^g(\hat{\omega}))\int_{R_e^g(\hat{\omega})}(J(\omega',\hat{\omega})-V)dF_g(\omega')G_\omega^g(\hat{\omega})d\hat{\omega}\Bigg)\Bigg], \end{aligned} \tag{B6}$$

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 $S_g = u_g\lambda(s_u^g) + (1-u_g)[\tilde{\rho}_g + \int \tilde{\lambda}_g^e(s_e^g(\hat{\omega}))G_\omega^g(\hat{\omega})]d\hat{\omega}$ and where $G_\omega^g(\omega)$ is the cumulative distribution function of match output ω for worker 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:

$$W_g(\omega',\omega) = \tau_g(K_g(\omega') - V) + (1-\tau_g)K_g(\omega). \tag{B7}$$

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

$$W_g(\omega',0) = \tau_g(K_g(\omega') - V) + (1-\tau_g)U_g. \tag{B8}$$

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 cost of the match, $w_g^{NB}(\omega,\zeta)$. In fact, we can define a Nash-Bargain transfer $t_g^{NB}(\omega)$ such that $t_g^{NB}(\omega) = w_g^{NB}(\omega,\zeta) + \nu_g(a_g(\zeta) - \bar{a})$ and $y - \zeta c_a(a_g(\zeta)) - w_g^{NB}(\omega, a_g(\zeta)) = \omega - t_g^{NB}(\omega)$, where $\nu_g = \zeta c_a'(a_g(\zeta))$. One can easily prove that τ_g^{NB} only depends on ω and not its components.

Using the Nash-bargaining solutions, one can simplify the value functions as follows. The joint value of a match can be rewritten as:

$$\begin{aligned} K_g(\omega) &= \max_{\bar{s}_e \geq s \geq 0, R_\delta, R_e}\Bigg\{\omega - c_e^g(s) + \frac{1}{1+r}\Bigg[K_g(\omega) - [\delta_g + \tilde{\rho}_g(\theta)](K_g(\omega) - U_g - V) \\ &+ \tilde{\rho}_g(\theta)\int_{R_\delta}\tau_g(K_g(\omega') - V - U_g)dF_g(\omega') \\ &+ \tilde{\lambda}_g^e(s,\theta)\int_{R_e}[\tau_g(K_g(\omega') - K_g(\omega)) + (1-\tau_g)V]dF_g(y')\Bigg]\Bigg\}. \end{aligned} \tag{B9}$$

The value of unemployment can be rewritten as:

$$U_g(x) = \max_{\bar{s}_u \geq s \geq 0, R_u} \Bigg\{ b_g - c_u^g(s) + \frac{1}{1+r}\Big[U_g + \lambda_g^u(s,\theta) \int_{R_u} (\tau_g(K_g(\omega) - U_g - V))dF_g(\omega)\Big]\Bigg\}. \tag{B10}$$

The value of a vacancy can be rewritten as:

$$\begin{aligned} V &= -c + \frac{1}{1+r}\Bigg[V + q(\theta)\sum_g \sum_x \pi(x)\Bigg(\frac{u_g}{S}\lambda_g^u(s_u^g)\int_{R_u^g}(1-\tau_g)(K_g(\omega') - U_g - V)dF_g(\omega') \\ &+ \frac{1-u_g}{S}\tilde{\rho}_g(x)\int_{R_\delta^g}(1-\tau_g)(K_g(\omega') - U_g - V)dF_g(\omega') \\ &+ \frac{1-u_g}{S}\int \tilde{\lambda}_g^e(s_e^g(\hat{\omega}))\int_{R_e^g(\hat{\omega})}(1-\tau_g)(K_g(\omega') - K_g(\hat{\omega}) - V)dF_g(\omega')dG_\omega^g(\hat{\omega})\Bigg)\Bigg]. \end{aligned} \tag{B11}$$

Given these simplified value functions, the first order condition w.r.t. s for employed and unemployed individuals, respectively, are:

$$(1+r)c_e'(s_e^g(\omega)) = \tilde{\lambda}_e^{g'}(s_e^g(\omega),\theta)\int_{R_e^g(\omega)}[\tau_g(K(\omega') - K(\omega)) + (1-\tau_g)V]dF_g(\omega') \tag{B12}$$

$$(1+r)c_u^{g'}(s_u^g) = \lambda_u^{g'}(s_u^g,\theta)\int_{R_u^g}\tau_g[K(\omega') - U_g - V]dF_g(\omega'), \tag{B13}$$

and the first order conditions for the reservation productivities are:

$$K_g(R_\delta^g) = U_g + V \tag{B14}$$

$$K_g(R_u^g) = U_g + V \tag{B15}$$

$$K_g(R_e^g(\omega)) = K_g(\omega) - \frac{1-\tau_g}{\tau_g}V. \tag{B16}$$

Together with the zero-profit condition, this implies that $R_e^g(\omega) = \omega$ and $R_\delta^g = R_u^g$.

B.2 Stationary Distribution and Equilibrium

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

$$u_g\lambda_g^u(s_u^g,\theta)[1 - F_g(R_u^g)] = (1-u_g)[\delta_g + \tilde{\rho}_g(\theta)F_g(R_\delta^g)]. \tag{B17}$$

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

$$\begin{aligned} &u_g\lambda_g^u(s_u^g,\theta)[F_g(y) - F_g(R_u^g)] + (1-u_g)\tilde{\rho}_g(\theta)[F_g(\omega) - F_g(R_\delta^g)] = \\ &(1-u_g)[\delta_g + \tilde{\rho}_g(\theta)]G_\omega^g(\omega) + (1-u_g)\int^\omega [1 - F_g(\max\{R_e(\hat{\omega}),\omega\})]\tilde{\lambda}_g^e(s_e^g(\hat{\omega}),\theta)dG_\omega^g(\hat{\omega}), \end{aligned} \tag{B18}$$

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 2 *A stationary equilibrium is defined as the search efforts s_u^g and $s_e^g(\omega)$, the amenity production $a_g(\zeta)$, the reservation outputs R_u^g, R_δ^g, and $R_e^g(\omega)$, the unemployment rates u_g, the distributions $G_\omega^g(\omega)$, the labor market tightness θ, and the value functions $K_g(\omega)$, $U_g(\omega)$, and V, that for all ω and g satisfy equations (8)-(10), the first-order conditions (B2) and (11)-(15), the steady-state conditions (16) and (17), and the zero-profit condition $V = 0$.*

The stationary equilibrium is independent of the offered values $W(\omega', \omega)$ and $J(\omega', \omega)$ 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 Supplemental Appendix, we derive the wage functions, $w(\omega', \zeta')$, implied by these offered values.

B.3 Functional Forms and Calibration

See the main text for a complete description.

B.4 Solving the model

This model is identical to the one in Faberman et al. (2022), except that match output is defined differently and the distributions of match output potentially differ by gender as well as all other parameters indexed by g.

B.4.1 Integration of CDF of y and $a_g(\zeta)$

We have defined the match output, including the amenity production, as follows:

$$\omega = \max_a (py + \nu_g(a - \bar{a}) - \frac{\zeta(1+\tau_a)}{1+c_1} a^{1+c_1}) \tag{B19}$$

where $\bar{a}$ is a reference level of the amenity, and τ_a is a tax on amenity production, which we assume to be equal to zero in our baseline calibration. We also assume $c_1 = 1$ in our baseline calibration, but allow here for a more general formulation.

Firms and workers decide on the jointly optimal production. The FOC implies:

$$a_g(\zeta) = \left(\frac{\nu_g}{\zeta(1+\tau_a)} \right)^{\frac{1}{c_1}} \tag{B20}$$

and

$$\begin{aligned}\omega &= py + \nu_g\left(\frac{\nu_g}{\zeta(1+\tau_a)}\right)^{\frac{1}{c_1}} - \frac{\zeta(1+\tau_a)}{1+c_1}\left(\frac{\nu_g}{\zeta(1+\tau_a)}\right)^{\frac{1+c_1}{c_1}} - \nu_g\bar{a} \\ &= py + \frac{c_1}{1+c_1}\nu_g^{\frac{1+c_1}{c_1}}\left(\zeta(1+\tau_a)\right)^{-\frac{1}{c_1}} - \nu_g\bar{a} \\ &= py + \tilde{\nu}_g c - \nu_g\bar{a}. \end{aligned} \tag{B21}$$

where $c = \zeta^{-\frac{1}{c_1}}$ and $\tilde{\nu}_g = \frac{c_1}{1+c_1}\nu_g^{\frac{1+c_1}{c_1}}(1+\tau_a)^{-\frac{1}{c_1}}$. Given these assumptions, we can write the distribution function $F_g(\omega)$ as:

$$\begin{aligned}F_g(\omega) &= \int F_{\tilde{y}}\left(\frac{\omega - \tilde{\nu}_g c + \nu_g\bar{a}}{p}\right)dF_c(c) \\ &= \int F_y\big((\omega+\nu_g\bar{a})p^{-1} - \kappa_g c\big)dF_c(c) \end{aligned} \tag{B22}$$

$$dF_g(\omega) = \frac{1}{p}\int dF_y\big(\omega p^{-1} - \kappa_g c\big)dF_c(c), \tag{B23}$$

where $\kappa_g = \frac{\tilde{\nu}_g}{p}$. The problem with this general form of the distribution function of the flow values is that it's computationally difficult to implement. The solution we have embraced so far is to posit a parametric distirbution for the ω's and a's and back the distribution of y's. The problem with this is that it prevents to do counterfactuals on the distribution of a (because we want to hold the distribution of y fixed). The other solution, which we pursue here is that we are assuming a uniform distribution of c on interval c_l to c_v.

$$F_g(\omega) = \frac{1}{c_v - c_l}\int_{c_l}^{c_v} F_y((\omega+\nu_g\bar{a})p^{-1} - \kappa_g c\big)dc \tag{B24}$$

$$\begin{aligned}dF_g(\omega) &= \frac{1}{p(c_v - c_l)}\int_{c_l}^{c_v} dF_y((\omega+\nu_g\bar{a})p^{-1} - \kappa_g c\big)dc \\ &= \frac{F_y((\omega+\nu_g\bar{a})p^{-1} - \kappa_g c_l) - F_y((\omega+\nu_g\bar{a})p^{-1} - \kappa_g c_v)}{\kappa_g p(c_v - c_l)}. \end{aligned} \tag{B25}$$

The latter can be computed very easily. For the CDF, however, it's more complicated.

$$\begin{aligned}F_g(\omega) &= \int^{\omega} \frac{F_y((x+\nu_g\bar{a})p^{-1} - \kappa_g c_l) - F_y((x+\nu_g\bar{a})p^{-1} - \kappa_g c_v)}{\kappa_g p(c_v - c_l)}dx \\ &= \frac{1}{\kappa_g p(c_v - c_l)}\int^{\omega}[F_y((x+\nu_g\bar{a})p^{-1} - \kappa_g c_l) - F_y((x+\nu_g\bar{a})p^{-1} - \kappa_g c_v)]dx. \end{aligned} \tag{B26}$$

Using variable substitution and integration by parts, we get:

$$
\begin{aligned}
\int^{\omega} & [F_y((x+\nu_g\bar{a})p^{-1}-\kappa_g c_l)-F_y((x+\nu_g\bar{a})p^{-1}-\kappa_g c_v)]dx \\
= & \; p\int_{(\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v}^{(\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l} F_y(x)dx \\
= & \; (\omega+\nu_g\bar{a}-p\kappa_g c_l)F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l) \\
& -(\omega+\nu_g\bar{a}-p\kappa_g c_v)F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v) \\
& -p\int_{(\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v}^{(\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l} x dF_y(x). \qquad \text{(B27)}
\end{aligned}
$$

and thus:

$$
\begin{aligned}
F_g(\omega) = & \; \frac{(\omega+\nu_g\bar{a}-p\kappa_g c_l)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l) \\
& -\frac{(\omega+\nu_g\bar{a}-p\kappa_g c_v)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v) \\
& -\frac{1}{\kappa_g(c_v-c_l)}\int_{(\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v}^{(\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l} x dF_y(x). \qquad \text{(B28)}
\end{aligned}
$$

Let's assume now that distribution of y is normal with mean μ_y and σ_y, then:

$$
\int_{\omega-v}^{\omega-l} u\frac{dF_y(u)}{F_y(\omega-l)-F_y(\omega-v)}du = \mu_y+\sigma_y^2\frac{dF_y(\omega-v)-dF_y(\omega-l)}{F_y(\omega-l)-F_y(\omega-v)} \qquad \text{(B29)}
$$

and thus

$$
\begin{aligned}
F_g(\omega) = & \; \frac{(\omega+\nu_g\bar{a}-p\kappa_g c_l)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l) \\
& -\frac{(\omega+\nu_g\bar{a}-p\kappa_g c_v)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v) \\
& -\frac{\mu_y}{\kappa_g(c_v-c_l)}(F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l)-F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v)) \\
& -\frac{\sigma_y^2}{\kappa_g(c_v-c_l)}(F_y'((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v))-F_y'((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l)), \qquad \text{(B30)}
\end{aligned}
$$

and thus

$$
\begin{aligned}
F_g(\omega) = & \; \frac{(\omega+\nu_g\bar{a}-p\kappa_g c_l-\mu_y p)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l) \\
& -\frac{(\omega+\nu_g\bar{a}-p\kappa_g c_v-\mu_y p)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v) \\
& -\frac{\sigma_y^2}{\kappa_g(c_v-c_l)}(F_y'((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v))-F_y'((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l)). \qquad \text{(B31)}
\end{aligned}
$$

To sum up, the PDF and CDF of ω are:

$$dF_g(\omega) = \frac{F_y((\omega+\nu_g\bar{a})p^{-1}+\kappa_c-\kappa_g c_l)-F_y((\omega+\nu_g\bar{a})p^{-1}+\kappa_c-\kappa_g c_v)}{\kappa_g p(c_v-c_l)} \tag{B32}$$

$$\begin{aligned} F_g(\omega) = & \frac{(\omega+\nu_g\bar{a}-p\kappa_g c_l-\mu_y p)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l) \\ & -\frac{(\omega+\nu_g\bar{a}-p\kappa_g c_v-\mu_y p)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v) \\ & -\frac{\sigma_y^2}{\kappa_g(c_v-c_l)}(F_y'((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v))-F_y'((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l)). \end{aligned} \tag{B33}$$

B.5 Additional Results

Table B1: The Gender Wage and Value Gaps in the Model, Not Cumulative

	Gender wage gap:		Gender job value gap:	
	(logs)	(% change)	(logs)	(% change)
Calibrated model	0.213		0.042	
Model counterfactuals:				
- Same seach costs and efficiency	0.218	2.3%	0.046	9.5%
- Same re-allocation/separation rates	0.209	-1.9%	0.038	-9.5%
- Same value of non-market time	0.118	-44.6%	-0.049	-216.7%
- Same preferences for amenities	0.038	-82.2%	0.042	0.0%

Notes: The table reports the estimates of the gender wage and value gap in the model. The model counterfactuals report results of the model where the parameters of women are set to the same value as for men. In this table, the model counterfactuals are *not cumulative* and thus shows results where we change the parameters for women one set at a time.

Table B2: Gender Gaps in the Model (Calibration with $\gamma_f = 0.8$), Cumulative

	Gender wage gap:		Gender job value gap:	
	(logs)	(% of total)	(logs)	(% of total)
Calibrated model	0.251		0.078	
Model counterfactuals:				
+ Same seach costs and efficiency	0.255	1.6%	0.082	5.1%
+ Same re-allocation/separation rates	0.229	-8.8%	0.053	-32.1%
+ Same value of non-market time	0.172	-31.5%	0.002	-97.4%
+ Same preferences for amenities	0.000	-100%	0.000	-100%

Notes: The table reports the estimates of the gender wage and value gap in the model. The model counterfactuals report results of the model where the parameters of women are set to the same value as for men. In this table the model counterfactuals are *cumulative* such that in the last row all parameters for women are the same as for men. Table B3 reports results where we change the parameters for women one at a time.

Table B3: Gender Gaps in the Model (Calibration with $\gamma_f = 0.8$), Not Cumulative

	Gender wage gap:		Gender value gap:	
	(logs)	(% of total)	(logs)	(% of total)
Calibrated model	0.251		0.078	
Model counterfactuals:				
- Same seach costs and efficiency	0.255	1.6%	0.082	5.1%
- Same re-allocation/separation rates	0.273	8.8%	0.095	21.8%
- Same value of non-market time	0.118	-53%	-0.050	-164.1%
- Same preferences for amenities	0.074	-70.5%	0.080	2.6%

Notes: The table reports the estimates of the gender wage and value gap in the model. The model counterfactuals report results of the model where the parameters of women are set to the same value as for men. In this table, the model counterfactuals are *not cumulative* and thus shows results where we change the parameters for women one set at a time.