NETWORK LISER

Discussion Paper Series

IZA DP No. 18418

February 2026

Job Search, Job Amenities, and the Gender Pay Gap

R. Jason Faberman
Federal Reserve Bank of Chicago
and IZA@LISER

Andreas I. Mueller
University of Zürich, CEPR, IZA@LISER
and RFB

Ayşegül Şahin
Princeton University, NBER and IZA@LISER

IZA@LISER NETWORK
ISSN: 2365-9793

IZA DP No. 18418 February 2026

Job Search, Job Amenities, and the Gender Pay Gap*

Abstract

This paper studies gender gaps in labor-market outcomes, with a focus on job ladder dynamics. We show that women experience substantially lower wage growth conditional on prior wages despite nearly identical job-to-job transition rates for men and women. To reconcile these observations, we document gender differences in the valuation of nonwage job amenities and in job search behavior, and develop a multi-dimensional job-ladder model with endogenous search effort where workers value both wages and amenities. The model allows for gender heterogeneity in separation rates, search effort, the value of nonemployment, amenity valuations, and bargaining power, enabling a joint analysis of gender wage and employment gaps. A quantitative decomposition shows that differences in preferences for nonwage amenities account for nearly 40 percent of the gender pay gap. Differences in the value of nonemployment and bargaining power explain most of the remainder, with only a limited role for differences in separation rates and search behavior. Finally, we show that increases in job amenities — such as the expansion of remote work — raise the gender wage gap while reducing gender differences in employment.

JEL classification

J16, J60

Keywords

gender wage gap, job search, job amenities, on-the-job search

Corresponding author

R. Jason Faberman
jfaberman@frbchi.org

* A previous version of this paper was circulated under the title "Job Search and the Gender Wage Gap". The authors thank Marie Lalanne, Ilse Lindenlaub, Ben Lochner, Robert Shimer, Gianluca Violante, conference participants at the ASSA Meetings, Barcelona Summer Forum, Dolomiti Macro Meetings, Goethe Conference on Firms in the Labor Market, Kiel Conference on the Macroeconomics of Labor Markets, Midwest Economic Association Meetings, NYU Conference on Macroeconomics, SaM Conference, Society of Economic Dynamics, Society of Labor Economics, and Xamsterdam Conference, as well as seminar participants at Columbia University, Princeton University, Queens University, UC-San Diego, and UMass-Boston for helpful suggestions and comments. We also thank Thomas Haasl, Elizabeth Kepner, and Becky Schneirov for excellent research assistance. The views expressed here are solely those of the authors and do not reflect the views of the Federal Reserve Bank of Chicago or the Federal Reserve System.

1 Introduction

The gender wage gap remains significant, and women continue to participate in the labor market at lower rates than men. After decades of convergence, progress toward closing both gaps has largely stalled over the past twenty years. Our analysis focuses on the 2013–2022 period, during which the gaps have been remarkably stable: the gender wage gap has hovered around 20 percent, while the gap in employment-to-population ratios has remained near 10 percentage points.

Earlier work highlighted education and occupational choice as key contributors to the gender wage gap (e.g., Groshen (1991); Blau & Kahn (2000)). As women's educational attainment has surpassed men's, education's importance disappeared. Yet occupation choices still account for part of the wage differentials (e.g., Blau & Kahn (2017); Bertrand *et al.* (2010)). We revisit these facts using both the Current Population Survey (CPS) and the Survey of Consumer Expectations (SCE). We find that the *gender earnings gap* averaged around 30 percent and the *hourly wage gap* about 20 percent in this period controlling for age, race, education, and occupation. Occupation accounts for roughly 25–30% of these gaps.

Potential explanations for the remaining gender wage gap emphasize structural and behavioral forces such as nonlinear pay structures (Goldin (2014); Erosa *et al.* (2022); Kleven *et al.* (2019); gender differentials in sorting by occupation and firm (Blau & Kahn (2017); Bertrand *et al.* (2010), Moser & Morchio (2024), Xiao (2024)); job amenity preferences and family constraints (Goldin (2014); Mas & Pallais (2017); Cortés & Pan (2018)); women being less assertive in wage negotiations and during the job search process (Lochner & Merkl (2025), Fluchtmann *et al.* (2024), Cortés *et al.* (2023), Roussille (2024)) and the glass ceiling that prevents women from reaching higher rungs of the job ladder (Albrecht *et al.* (2003), Blau & Kahn (2017)). These explanations bring the job search process and the job ladder to the forefront of gender wage gap analysis.

This paper identifies key differences in the job ladder for men and women, documenting a set of stylized facts. We show that women experience higher separation rates from employment than men, yet exhibit nearly identical job-to-job transition rates. In other words, employed women are just as likely as men to move directly to another employer but are more likely to exit to nonemployment.

Prior work has highlighted gender differences in labor market transitions, especially those involving participation, but the striking similarity in employer-to-employer transitions has received limited attention.[1] This fact holds across three datasets—the CPS, SCE, and the SIPP—with and without controlling for a rich set of observables.

The uniformity in job-to-job transition rates masks important differences in wage growth. We find that, conditional on prior wages, women experience annual wage increases that are roughly 11 percentage points smaller than men's wage increases. This pattern implies that women climb a flatter job ladder. Given the central role of job-to-job mobility in reallocation and wage growth (Topel & Ward, 1992; Postel-Vinay & Robin, 2002; Moscarini & Postel-Vinay, 2023), differential returns to job switching and on-the-job wage growth are likely to be important contributors to the persistence of the gender wage gap. Understanding the sources and drivers of these differences is crucial for evaluating potential policy responses.

We identify two main potential explanations for the gender differences in the job ladder. The first is that men and women evaluate the wage and nonwage components of jobs asymmetrically. We document this using both stated preferences and realized outcomes. Evidence from the SCE shows that women report reservation wages that are roughly 20 percent lower than men's, prefer fewer work hours, and are less willing to accept changes in their jobs such as increasing hours, relocating, or increasing their commute. These stated differences are mirrored in actual labor market outcomes. Using data on job satisfaction among employed individuals from the SCE, we find that men's satisfaction is more strongly tied to their wages, whereas women place greater value on shorter hours and family-oriented benefits.

To provide systematic evidence on sorting by wages and amenities, we construct an occupation-level amenity index combining measures of physical demands and work pace from O*NET, work flexibility from the 2017–18 ATUS Leave Module, and teleworkability from Dingel & Neiman (2020). We show that women are not only more likely to work in higher-amenity occupations, but also experience larger increases in amenities and smaller wage gains when switching occupations. We

[1] An exception is Fallick & Fleischman (2004), who noted this in their paper but did not investigate this pattern. For gender differences in flow rates more generally, see Albanesi & Şahin (2018).

interpret these findings as strong evidence in favor of a multi-dimensional job ladder.

The second potential channel is job-search behavior. Higher separation rates into nonemployment imply that women are more likely to re-enter the labor market from lower rungs of the job ladder. Because on-the-job search effort and its effectiveness determine the speed of job-ladder ascent (Faberman *et al.*, 2022), differences in search behavior can generate persistent wage gaps. We find that women search more intensively on the job, but that their search effort translates into job offers at a lower rate. Consequently, men and women receive similar numbers of job offers overall, resulting in comparable rates of job-ladder ascent.

Our main takeaway is that the job ladder is multi-dimensional, and men and women climb the ladder along different dimensions. While our empirical analysis provides several measures in characterizing these differences in job ladders, quantifying how much of the gender wage gap can be attributable to each of the differences requires an equilibrium model disciplined by these facts. The question of how the gender wage gap would respond to changes in the structure of the labor market—e.g., the emergence of new amenities such as remote work— requires an equilibrium model with a multi-dimensional job ladder.

We develop an equilibrium on-the-job search model where workers value both the wage and non-wage aspects of a job, and therefore climb *a multi-dimensional job ladder*. The model consists of two labor market states—employment and nonemployment—allowing us to capture the gender gap in employment-to-population ratios. Jobs differ in both productivity and amenity levels. Amenities are costly to provide, and firms choose how much to provide based on the average amenity valuation in the economy; equivalently, firms do not provide gender-specific amenities in our baseline model. Wages are set through sequential auctions and renegotiated when the worker receives an outside offer. We interpret amenities as fixed characteristics of the jobs; for example some jobs can offer flexible schedules while some have more rigid schedules due to the nature of work required. Therefore, when the worker receives an outside offer, the margin of adjustment for counteroffers is the wage not the amenity.

Motivated by our empirical analysis, we allow amenity valuations, search behavior, value of nonemployment and bargaining power to differ by gender. The model is calibrated to match empirical moments from our data as well as commonly-used moments in the literature. A key parameter is the value of amenities for women relative to men. To discipline this parameter, we use evidence from Maestas *et al.* (2023), who use a hypothetical choice framework to elicit workers' willingness to pay for non-monetary job attributes. While both men and women value features such as flexibility and remote work, women exhibit an overall willingness to pay for amenities that is roughly 11% higher than that of men. Another key object is the value of nonemployment which affects workers' threat point in this class of models. Women have a lower value of nonemployment because of their lower reservation wages and higher acceptance rates of offers. The model successfully matches the gender wage gap in the data and implies that amenities account for nearly 40 percent of the gender wage gap. Therefore, a substantial gender *job value gap* remains even after accounting for amenities.

Since jobs have two characteristics in the model —wages and amenities—, workers climb a *job value ladder* rather than a pure wage ladder. Because women place greater value on amenities, they are more willing to accept offers from lower-productivity firms that provide better nonwage amenities. As a result, there is about an 8.5% realized gender productivity gap in the model. This not only leads to lower wage growth for women upon job switching, but also constrains wage growth within jobs, as lower-productivity firms have less room to raise wages in response to outside offers. This mechanism is important when we decompose the gender wage and job value gaps into four channels: separation rates and search parameters, amenity preferences, the value of nonemployment and bargaining weights. The first channel accounts for roughly 5% of the gender wage gap while amenities and value of nonemployment each account for roughly 40% of the gap. The remainder is due to differences in bargaining power. The gender job value gap is about two thirds of the gender wage gap and this difference is accounted for mostly by differences in value of nonemployment and bargaining weights.

A natural question is how changes in amenity provision would affect gender differences in wages. We consider two experiments to evaluate this question. In the first, firms set amenity levels to target men (i.e., they set a relatively lower weight on amenities). In the second, firms choose amenity levels to target women, for example by offering more generous parental leave or family-oriented benefits. When firms target amenities toward men, it reduces the gender wage gap but widens the gender employment gap. In this case, women's reservation wages increase, leading them to accept high-productivity jobs. When firms tailor amenities to women, their participation rises since lower-productivity jobs become more attractive, but this then widens the gender wage gap.

An application of our framework is the emergence of remote work after the onset of the COVID pandemic. A common narrative is that the expansion of remote work should narrow the gender gap by providing flexibility and helping balance market and home production. Telework has already been identified as a job amenity prior to the pandemic. For example, Maestas *et al.* (2023) and Mas & Pallais (2017) estimate that workers are willing to forego roughly 4–5% of wages for the option to work remotely, with women valuing this amenity about 1.7 percentage points more than men. Willingness-to-pay estimates for remote work after the pandemic are even higher. For example, Barrero *et al.* (2021) estimate valuations around 7%. We use our model to assess the implications of the recent rise in remote work, which accounted for roughly 25% of paid working days in 2023.[2] Recent evidence shows that women were more likely to telework than men after restrictions related to the pandemic were over.[3] We analyze the effects of the increased prominence of remote work through two counterfactual exercises. In the first experiment, we model the increase in remote work as a higher willingness to pay for this amenity for both men and women, and in the second, we model it as a decline in firms' cost of providing remote work. In both experiments, we find that an expansion of remote work increases the gender wage gap while reducing the gender employment gap. That is because women become even more likely to sort into high-amenity jobs, while men are more likely to sort into higher productivity jobs, increasing the gender wage gap. At the same time, the higher amenity value lowers reservation wages for both groups—especially for women—making low-productivity jobs more acceptable and narrowing the employment gap. Thus, the gender employment gap shrinks even as the gender wage gap rises. While it is still early to see the full effects of rising remote work on gender gaps in labor market outcomes, these implications of the

[2] The share of fully-remote paid working days in the U.S. surged from 6–7% to more than 60% at the onset of the pandemic and has stabilized roughly at 25% in 2023 at a much higher rate than before the pandemic.

[3] In the first quarter of 2024, women had a telework rate of 24.9%, higher than men's rate of 21.1%. See https://www.bls.gov/opub/btn/volume-14/telework-trends.htm

model are consistent with the widening of the gender wage gap and shrinking of the participation gap in the post-pandemic period.[4]

Related Literature. Our paper contributes to two strands of literature. The first is the extensive literature on gender differences in labor market outcomes focusing on the role of nonwage amenities and job search behavior in the context of specific amenities. Mas & Pallais (2017), Wiswall & Zafar (2018), Le Barbanchon *et al.* (2021), Maestas *et al.* (2023), and D'Agelis (2023) all present evidence that women have stronger preferences for nonwage characteristics of jobs such as flexibility, shorter commute, parental leave etc. A small but growing literature emphasizes the importance of the search process. Lochner & Merkl (2025) show that women in Germany apply more to flexible jobs; Fluchtmann *et al.* (2024) document application differences in Denmark; Cortés *et al.* (2023) show risk aversion differences among MBA graduates, Roussille (2024) documents an ask-gap in online offers and Bandiera *et al.* (2025) studies the role of job search in the gender employment gap in Pakistan. We also build on previous work examining occupational and firm-level sorting such as Blau & Kahn (2017), Cortés & Pan (2018), Sorkin (2018), Erosa *et al.* (2022), Moser & Morchio (2024) and Xiao (2024). We contribute to this literature by identifying job ladder differences between men and women and their drivers for the U.S. and providing a model-based decomposition of the gender wage gap in the 2013–2022 period.

Our second contribution is related to the literature on models of on-the-job search. Building on influential work by Burdett & Mortensen (1998), recent contributions emphasized the role of on-the-job search for wage growth such as Christensen *et al.* (2005), Cahuc *et al.* (2006) and Bagger & Lentz (2019). A related literature examines job amenities (e.g., Hwang *et al.* (1998), Bonhomme & Jolivet (2009), Xiao (2024)), employer wage setting (e.g., Amano-Patiño *et al.* (2025)), and multi-dimensional sorting (e.g., Lindenlaub & Postel-Vinay (2023)). We extend this literature by allowing employers to endogenously choose amenity provision when different groups of workers value amenities asymmetrically.

[4] According to the Census Bureau, the gender wage gap widened for both in 2023 and 2024 for full-time workers. This was the largest gender gap since 2016. At the same time, the participation gap between men and women went down from 11.5 percentage points in 2019 to 10.5 percentage points in 2024. See for example: The https://www.cnbc.com/2025/09/11/for-the-first-time-in-over-60-years-the-gender-pay-gap-widened-2-years-in-a-row.html.

The paper proceeds as follows. Section 2 summarizes the data sources we use. Section 3 presents empirical evidence on the gender wage gap, labor market transitions including job-to-job transitions and job search behavior. Section 4 shows that men and women differ both in their amenity preferences and realized amenities. Section 5 develops a multi-dimensional job ladder model and provides a quantitative analysis of gender gaps. Section 6 concludes.

2 Data Sources

We rely on two main data sources: the Current Population Survey (CPS) and the Job Search Supplement to the Survey of Consumer Expectations (SCE), designed by Faberman *et al.* (2022) and administered by the Federal Reserve Bank of New York. While the CPS provides a larger and higher-frequency data source, the SCE complements it by offering detailed information on job search behavior and job preferences.

The CPS is the primary household survey for the U.S., which is administered monthly to about 100,000 individuals per month. Individuals in the CPS are surveyed for four months, then are out for eight months, and are surveyed again for another four months, giving the data a limited longitudinal dimension. Respondents at the end of each four-month period (known as the Outgoing Rotation Group) are asked about their earnings. This design allows us to measure monthly transitions across labor-market states and to estimate individual earnings and twelve-month earnings changes.

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 Job Search supplement of the SCE was first administered in October 2013, and has been fielded annually each October since. The supplement asks a broad range of questions on employment status, job search behavior, and job search outcomes.[5] Demographic data are also available for respondents through the monthly portion of the SCE survey. 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

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

job satisfaction and work preferences.

Our analysis draws on data from the CPS and the SCE Job Search supplement, restricted to individuals aged 25 to 64. The CPS data are pooled from July 2013 to December 2022 and include over 4.55 million observations, while the SCE data are pooled across the October 2013–2022 surveys and include just over 7,900 observations.

3 Gender Gaps in Pay and Labor Market Transitions

In this section, we document gender differences in earnings and hourly wages both in the CPS and the SCE. We then analyze gender differences in employment transitions as well as job search behavior and outcomes.

3.1 Gender Differences in Pay and Pay Growth

Table 1 documents the gender pay gap estimated using our CPS and SCE samples. It shows that the gender gap remains large across both samples even after controlling for observable demographics and occupation.[6] After applying our controls, women earn roughly 20 percent lower hourly wages than men and about 30 percent lower weekly earnings than men, consistent across both surveys. Occupation accounts for roughly 25–30 percent of the observed differences but a substantial residual gap persists. Table A1 shows that additionally controlling for marital status or children does little to narrow the gender pay gaps further, underscoring that neither household composition nor occupational sorting fully explains the gender wage gap over our sample period.

Table 2 documents that there is also a notable gender difference in pay growth consistent with the persistence of the gender wage gap. The table reports the year-over-year earnings gains of individuals who are currently employed and were employed in the CPS twelve months prior. Note that this is a broad group of individuals who either were employed at the same job throughout, switched jobs, or incurred some nonemployment spell in between. If we only condition on the same

[6]Throughout much of our analysis, we control for a relatively parsimonious set of observable characteristics. Where noted, these include fixed effects for time period (calendar months in the CPS, or years and the SCE), state, five-year age categories, three education groups (high school or less, some college, college or more), four race groups (White, Black, Hispanic, other), and detailed occupation, either by four-digit Census code or 3-digit Standard Occupation Code (SOC).

Table 1: The Gender Pay Gap using Two Measures of Pay: Hourly Wages and Weekly Earnings

	CPS Data				**SCE Data**	
	All		*HH Heads*		*HH Heads*	
Dependent variable: *log real hourly wage*						
Female coefficient	−0.224	−0.161	−0.276	−0.193	−0.270	−0.205
	(0.001)	(0.001)	(0.002)	(0.002)	(0.015)	(0.015)
R^2	0.296	0.429	0.330	0.457	0.272	0.381
Dependent variable: *log real weekly earnings*						
Female coefficient	−0.351	−0.245	−0.426	−0.296	−0.395	−0.307
	(0.001)	(0.001)	(0.002)	(0.002)	(0.018)	(0.019)
R^2	0.259	0.399	0.301	0.432	0.253	0.373
Time, state controls	Yes	Yes	Yes	Yes	Yes	Yes
Age, educ., race controls	Yes	Yes	Yes	Yes	Yes	Yes
Occupation controls		Yes		Yes		Yes
N	1,191,509		477,942		6,227	

Notes: The table reports coefficient estimates on a female dummy in separate regressions that include the controls listed. Age controls are fixed effects for 5-year age groups, education controls for high school or less, some college, and college or more, and race controls for four race categories (White, Black, Hispanic, other). Occupation controls include 4-digit Census occupation (CPS) or 3-digit SOC (SCE). The dependent variable is the log real hourly wage or the log real weekly earnings. Samples include employed individuals from the CPS (first four columns) and from the SCE Job Search Supplement (last two columns). Robust standard errors in parentheses.

observables we use in Table 1, we find almost no gender gap in the growth rates of hourly wages or weekly earnings. Due to more frequent labor market disruptions, women may, on average, be further down on the job ladder and thus experience large wage gains just because they have further to climb than men. Consistent with this interpretation, once we additionally control for prior wages or earnings, we find that men's hourly wage growth exceeds women's by 11 log points, and men's weekly earnings growth exceeds women's by 14.1 log points. Accounting for position on the wage ladder through prior pay therefore reveals a sizable gender gap in pay growth.[7]

[7] While it is not possible to identify workers who switched jobs with complete accuracy in the CPS, in Table A2 we report the year-over-year earnings gains of individuals who are currently employed and were employed in the CPS twelve months prior who reported transitioning into their current job within the prior three months (i.e., are recent hires). 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, and are unobserved for eight months after reporting their year-ago earnings. We will miss job switches that occurred during the intervening eight months, and we cannot identify those who had a nonemployment spell during that period. As a robustness check, we repeat the exercise restricting the sample to those who are employed in the same occupation in the months immediately before and after the intervening eight-month period. In both exercises, we find substantially smaller pay growth for women relative to men when we control for prior wages or earnings. Furthermore, in Table A3 we find that our results are robust to restricting the sample to individuals without children in the household.

Table 2: Gender Gaps in Pay Growth

Dependent variable	*Change in log real hourly wage*			*Change in log real weekly earnings*		
	(1)	(2)	(3)	(1)	(2)	(3)
Female coefficient	-0.005	0.002	−0.110	-0.000	0.005	−0.141
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R^2	0.001	0.007	0.350	0.001	0.006	0.311
Month, state controls	Yes	Yes	Yes	Yes	Yes	Yes
Age, education, race controls		Yes	Yes		Yes	Yes
Occupation controls		Yes	Yes		Yes	Yes
(log) year-ago hourly wage			Yes			
(log) year-ago weekly earnings						Yes
N	371,179					

Notes: Table reports the coefficient estimates from regressing the log year-over-year change in either the hourly wage or weekly earnings on a female dummy in separate regressions that include the controls indicated within each column. The sample used is all individuals employed in the current month and one year ago in the final Outgoing Rotation Group of the CPS sample. Robust standard errors are in parentheses.

3.2 Gender Differences in Labor Market Transitions

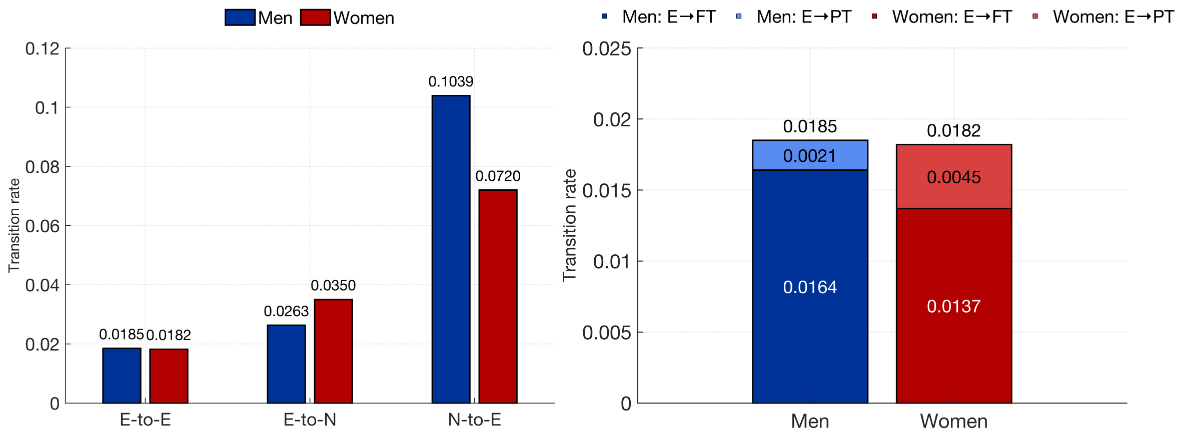
While gender differences in labor market flows are well documented, much of the literature has abstracted from job-to-job transitions. The left panel of Figure 1 shows that job-to-job transition rates are nearly identical for men and women, in contrast to pronounced gender differences in transitions between employment and nonemployment. The uniformity of job-to-job transitions across men and women is a relatively new fact that we corroborate in our appendix using three distinct data sources (the CPS, the SCE, and the Survey of Income and Program Participation, SIPP). Tables A4 and A5 show that across all surveys, and conditional on observable demographics and occupation, we find no statistically significant gender differences in job-to-job transition rates.[8]

While job-to-job transition rates are nearly identical for men and women, transitions between employment and nonemployment differ markedly by gender. As Figure 1 shows, women are more likely to separate from employment and less likely to re-enter employment from nonemployment, generating large gender gaps in participation and employment. In our CPS sample, the employment-to-population ratio is 79.1% for men, compared with 66.5% for women.[9]

[8] 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.

[9] These gaps persist after conditioning on observables and remain sizable even when restricting the sample to individuals without children (see Appendix Table A5).

Figure 1: Worker Transition Rates by Gender



Notes: Figure reports authors' estimates of mean monthly worker transitions by gender from their CPS sample for all individuals observed in two consecutive months. The left panel reports job-to-job transition rates (E-to-E) as a percent of prior month's employed, employment outflow rates (E-to-N) as a percent of prior month's employed, and employment inflow rates (N-to-E) as a percent of prior month's nonemployed. The right panel reports the job-to-job transition rates decomposed into transitions into full-time jobs (darker shading) and part-time jobs (lighter shading).

The right panel of Figure 1 shows that the similarity in job-to-job transition rates masks important differences in the types of jobs men and women switch to. Women are substantially more likely to transition into part-time jobs: roughly 25% of their job-to-job transitions lead to part-time jobs, compared with about 10% for men. We show that controlling for demographics, occupation, and household composition can only explain between one-third and one-half of the gender gaps in job switches to full-time or part-time employment, and that applying these controls actually widens the gender gap in transitions into and out of employment (see Table A5). Furthermore, if we condition our sample on individuals without children, we find sizable gender gaps remain. Women without children are significantly more likely to transition out of the labor force or into part-time work, and significantly less likely to transition into the labor force or into full-time work, relative to men without children.

3.3 Job Search Behavior

In Figure 1, we showed that similar job-to-job transition rates between men and women mask notable heterogeneity in job search behavior by gender, notably in the work hours they seek. In this section, we document gender differences in search behavior.

Table 3: Job Search Behavior by Gender

	Employed		Nonemployed	
	Men	**Women**	**Men**	**Women**
Search Effort				
Applications sent in last four weeks	0.80	1.04	1.65	2.28
	(0.07)	(0.07)	(0.24)	(0.24)
Hours spent searching in last seven days	0.76	1.10	2.14	2.17
	(0.06)	(0.07)	(0.22)	(0.21)
Search Outcomes				
Fraction with an unsolicited offer in last four weeks	0.025	0.023	0.034	0.015
	(0.003)	(0.003)	(0.007)	(0.004)
Fraction with any offer in last four weeks	0.127	0.144	0.121	0.134
	(0.006)	(0.006)	(0.012)	(0.012)
Offer yield	0.159	0.138	0.073	0.059
Excluding Search for Additional Work Only				
Applications sent in last four weeks	0.66	0.73	1.65	2.28
	(0.06)	(0.06)	(0.24)	(0.24)
Fraction with any offer in last four weeks	0.112	0.114	0.121	0.134
	(0.006)	(0.006)	(0.012)	(0.012)
Offer yield	0.170	0.159	0.073	0.059
N	3,196	3,155	705	882

Notes: Estimates come from authors' tabulations from their SCE Job Search Supplement sample. Total offers received include formal offers and offers respondents declined before they could be made. Offer yield is defined as the fraction with an offer per application sent, employment status is defined four weeks prior to the survey interview for all variables except hours spent searching, whose employment status is defined at the time of the interview. Standard errors are in parentheses.

Table 3 reports job search effort and search outcomes by gender and employment status for multiple metrics. On average, women search more than men, regardless of whether we consider the number of job applications sent in the last month or hours spent searching in the last week, and whether we exclude applications for additional jobs rather than new ones. Women are also more likely than men to receive a job offer,[10] but are somewhat less likely to receive an unsolicited offer (i.e., an offer made without any search effort). Taken together, these patterns imply that women receive slightly fewer offers per application submitted, regardless of employment status, suggesting that their search efforts are relatively less effective. However, differences in offer yields—defined as the fraction receiving an offer divided by the number of applications—are relatively small.

We show that these patterns hold along the extensive margin as well—i.e., women are more

[10] Our measure of job offers includes formal offers, unsolicited offers, and unrealized offers (i.e., offers that were rejected before being made formally).

likely to search regardless of search effort. Consistent with the evidence in Figure 1, women are more likely to look for part-time work, and among the employed, women are more likely to be seeking a job in addition to their current one (see Appendix Table A6). The patterns in Table 3 generally hold among the employed after applying our controls for demographics and occupation, but these controls account for most of the observed gender differences in search effort and (total) offers received among the nonemployed (see Appendix Table A7).[11]

4 Gender Differences in Job Amenities

The lower wage growth women experience indicates that the job ladder is flatter for women—conditional on prior earnings, women experience lower wage growth. One possibility is that women place greater value on nonwage amenities, leading them to sort into jobs with characteristics that offer lower wage growth in return for better amenities. In this section, we start by documenting differences in stated preferences of men and women in terms of characteristics of jobs including nonwage amenities. We then analyze these patterns in the realized outcomes.

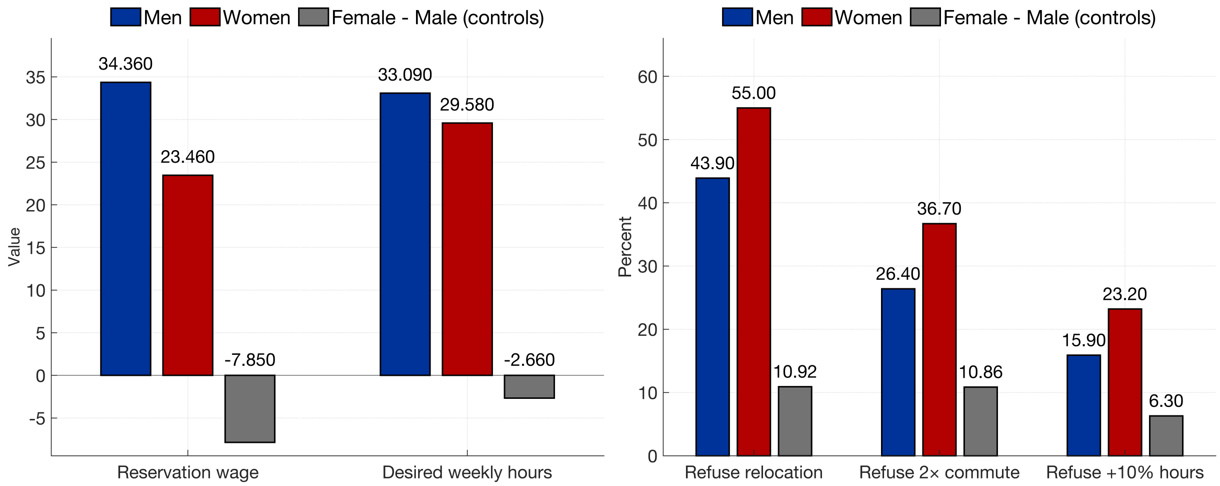
4.1 Reservation Wages and Amenity Preferences

We begin with an analysis of how men and women potentially trade off wages for amenities. 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 respondents represent just over three-quarters of our sample).

We estimate the gender gaps in the reservation wages and desired weekly work hours, applying the same controls for demographics and occupation as in earlier exercises, in addition to employment status, and report these alongside their unconditional means in the left panel of Figure 2. We find that women have a reservation wage that is about 23% lower than men's when we apply all of our

[11] In unreported results, we also find that these patterns generally hold regardless of whether respondents have children (for both the employed and nonemployed).

Figure 2: Reservation Wages, Desired Work Hours, and Disamenity Valuations by Gender



Notes: Figure reports mean estimates by gender of individuals self-reported reservation wages, desired work hours, and valuations of hypothetical job disamenities, along with their estimated gender gap conditional on observables. Estimates are from all individuals who either looked for work or stated they might take a job if offered to them in the SCE Job Search Supplement sample. The left panel reports estimates for the respondents' hourly reservation wage and desired work hours. The right panel reports the fraction of respondents who would reject the listed job disamenity at any offered wage (a relocation, a doubling of their commute, or a 10 percent increase in work hours, respectively). Estimated gender gaps control for state, year, age, race, education, the three-digit occupation of the respondent's current/most recent job, and employment status. All estimated gaps are significant at the 1 percent level.

controls. Women also prefer fewer work hours than men, preferring to work 3.5 fewer hours per week unconditionally, and 2.7 fewer hours per week after applying our controls.[12]

The right panel of Figure 2 shows the fraction of individuals who would not take a job (at any wage) if the listed job characteristic changed to become a greater disamenity. We report the unconditional shares separately by gender, along with their unconditional and conditional gender gaps. The disamenities we focus on are a hypothetical need to relocate, a doubling of one's commute, and a 10 percent increase in required work hours. While women may have lower reservation wages, they also have 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

[12]In log terms, the reservation wage gap is 23.3 log points, and the desired hours gap is 9.3 log points, after applying our controls.

Table 4: Wages, Job Characteristics, and Job Satisfaction by Gender

	Men		**Women**	
	(1)	(2)	(1)	(2)
Dependent variable: *Overall Job Satisfaction* (1−5 Scale)				
log real hourly wage	0.315	0.272	0.191	0.141
	(.038)	(.039)	(.041)	(.043)
log usual work hours	0.066	−0.003	−0.111	−0.226
	(.068)	(.071)	(.057)	(.063)
Any quality-of-life or childcare benefits		0.065		0.255
		(.048)		(.055)
Commute time		−0.021		−0.010
		(.007)		(.008)
Any health, dental, or life benefits		0.044		0.049
		(.072)		(.069)
Any retirement or equity benefits		0.190		0.168
		(.063)		(.061)
R^2	0.131	0.141	0.100	0.116
Month, state controls	Yes	Yes	Yes	Yes
Age, education, race controls	Yes	Yes	Yes	Yes
Occupation controls	Yes	Yes	Yes	Yes
N	2,755		2,708	

Notes: The table reports coefficient estimates from regressing a self-reported measure of job satisfaction (measured on a one to five scale) on the listed regressors in separate regressions by gender. All regressions control for year, state, age, education, race, and three-digit occupation. We use the square root of commute time. The sample is all employed individuals in the SCE Job Supplement from 2014 forward. Robust standard errors in parentheses.

higher hours than their desired hours. In all three cases, adding our controls does little to alter the estimates. We show that restricting the sample to those without children in the household yields similar results. The reservation wage gap between men and women is somewhat smaller for men and women without children, but otherwise the gaps are very similar to those we report in Figure 2 (see Appendix Table A8).

The SCE also asks about job satisfaction of all employed respondents, which they are asked to rate on a 1 to 5 scale, with 5 representing the highest satisfaction. While men and women have similar job satisfaction scores, there are notable gender differences in how respondents' job satisfaction is related to the wage and nonmonetary amenities of their jobs.[13] Table 4 presents regression estimates of the relationship between overall job satisfaction and wages, work hours, and other

[13] In the SCE data, men have a mean job satisfaction measure of 3.86 and women have a mean job satisfaction measure of 3.76.

job characteristics for men and women. Across specifications, wages are positively associated with satisfaction for both, but the relationship is notably stronger for men. By contrast, usual work hours have little effect on men's satisfaction but are negatively related to women's satisfaction. Benefits also display gender differences. Benefits related to quality-of-life and childcare are positively related to satisfaction for both men and women, but the coefficient is more than three times larger for women. Retirement and equity benefits and commute time have similar relations for men and women.[14] Overall, these correlations suggest that women place greater weight than men on nonwage amenities—particularly those related to job flexibility—while men's job satisfaction is more tightly linked to pay.

4.2 Gender Differences in Realized Job Amenities

Our findings indicate that men and women evaluate various job characteristics differently and trade off wages for better amenities in their job search to different degrees. This view is supported in recent work by Maestas *et al.* (2023), who find that women are more willing to forego monetary compensation for job amenities than men. Their findings are based on a survey that focuses on nonmonetary job traits and elicits information on willingness-to-pay for job characteristics such as flexibility, physical demands, teleworkability, scheduling and leave time.

We construct an occupation-level index of job amenities that we can match to respondents in the CPS in the spirit of survey evidence in Maestas *et al.* (2023). Our index uses measures of the nonmonetary job characteristics comparable to theirs. The index components are based on three sources: measures of physical activity and the pace of work come from O*NET data on Work Context; measures of work flexibility come from the American Time Use Survey (ATUS) 2017–18 Leave Module; and a measure of teleworkability comes from Dingel & Neiman (2020). We intentionally leave out benefits that are tied to monetary compensation such as retirement benefits, stock options and health insurance. The index is a weighted average of its components, each normalized to be between zero and one, where the weights are willingness to pay estimates from Maestas *et al.* (2023) and Barrero *et al.* (2021). A value of one corresponds to the best possible

[14] In Table A9, we find that these results remain very similar when we restrict the sample to individuals without children in the household.

value for that job amenity observed in the occupational data. Since we weight the components in the index by willingness to pay estimates, the maximum value of the index is 0.35, the sum of the weights. The average worker in the economy going from an occupation with an index value of zero to the maximum-amenity occupation would be equally well off with their wage being 35% lower. This likely understates the full extent of amenity dispersion, as the index does not capture within-occupation variation in amenities. Moreover, our measure excludes some amenities considered in Maestas *et al.* (2023), who report a willingness to pay of 0.55 for moving from the worst to the best amenity job in their data.[15] We derive our index estimates by roughly three-digit occupations (and greater detail where the data allow) and match them to all employed individuals in our CPS sample by occupation. We detail the construction of the amenity index in Appendix B.

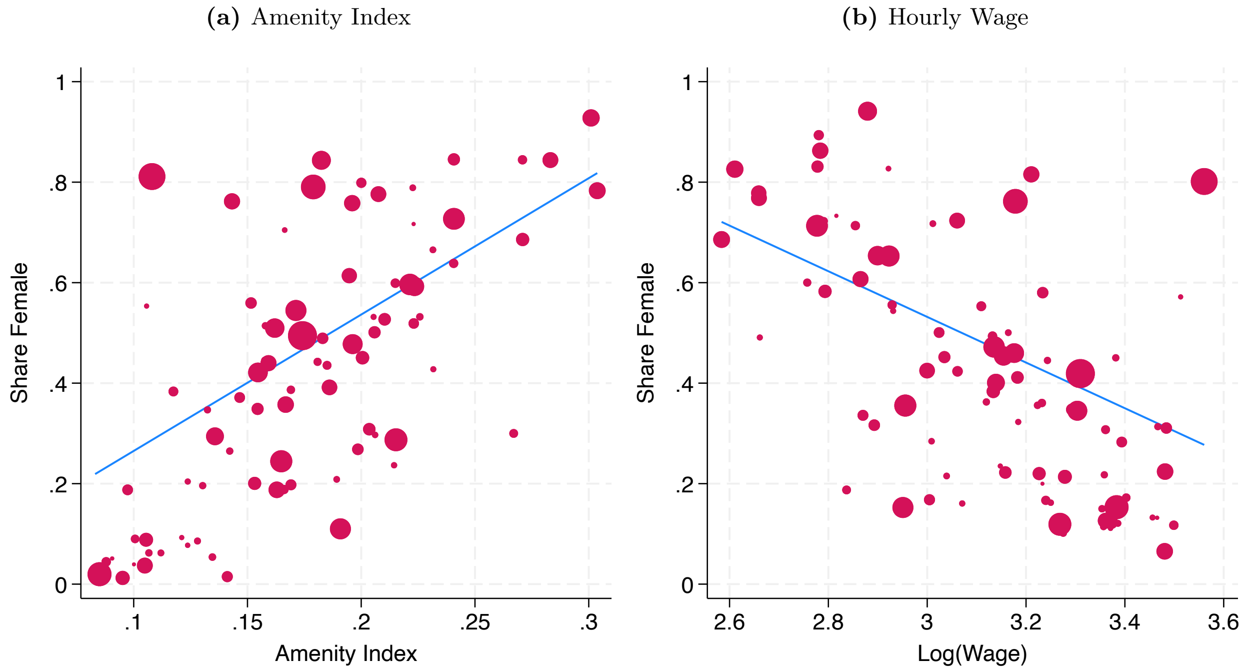
Earlier studies, such as Goldin (2014) and Blau & Kahn (2017), documented that women are more likely to work in lower-wage occupations. We also showed in Table 1 that occupation explains 25% to 30% of the gender wage gap consistent with this observation. In Figure 3, we find the opposite is true for amenities: the female share of occupations increases with the amenity index but decreases with occupation-level wages. Each scatter plot shows the relationship controlling for the other variable (i.e., from a regression of female share on wages and amenities jointly). The same pattern holds when looking at the univariate correlations instead of the partial correlations, but are quantitatively less strong because of the overall positive correlation of amenities and wages across occupations, as shown in Appendix Table A10.[16] We also consider average gender differences in occupation-level amenities for each component separately in Table B2 and find that there are positive gender gaps in six out of the seven components, and especially for telecommuting, pace of work, schedule and work flexibility.

Table 5 considers individuals who were employed both in the current month and one year earlier in the final CPS Outgoing Rotation Group. These regression results speak directly to gender

[15] Some amenities they consider—such as training opportunities—are excluded because they are likely to capture future wage growth. We also exclude paid time off, as we do not observe a sufficiently detailed measure of its availability.

[16] See Appendix Figure B1 for positive correlation between occupation-level amenities and wages. Furthermore, we find in Appendix Table A10 that our results are robust and even slightly stronger when we residualize our wage and amenity measures by age, education and race.

Figure 3: Female Shares by Occupation-level Amenities and Wages



Notes: The figures show partial correlations of the occupation-level (a) amenity index and (b) hourly log wages with the share of women in that occupation. In other words, the figure (a) shows the partial correlation of the amenity index with the female share, controlling for average occupation-level log hourly wages, whereas figure (b) shows the partial correlation of the average log hourly wage with the female share, controlling for the average occupation-level amenity index. The size of the circles correspond to the relative size of the employment in that occupation and the linear regression line is weighted by employment in each occupation. Our three-digit occupation estimates are aggregated across all employed in the Outgoing Rotation Group of our CPS sample. See Appendix B for details of the amenity index's construction.

differences in job-ladder dynamics and are comparable to the individual pay-growth regressions reported in Table 2, with the key distinction that the changes documented here arise solely from occupation switches. We find that, conditional on their initial position on the amenity ladder, women experience somewhat larger amenity gains than men, but substantially smaller gains in occupational wages once we condition on their initial position on the job ladder (as captured by the amenity or wage level of their job one year earlier).[17] Because our dependent variables—the amenity index and occupation-level wages—are measured at the occupation level, they do not capture job-ladder movements within occupations. Comparing the gender gaps in individual-level wage growth reported in Table 2 with those in occupation-level wage growth in Table 5 provides a

[17]Appendix Table A11 shows that these results are robust to restricting the sample to individuals without children in the household.

Table 5: Estimated Gender Gaps in Job Amenity and Wage Changes at the Occupation Level

Dependent variable:	*Change in Amenity Index*		*Change in Occupation log Wage*	
	(1)	(2)	(1)	(2)
Amenity Changes and Wage Growth, All Employed				
Female coefficient	0.0001	0.0052	0.002	-0.049
	(0.0015)	(0.0026)	(0.012)	(0.018)
R^2	0.001	0.150	0.004	0.191
Month, state controls	Yes	Yes	Yes	Yes
Age, education, race controls	Yes	Yes	Yes	Yes
Year-ago amenity index		Yes		
(log) year-ago occupation wage				Yes
N	371,085		347,596	

Notes: Table reports the coefficient estimates from the regression of the listed dependent variable on a female dummy and the listed controls. See Appendix B for details of the amenity index's construction. The sample used is all individuals employed with positive hours and earnings in both the current month and one year ago in the CPS sample. Standard errors are clustered by 4-digit Census occupation and in parentheses.

gauge of the gap missed when using occupational data. For example, individual wage gains exhibit a gender gap of -11 log points, whereas occupational wage gains display a gap of -4.9 log points. To summarize, these findings suggest that women face a steeper job ladder in amenities but a substantially flatter wage ladder.

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

Taken together, our empirical evidence suggests that men and women value different dimensions of jobs differently. In this sense, women are more likely to climb the multi-dimensional job ladder along the amenity dimension, while men are more likely to climb along the wage dimension. This interpretation builds on Maestas *et al.* (2023), who find a higher willingness to pay for nonmonetary amenities for women than men and is also consistent with Mas & Pallais (2017), who find that women place a higher value on working from home and avoiding irregular work schedules than do men; Wiswall & Zafar (2018), who find that undergraduate women are willing to give up 7% of their pay to have a job that includes the option of part-time hours, while men are willing to give up only 1% of pay; Le Barbanchon *et al.* (2021), who find that women are willing to accept a lower wage to avoid a longer commute and D'Agelis (2023), who finds that early-career women are willing to accept lower wages in order to obtain greater parental leave. The tradeoff between wages and job amenities is a key feature of the model we develop next.

We set up an equilibrium search model with on-the-job search and endogenous search effort where workers value both the wage and nonwage aspects of a job as in Rosen (1986) and therefore climb *a multi-dimensional job ladder*. 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. We build on Cahuc *et al.* (2006) and Bagger & Lentz (2019) and extend their framework along three dimensions. First, we introduce a match-specific amenity, similar to Hwang *et al.* (1998) and Bonhomme & Jolivet (2009). Second, our model consists of two worker states—employment and nonemployment—instead of focusing on unemployment which allows us to capture gender differences in participation decisions. Third, we allow for differences in search costs and search effectiveness by employment status following Faberman *et al.* (2022).

5.1 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 nonemployed, with $j \in \{e, n\}$ denoting their employment status. Note that nonemployment includes workers who are either unemployed or not in the labor force which we take into account when we calibrate our model. This choice is motivated by the observation that there is no gender unemployment gap in the data while employment rates are still lower for women.[18]

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 nonemployment. Workers search for work both on and off the job, exerting an endogenous level of search effort, s, to generate job offers. Offer arrival rates potentially differ by gender and employment status. Offers

[18] See Albanesi & Şahin (2018) for an analysis of full convergence of unemployment rates by gender with the exception of recessions when male unemployment rate typically exceeds female unemployment rate.

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.

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 $\zeta h(a)$ where ζ is a cost shifter that differs across firms and leads to dispersion in the provision of job amenities. Firms provide a level of amenities that maximizes the joint match surplus of the worker and the firm which is formally $\max_a \bar{\nu}(a - \bar{a}) - \zeta h(a)$. Therefore, the optimal amenity production satisfies

$$h'(a(\zeta)) = \frac{\bar{\nu}}{\zeta}, \tag{1}$$

which implies that the amenity production is increasing in the firm's targeted marginal amenity valuation, $\bar{\nu}$, and decreasing in the firms' amenity cost shifter, ζ. In our baseline model, we assume that firms target the average amenity valuation of searchers in the economy and later consider alternatives.

The match produces py, where p is an aggregate productivity shifter and y is the match-specific productivity. The flow value of the job match, ω, is

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

We let F_y be the distribution of match-specific productivity and F_ζ be the distribution of amenity cost shifters.

Joint Match Value. We assume that firms' and workers' search and separation decisions are jointly optimal, which makes the problem tractable in general equilibrium as in Bagger & Lentz (2019). One can show that the joint flow value of the match, ω, is the only state variable to keep track of for an employed worker.[19] The joint value of a match, $K_g(\omega)$, thus satisfies:

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

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 nonemployment, N_g is the value of nonemployment, and V is the value of a job vacancy. Furthermore, $F_g(\omega) = \int F_y(\frac{1}{p}[\omega + \hat{\zeta} h(a(\hat{\zeta})) - \nu_g(a(\hat{\zeta}) - \bar{a})]) dF_\zeta(\hat{\zeta})$, and $dF_g(\omega) = \frac{1}{p} \int dF_y(\frac{1}{p}[\omega + \hat{\zeta} h(a(\hat{\zeta})) - \nu_g(a(\hat{\zeta}) - \bar{a})]) dF_\zeta(\hat{\zeta})$. 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.[20] A worker who receives an exogenous separation shock flows into nonemployment. 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 nonemployment. The value of nonemployment satisfies:

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

where b_g is the gender-specific flow value of nonemployment, $\lambda_g^n(s,\theta) = \lambda_g^n(s)\lambda(\theta)$ is the probability of matching with a firm, and R_g^n is the nonemployed worker's optimal reservation match value.

Vacancy Posting. Firms pay a per-period vacancy posting cost, k, 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

[19] 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.

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

outside option of the worker is a match with flow value ω, and with $\omega = 0$ if the worker's outside option is nonemployment. The value of a vacancy satisfies:

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

Aggregate effective search effort is $S = \sum \pi_g S_g$, where the effective number of searchers is $S_g = n_g\lambda(s_g^n,\theta)+(1-n_g)[\tilde{\rho}_g(\theta)+\int\tilde{\lambda}_g^e(s_g^e(\hat{\omega}),\theta)G_g(\hat{\omega})]d\hat{\omega}$ 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 nonemployed workers satisfies:

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

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 $t_g^{NB}(\omega) = w_g^{NB}(\omega,a(\zeta))+\nu_g(a(\zeta)-\bar{a})$ and $\omega - t_g^{NB}(\omega) = py - w_g^{NB}(\omega,a(\zeta)) - \zeta h(a(\zeta))$. 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 nonemployment. To simplify the presentation, we impose the equilibrium zero profit condition $V = 0$. We can rewrite the value of a match as:

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

The value of nonemployment becomes:

$$N_g \quad = \quad \max_{s,R^n} \Bigg\{ b_g - c_g^n(s) + \frac{1}{1+r}\Big[N_g + \lambda_g^n(s,\theta) \ \int_{R^n} \tau_g(K_g(\omega') - N_g) dF_g(\omega') \Big] \Bigg\}. \tag{9}$$

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

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

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

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

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

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

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

$$K_g(R_g^n) = N_g \tag{14}$$

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

which imply that $R_g^e(\omega) = \omega$ and $R_g^\delta = R_g^n$.

Stationary Distribution and Equilibrium. The steady-state nonemployment rate, n_g, is identified by equalizing the inflows and outflows as follows:

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

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:

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

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^n and $s_g^e(\omega)$, amenities $a(\zeta)$, reservation productivities R_g^n, R_g^δ, and $R_g^e(\omega)$, nonemployment rates n_g, distributions $G_g(\omega)$, labor market tightness θ, and value functions $K_g(\omega)$, N_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 wages, $w_g^{NB}(\omega, a(\zeta))$.

5.2 Model Calibration

We calibrate our model to a monthly frequency and parameterize it in two blocks. Parameters in the first block are set externally and based on the existing literature. Parameters in the second block are set internally to match moments from the data using mostly the CPS and the SCE. Note that we define labor market states as employed (E) and nonemployed (N) and do not distinguish between the unemployed and those out of the labor force among the nonemployed. 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 start by setting the interest rate r to target a 4 percent annual discount rate. We summarize our remaining choices for externally-calibrated parameters below and also in Panel A of Table 6.

Search Costs. We assume a functional form for the search cost function identical to Faberman *et al.* (2022) but allow the scaling parameters to vary by gender, following our empirical evidence:

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

In our baseline calibration, we use $\gamma^e = 3.6$ based on the estimates from Faberman *et al.* (2022). We choose γ^n to match the search-UI elasticity in Krueger & Mueller (2010).

Matching technology and offer arrivals. Matching between firms and workers is random across both labor force states and is governed by a Cobb-Douglas matching function $M(S, v) = \mu S^\eta v^{1-\eta}$ which satisfies the standard properties. Labor market tightness, $\theta = v/S$, is defined as vacancies, v, per effective number of searchers, S. Offers arrive at a rate $\lambda_g^j(s) = \alpha_g^j + \beta_g^j s$, and we obtain our estimates for α_g^j using unsolicited offer rates and β_g^j using the search effort and offer arrival rates observed in the data. We set the flow cost of vacancies k to be consistent with a steady-state ratio of vacancies to job seekers equal to 1.

Match-specific Productivity. We assume that the distribution of productivity y is log-normal with mean $\mu_y = 0.35$ and standard deviation $\sigma_y = 0.27$. 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 match the estimated frictional wage dispersion in Hall & Mueller (2018).

Amenity Production. 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: $\zeta h(a) = \frac{\zeta}{2}a^2$, which implies that optimal amenity production is $a(\zeta) = \frac{\bar{\nu}}{\zeta}$. This further implies that the net value of the amenity production at the match level is $\nu_g(a(\zeta) - \bar{a}) - \zeta h(a(\zeta)) = \frac{\bar{\nu}}{\zeta}\left(\nu_g - \frac{\bar{\nu}}{2}\right) - \nu_g \bar{a}$. We normalize $\nu_m = 1$ and assume that the cost shifters are distributed such that the optimal amenities, $a(\zeta) = \frac{1}{\zeta}$, are distributed uniformly with mean 1. We set the standard deviation of $a(\zeta) = \frac{1}{\zeta}$ to 0.32 as in Hall & Mueller (2018). We set the reference

Table 6: Model Parameterization

A. Externally Calibrated			B. Internally Calibrated		
Parameter	Value	Source/Target	Parameter	Value	Target
r	0.9966	Annual 4% discount rate	κ_m^n, κ_f^n	0.038, 0.014	Search effort, N
k	0.57	$\theta = 1$	κ_m^e, κ_f^e	0.008, 0.004	Search effort, E
p, μ	1.00, 1.00	Normalizations	α_m^n, α_f^n	0.049, 0.016	Unsolicited offers, N
η	0.50	Petrongolo & Pissarides (2001)	α_m^e, α_f^e	0.020, 0.015	Unsolicited offers, E
μ_y, μ_a	0.35, 1.00	Normalization	β_m^n, β_f^n	0.077, 0.053	Offer arrival, N
σ_y, σ_a	0.27, 0.32	Hall & Mueller (2018)	β_m^e, β_f^e	0.094, 0.068	Offer arrival, E
γ^e	3.60	Faberman *et al.* (2022)	b_m, b_f	1.361, 1.265	Acceptance rate, N
γ^n	1.00	Search–UI elasticity	ρ_m, ρ_f	0.017, 0.020	Acceptance rate, E
ν_m, ν_f	1.00, 1.137	Maestas *et al.* (2023)	δ_m, δ_f	0.019, 0.026	Nonemployment rate
$\bar{\nu}$	1.066	Offer-weighted average of ν_m and ν_f	τ_m, τ_f	0.50, 0.32	Res. gender wage gap

Notes: See Appendix Table C2 for details on the targeted moments and their data sources as well as the model fit.

level of the amenity to the average of the distribution (i.e., $\bar{a} = \mu_a = 1$).

Amenity Preferences. For the amenity valuation of women, we refer to Maestas *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.* (2023) pins down the relative willingness to pay $\frac{\nu_f}{\nu_m} = 0.588/0.517 = 1.137$. For the amenity preference target, $\bar{\nu}$, in the baseline calibration we assume it to be the offer-weighted average of ν_g for men and women, but we perform a series of experiments below for alternative assumptions about this parameter.

Internally-calibrated Parameters. Panel B of Table 6 reports the estimates for our internally-calibrated parameters. We target moments from what we consider our most robust evidence from the SCE and CPS. We report these moments and detail how we construct them in Appendix C.1. For offer arrival and acceptance rates, we proportionally adjust the estimates from the SCE to match the job-finding and job-to-job transition rates in the CPS. The parametrization implies that men tend to face higher search costs and have somewhat higher effectiveness in job search (measured by offer arrival rates per unit of search effort). Perhaps surprisingly, men have a slightly higher flow value of nonemployment since we calibrate this parameter to match acceptance rates of offers—which tend to be higher for women. One interpretation of men having higher flow value of

Table 7: Gender Gaps in the Model

Panel A. Targeted Gender Gaps		**Panel B. Untargeted Gender Gaps**	
Gap	**Value**	**Gap**	**Value**
Wage gap (*logs*)	-0.205	Job value gap	-0.142
Employment gap	-0.125	Job amenity gap	0.062
N-to-E rate gap	-0.032	Realized productivity gap	-0.085
E-to-N rate gap	0.009	Conditional wage growth rate gap	-0.146
Job-to-job transition rate gap	0.000	Conditional amenity growth rate gap	0.021

Notes: Panel A reports targeted gaps while Panel B reports model-implied gaps from the calibrated model. All gaps are defined as the difference between women's and men's values. Wage regressions are based on workers continuously employed in last 4 months in the simulated data. Conditional growth rates control for workers' prior wages or amenities, see Appendix Table C4 for details.

nonemployment is related to the composition of nonemployment which includes the unemployed as well as workers not the in the labor force. In our data, 21% nonemployed men are unemployed while only 11% of nonemployed women are unemployed. Given the eligibility rules for unemployment insurance, women are less likely to collect benefits conditional on being nonemployed. Women have higher separation rates—reflecting their higher job turnover in the data—and a lower bargaining weight, which is calibrated towards matching the residual gender wage gap in Table 1. While we don't take a stand on the sources of the implied lower bargaining weight of women, it is consistent with discrimination as well as studies that find that women are less aggressive in wage negotiations. Appendix Table C2 shows that our calibrated model closely matches all the targeted moments.

Model's Implications for Gender Gaps. We calibrate the model to target the observed gender gaps in wages, transition rates, and employment with gaps defined as the difference between women's and men's values. These targeted statistics are reported in Panel A of Table 7, and the model matches them exactly by construction. The model also generates implications for gender gaps that are not targeted and, in some cases, do not have direct empirical counterparts. These untargeted model-generated gaps are shown in Panel B of Table 7. The model implies an amenity gap of about 6.3%, which is insufficient to offset the gender wage gap, resulting in a job value gap of roughly 14%. In equilibrium, women accept lower-productivity jobs when they offer higher amenities, generating a productivity gap of about 8.5% between men and women. This gap arises even though men and women are ex ante equally productive, highlighting the role that amenities play in the sorting of men and women into differing jobs. Finally, we simulate the model and compute annual wage and amenity growth rates for men and women, conditioning on their positions on the wage and amenity ladders. Men experience higher wage growth, while women experience higher amenity growth, in line with the empirical results in Tables 2 and 5.[21] This is due to wage growth on the job arising from outside offers and from switching jobs. Women tend to switch jobs more often in response to higher offered amenities while men tend to switch jobs in response to higher wages. We find that amenities partially offset gender differences in both wage levels and wage growth. However, these offsetting effects are not large enough to eliminate the gender gap in job values.

5.3 Decomposition of Gender Gaps

Our model can be used to decompose the various gender gaps into their different sources. Specifically, we group parameters into four different contributors and set women's parameters equal to men's progressively: *(1) job ladder parameters:* reallocation and separation rates (ρ_g, δ_g) and parameters that govern job search costs and search behavior (κ_g^n, κ_g^e, α_g^n, α_g^e, β_g^n, β_g^e); *(2) amenity preferences:* ν_g; *(3) non-market value:* b_g; *(4) bargaining weights:* τ_g.

Table 8 summarizes the decomposition results and shows that different parameters drive to different gender gaps. Job ladder parameters account for roughly 5% of the gender wage gap, most of the employment gap, about 13% of the job value gap, and almost 40% of the realized productivity gap. Amenity preferences play a central role in generating the negative gender wage gap and the positive gender amenity gap but have little effect on the job value gap. Instead, the job value gap arises primarily from differences in the value of nonmarket time and in bargaining weights: women accept jobs that with lower match values and receive a smaller share of that value due to their weaker bargaining power. If women had a higher value of nonemployment, the gender employment gap would have been even higher according to our model, because women would be even pickier in accepting job offers. The opposite holds when we equalize the bargaining shares in the model. Overall, the counterfactuals reveal the role of the different mechanisms in driving each

[21] See Appendix Table C4 for details of these regressions in model simulated data.

Table 8: Gender Gaps in Wages, Employment, Job Values, Amenities, and Productivity

	Wage Gap (*logs*)	**Empl. Gap** (*ppts*)	**Job Value Gap**	**Amenity Gap**	**Realized Productivity Gap**
Calibrated model	-0.205	-0.125	-0.142	0.062	-0.085
Model counterfactuals:					
+ Same job ladder parameters	-0.195	-0.009	-0.110	0.065	-0.053
+ Same amenity preferences	-0.119	-0.039	-0.122	0.000	-0.030
+ Same non-market value	-0.028	-0.272	-0.059	0.005	0.010
+ Same bargaining weights	0.000	0.000	0.000	0.000	0.000

Notes: The table reports gender gaps in wages, employment, job values, amenities, and productivity implied by the calibrated model. Counterfactual rows cumulatively set women's parameters equal to men's; thus the final row equalizes all parameters. Job ladder parameters include search costs, offer arrival rates, and separation rates. Appendix Table C3 reports the decomposition, in which one set of parameters is equalized at a time.

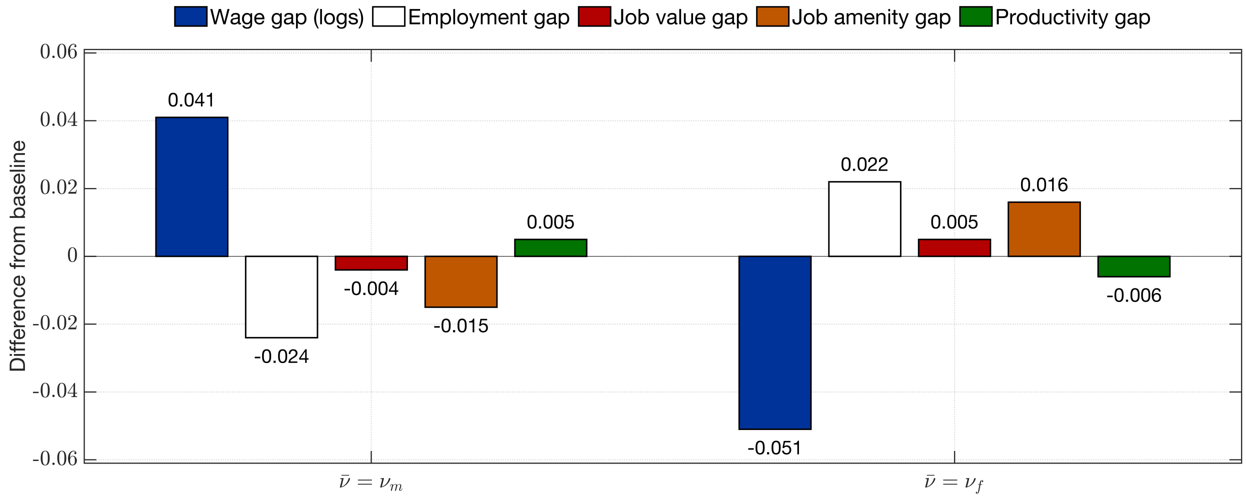
gender gap. This is important since different policies are likely to affect the various gender gaps in different—and potentially opposing—directions.

5.4 Changes in Amenity Provision by Firms

Our baseline model assumes that firms target the average amenity valuation of searchers in the economy. We next analyze how changes in amenity provision would affect gender differences in wages. We consider two experiments and report the results in Figure 4. In the first, firms set amenity levels to target men, as in earlier policies that provided equal but relatively modest parental leave benefits. In the second, firms choose amenity levels targeting women, for example by offering more generous family-oriented benefits. The first case where firms target amenities toward men reduces the gender wage gap but widens the gender employment gap. That is because women's reservation wages increase in response to the relatively weaker amenity offerings causing them to accept higher-productivity jobs. When firms tailor amenities to women, women's participation rates rise because lower-productivity jobs become more attractive. The gender wage gap widens through two channels: higher female participation and a higher provision of amenities, which women value more.[22]

[22] While it is less practically relevant, we also consider a case where firms offer gender-specific amenities in C5. This case leads to doubling of the gender wage gap without a change in the gender value gap since firms shift their compensation towards wages for men and towards amenities for women.

Figure 4: Changes in Amenity Provision

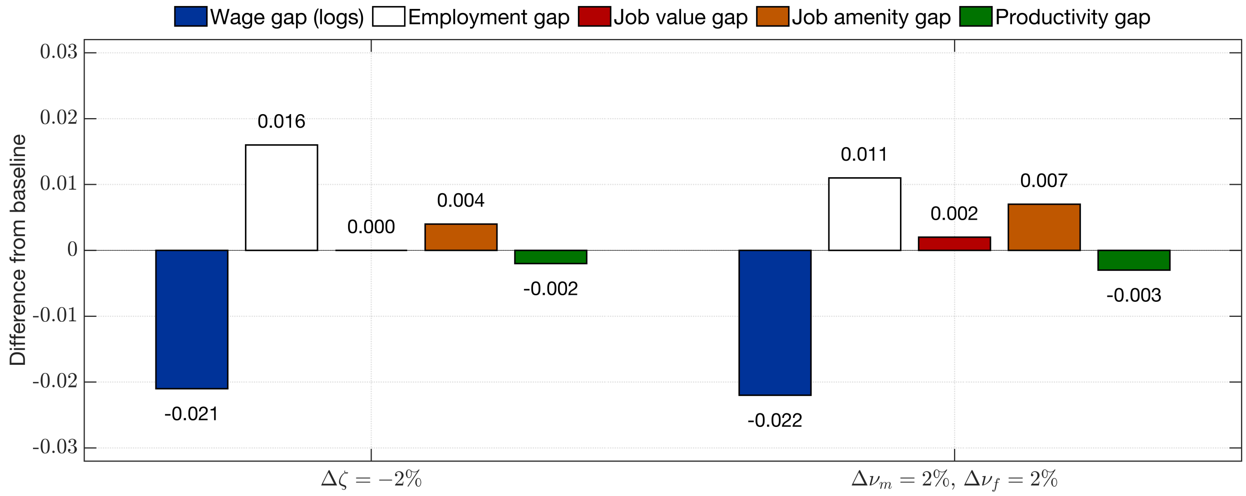


Notes: The figures show what happens to economy-wide gender gaps in wages, employment, job values, amenities and realized productivity in counterfactuals with different targets in amenity production, $\bar{\nu}$ (right-hand side), see Appendix Table C5 for details.

5.5 Application: Rise of Remote Work

A natural application of our framework is the emergence of remote work after the onset of the COVID pandemic. We analyze the effects of the increased prominence of remote work through two counterfactual exercises. In the first experiment, the increase in remote work is modeled as a decline in firms' cost of providing it by reducing ζ by 2%. In the second, we model the rise in remote work as a higher willingness to pay for this amenity for both men and women by increasing ν_m and ν_f each by 2%. Figure 5 shows that the expansion of remote work increases the gender wage gap while reducing the gender employment gap. That is because women become even more likely to sort into high-amenity jobs while men are more likely to sort into higher-productivity jobs, increasing the gender wage gap. At the same time, the higher amenity value lowers reservation wages for both groups—especially for women—making low-productivity jobs more acceptable and narrowing the employment gap. Symmetrically, if remote work were to disappear, our model implies a narrowing of the gender wage gap and a widening of the gender employment gap. While it is still early to see the effects on the gender wage gap, these implications of the model are consistent with preliminary evidence on recent widening of the gender wage gap and shrinking of the participation

Figure 5: Changes in Amenity Production Costs and Preferences



Notes: The figures show what happens to economy-wide gender gaps in wages, employment, job values, amenities and realized productivity in counterfactuals with changes in the costs or preferences for amenity provision, see Appendix Table C5 for details.

gap. According to the Census Bureau, women working full-time year-round made 80.9 cents per dollar earned by men in 2024 compared to 81.9 cents per dollar in 2019—which was the biggest gender gap since 2016. At the same time, the participation gap between men and women went down from 11.5 percentage points in 2019 to 10.5 percentage points in 2024.[23]

6 Conclusion

Our paper analyzes the gender gaps in various important measures with a special focus on the gender wage gap for the 2013–2022 period. Our empirical analysis documents several key facts that challenge the conventional interpretation of the job ladder as being summarized by wages. Most notably, despite women facing higher separation rates from employment into nonemployment, their job-to-job transition rates are nearly identical to those of men. Yet, conditional on prior wages, women experience significantly smaller wage gains. At the same time, women place greater value on job characteristics such as flexibility, pace, and remote work options.

Motivated by these observations, we develop a multi-dimensional job-ladder model in which jobs

[23]For comparison purposes, we also consider a 2% increase in aggregate productivity. Table C5 shows that such a change increases the gender wage gap but reduces the employment gap.

differ not only in wages but also in nonwage amenities, and in which workers value these attributes differently by gender. The framework incorporates heterogeneity in separations, in the value of nonemployment, in amenity valuations, and in bargaining power. By allowing these dimensions to interact, the model produces rich implications for observed gender gaps in wages, employment, amenities, productivity, and overall job values. A key contribution of the paper is to show that gender gaps in job values cannot be fully understood without accounting for the amenity dimension and the differential trade-off men and women face in their decisions on job search and whether to accept or reject job offers.

Our decompositions highlight the quantitative importance of these forces. Differences in preferences for nonwage amenities and in the value of nonemployment explain the majority of the observed gender wage gap. Differences in search behavior and bargaining power play a secondary role, jointly accounting for roughly one-fifth of the wage gap. Finally, we show that even after incorporating the value of amenities, there remains a substantial gender gap in true job values—about half the size of the wage gap—suggesting that amenities do not fully compensate for wage differentials.

Differences in preferences for amenities by gender are supported by both our analysis of the SCE data as well as by various studies in the literature that use stated-preferences to elicit information about willingness to pay. While this is a reduced form way to capture the role of differences in choices made by men and women in their job search, it should not be interpreted as ruling out an important role for social norms and institutional frictions surrounding childcare and other household responsibilities. On the contrary, such norms and frictions are likely to shape both the constraints individuals face and the choices they make when searching for jobs and moving between employers. To shed light on this issue, we also provide analyses that control for marital status and the presence of children in the household. These controls have only a limited effect on our estimates, suggesting that the observed patterns are not driven solely by contemporaneous household circumstances. Rather, they are consistent with search and acceptance decisions that may reflect past and anticipated future constraints, expectations about family responsibilities, and the broader social norms that structure labor market opportunities for women.

Our framework is also useful for analyzing how changes in the amenity component of jobs shape gender disparities. The rise of remote work is a salient example. An increase in the value of remote work, or a decline in firms' cost of supplying it, improves women's relative employment rates but widens the gender wage gap because men and women differ in their marginal willingness to trade wage compensation for amenities. These results emphasize that focusing only on the gender wage gap provides an incomplete picture of men's and women's labor market disparities.

References

Albanesi, Stefania, & Şahin, Ayşegül. 2018. The Gender Unemployment Gap. *Review of Economic Dynamics*, **30**, 47–67.

Albrecht, James, Björklund, Anders, & Vroman, Susan. 2003. Is There a Glass Ceiling in Sweden? *Journal of Labor Economics*, **21**(1), 145–177.

Amano-Patiño, Noriko, Baron, Tatiana, & Xiao, Pengpeng. 2025. *Human Capital Accumulation, Equilibrium Wage-Setting, and Gender Pay Gap Dynamics*. Working Paper.

Bagger, Jesper, & Lentz, Rasmus. 2019. An Empirical Model of Wage Dispersion with Sorting. *The Review of Economic Studies*, **86**(1), 153–190.

Bandiera, Oriana, Jalal, Amen, & Roussille, Nina. 2025. *The Illusion of Time: Gender Gaps in Job Search and Employment*. NBER Working Paper 34051.

Barrero, Jose Maria, Bloom, Nicholas, & Davis, Steven J. 2021. *Why Working from Home Will Stick*. NBER Working Paper No. 28731.

Bertrand, Marianne, Goldin, Claudia, & Katz, Lawrence F. 2010. Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors. *American Economic Journal: Applied Economics*, **2**(3), 228–255.

Blau, Francine D., & Kahn, Lawrence M. 2000. Gender Differences in Pay. *Journal of Economic Perspectives*, **14**(4), 75–99.

Blau, Francine D., & Kahn, Lawrence M. 2017. The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature*, **55**(3), 789–865.

Bonhomme, Stéphane, & Jolivet, Grégory. 2009. The Pervasive Absence of Compensating Differentials. *Journal of Applied Econometrics*, **24**(5), 763–795.

Burdett, Kenneth, & Mortensen, Dale T. 1998. Wage Differentials, Employer Size, and Unemployment. *International Economic Review*, **39**(2), 257–273.

Cahuc, Pierre, Postel-Vinay, Fabien, & Robin, Jean-Marc. 2006. Wage Bargaining with On-the-Job Search: Theory and Evidence. *Econometrica*, **74**(2), 323–364.

Christensen, Bent Jesper, Lentz, Rasmus, Mortensen, Dale T., Neumann, George R., & Werwatz, Axel. 2005. On-the-Job Search and the Wage Distribution. *Journal of Labor Economics*, **23**(1), 31–58.

Cortés, Patricia, & Pan, Jessica. 2018. Occupation and Gender. *Pages 425–452 of: The Oxford Handbook of Women and the Economy*. Oxford University Press.

Cortés, Patricia, Pan, Jessica, Pilossoph, Laura, Reuben, Ernesto, & Zafar, Basit. 2023. Gender Differences in Job Search and the Earnings Gap: Evidence from the Field and Lab. *Quarterly Journal of Economics*, **138**(4), 2069–2126.

D'Agelis, Ilaria. 2023. *The Search for Parental Leave and the Early-Career Gender Wage Gap*. Working Paper.

Dingel, Jonathan I., & Neiman, Brent. 2020. How Many Jobs Can Be Done at Home? *Journal of Public Economics*, **189**, 104235.

Erosa, Andrés, Fuster, Luisa, Kambourov, Gueorgui, & Rogerson, Richard. 2022. Hours, Occupations, and Gender Differences in Labor Market Outcomes. *American Economic Journal: Macroeconomics*, **14**(3), 543–590.

Faberman, R. Jason, Mueller, Andreas I., Şahin, Ayşegül, & Topa, Giorgio. 2022. Job Search Behavior Among the Employed and Non-Employed. *Econometrica*, **90**(4), 1743–1779.

Fallick, Bruce, & Fleischman, Charles A. 2004. *Employer-to-Employer Flows in the U.S. Labor Market: The Complete Picture*. Finance and Economics Discussion Series 2004-34. Federal Reserve Board.

Fluchtmann, Jonas, Glenny, Anita M., Harmon, Nikolaj A., & Maibom, Jonas. 2024. The Gender Application Gap: Do Men and Women Apply for the Same Jobs? *American Economic Journal: Economic Policy*, **16**(2), 182–219.

Goldin, Claudia. 2014. A Grand Gender Convergence: Its Last Chapter. *American Economic Review*, **104**(4), 1091–1119.

Groshen, Erica L. 1991. The Structure of the Female/Male Wage Differential: Is It Who You Are, What You Do, or Where You Work? *Journal of Human Resources*, **26**(3), 457–472.

Hall, Robert E., & Mueller, Andreas I. 2018. Wage Dispersion and Search Behavior: The Importance of Nonwage Job Values. *Journal of Political Economy*, **126**(4), 1594–1637.

Hwang, Hae-shin, Mortensen, Dale T., & Reed, W. Robert. 1998. Hedonic Wages and Labor Market Search. *Journal of Labor Economics*, **16**(4), 815–847.

Kleven, Henrik, Landais, Camille, & Søgaard, Jakob Egholt. 2019. Children and Gender Inequality: Evidence from Denmark. *American Economic Journal: Applied Economics*, **11**(4), 181–209.

Krueger, Alan B., & Mueller, Andreas I. 2010. Job Search and Unemployment Insurance: New Evidence from Time-use Data. *Journal of Public Economics*, **94**(3–4), 298–307.

Le Barbanchon, Thomas, Rathelot, Roland, & Roulet, Alexandra. 2021. Gender Differences in Job Search: Trading off Commute against Wage. *Quarterly Journal of Economics*, **136**(1), 381–426.

Lindenlaub, Ilse, & Postel-Vinay, Fabien. 2023. Multidimensional Sorting under Random Search. *Journal of Political Economy*, **131**(12), 3497–3539.

Lochner, Benjamin, & Merkl, Christian. 2025. Gender-Specific Application Behavior, Matching, and the Residual Gender Earnings Gap. *The Economic Journal*, **136**(673), 97–124.

Maestas, Nicole, Mullen, Kathleen J., Powell, David, von Wachter, Till, & Wenger, Jeffrey B. 2023. The Value of Working Conditions in the United States and the Implications for the Structure of Wages. *American Economic Review*, **113**(7), 2007–2047.

Mas, Alexandre, & Pallais, Amanda. 2017. Valuing Alternative Work Arrangements. *American Economic Review*, **107**(12), 3722–3759.

Moscarini, Giuseppe, & Postel-Vinay, Fabien. 2023. *The Job Ladder: Inflation vs. Reallocation*. NBER WP 31466.

Moser, Christian, & Morchio, Iacopo. 2024. *The Gender Pay Gap: Micro Sources and Macro Consequences*. NBER Working Paper 32408.

Petrongolo, Barbara, & Pissarides, Christopher A. 2001. Looking into the Black Box: A Survey of the Matching Function. *Journal of Economic Literature*, **39**(2), 390–431.

Postel-Vinay, Fabien, & Robin, Jean-Marc. 2002. Equilibrium Wage Dispersion with Worker and Employer Heterogeneity. *Econometrica*, **70**(6), 2295–2350.

Rosen, Sherwin. 1986. The Theory of Equalizing Differences. *Pages 641–692 of:* Ashenfelter, Orley, & Layard, Richard (eds), *Handbook of Labor Economics*, vol. 1. Amsterdam: North-Holland.

Roussille, Nina. 2024. The Role of the Ask Gap in Gender Pay Inequality. *Quarterly Journal of Economics*, **139**(3), 1557–1610.

Sorkin, Isaac. 2018. Ranking Firms Using Revealed Preference. *Quarterly Journal of Economics*, **133**(3), 1331–1393.

Topel, Robert H., & Ward, Michael P. 1992. Job Mobility and the Careers of Young Men. *Quarterly Journal of Economics*, **107**(2), 439–479.

Wiswall, Matthew, & Zafar, Basit. 2018. Preference for the Workplace, Investment in Human Capital, and Gender. *Quarterly Journal of Economics*, **133**(1), 457–507.

Xiao, Pengpeng. 2024. *Equilibrium Sorting and the Gender Wage Gap*. Working Paper.

APPENDIX

A Additional Empirical Results

A.1 Gender Differences in Pay and Pay Growth

Table A1: Gender Wage Gap in Current Hourly Wage in the CPS

	All workers				Workers w/o Children
	(1)	(2)	(3)	(4)	(5)
Dependent variable: *log real hourly wage*					
Female coefficient	−0.179	−0.224	−0.161	−0.159	−0.145
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.048	0.296	0.429	0.431	0.402
N	1,191,509				697,041
Dependent variable: *log real weekly earnings*					
Female coefficient	−0.302	−0.351	−0.245	−0.243	−0.204
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
R^2	0.059	0.259	0.399	0.400	0.370
N	1,191,509				697,041
Dependent variable: *log real hourly wage (HH heads)*					
Female coefficient	−0.297	−0.276	−0.193	−0.187	
	(0.002)	(0.002)	(0.002)	(0.002)	
R^2	0.084	0.330	0.457	0.457	
N	482,608				
Dependent variable: *log real weekly earnings (HH heads)*					
Female coefficient	−0.445	−0.426	−0.296	−0.293	
	(0.002)	(0.002)	(0.002)	(0.002)	
R^2	0.105	0.301	0.432	0.432	
N	482,608				
Year, state controls	Yes	Yes	Yes	Yes	Yes
Age, education, race controls		Yes	Yes	Yes	Yes
Occupation controls			Yes	Yes	Yes
HH composition controls				Yes	

Notes: 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 log real weekly earnings and the sample is all employed individuals, excluding the self-employed, in the October 2013-22 waves of the SCE Job Search Supplement aged 25 to 64 for the SCE results. The CPS results use the listed restrictions over all individuals aged 25 to 64 in the Outgoing Rotation Groups between July 2013 and December 2022. Robust standard errors are in parentheses.

Table A2: Gender Gaps in Pay Growth for Recent Hires

Dependent variable	*Change in log real hourly wage*		*Change in log real weekly earnings*	
	(1)	(2)	(1)	(2)
Pay Growth, Recent Hires				
Female coefficient	0.003	−0.058	0.003	−0.084
× recent hire	(0.007)	(0.006)	(0.012)	(0.010)
Recent hire coefficient	0.008	0.018	0.014	0.029
	(0.007)	(0.006)	(0.008)	(0.007)
R^2	0.007	0.345	0.006	0.303
N	371,179			
Pay Growth, Recent Hires, Occupation-Restricted Sample				
Female coefficient	0.026	−0.052	0.005	−0.097
× recent hire	(0.016)	(0.013)	(0.018)	(0.015)
Recent hire coefficient	−0.009	0.013	−0.000	0.024
	(0.011)	(0.009)	(0.011)	(0.012)
R^2	0.007	0.331	0.007	0.287
N	180,175			
Month, state controls	Yes	Yes	Yes	Yes
Age, education, race controls	Yes	Yes	Yes	Yes
Occupation controls	Yes	Yes	Yes	Yes
(log) year-ago hourly wage		Yes		
(log) year-ago weekly earnings				Yes

Notes: Table reports the coefficient estimates from regressing the log year-over-year change in either the hourly wage or weekly earnings on a female dummy interacted with a dummy for whether the individual was a recent hire in separate regressions that include the controls indicated within each column plus a separate dummy for whether the worker was a recent hire. The sample used is all individuals employed in the current month and one year ago in the final Outgoing Rotation Group of the CPS sample (top panel), or the same sample further restricted to those who report the same occupation in their fourth and fifth CPS interviews (i.e., one year ago and four months ago). A recent hire is defined as someone who reported a job change within the prior three months and was employed continuously during that time. Robust standard errors are in parentheses.

Table A3: Gender Gaps in Pay Growth: All Workers vs. Workers without Children

	All		**All w/o Children**	
	(1)	(2)	(1)	(2)
Dependent variable: *Change in log real hourly wage*				
Female coefficient	0.002	−0.110	−0.000	−0.102
	(0.002)	(0.002)	(0.003)	(0.002)
R^2	0.007	0.350	0.010	0.353
Dependent variable: *Change in log real weekly earnings*				
Female coefficient	0.005	−0.141	0.000	−0.122
	(0.002)	(0.002)	(0.003)	(0.003)
R^2	0.006	0.311	0.009	0.310
N	371,179		214,310	
Month, state controls	Yes	Yes	Yes	Yes
Age, education, race controls	Yes	Yes	Yes	Yes
Occupation controls	Yes	Yes	Yes	Yes
Year-ago (log) hourly wage		Yes		Yes

Notes: Table reports the estimates from regressing the log year-over-year change in the hourly wage or weekly earnings on a female dummy in separate regressions that include the controls indicated within each column. The samples used are all individuals employed in the current month and one year ago in the final outgoing rotation group of the CPS sample, either with children present in the household (first two columns), or without children present (last two columns). Robust standard errors are in parentheses.

A.2 Gender Differences in Labor Market Transitions

Table A4: Gender Differences in Job-to-Job Transitions

	CPS Data	**SCE Data**	**SIPP Data**
Dependent variable: E-to-E transition rate			
Female coefficient	0.0004	0.0052	−0.0008
	(0.0002)	(0.0041)	(0.0002)
R^2	0.003	0.042	0.002
N	2,926,386	6,161	2,823,691

Notes: The table reports the coefficient estimates on a female dummy in separate regressions. The dependent variable is the job-to-job transition rate in the CPS and SIPP data, and the fraction of employed who accepted an offer in the last 4 weeks, excluding acceptances of secondary jobs. All regressions control for time period (month or year), state, age, education, race, and detailed occupation. The samples are all employed in the prior month in the CPS sample, the SCE Job Search Supplement sample, or among those aged 25 to 64 between 1995 and 2012 in the SIPP data. Robust standard errors are in parentheses.

Table A5: Gender Differences in Worker Transitions

	All Individuals			All w/o Children
	(1)	(2)	(3)	(4)
Dependent variable: E-to-E transition rate				
Female coefficient	−0.00019	0.00036	0.00026	0.00014
	(0.00016)	(0.00019)	(0.00019)	(0.00025)
R^2	0.0003	0.003	0.003	0.003
Dependent variable: E-to-Full-Time E transition rate				
Female coefficient	−0.0026	−0.0013	−0.0014	−0.0009
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
R^2	0.0004	0.002	0.002	0.002
Dependent variable: E-to-Part-Time E transition rate				
Female coefficient	0.0024	0.0017	0.0016	0.0010
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
R^2	0.001	0.005	0.005	0.005
N		2,926,386		1,699,976
Dependent variable: E-to-N transition rate				
Female coefficient	0.0089	0.0108	0.0106	0.0056
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
R^2	0.006	0.016	0.016	0.015
N		3,291,209		1,919,935
Dependent variable: N-to-E transition rate				
Female coefficient	−0.0322	−0.0387	−0.0375	−0.0183
	(0.0005)	(0.0005)	(0.0005)	(0.0006)
R^2	0.007	0.022	0.023	0.026
N		1,256,312		825,337
Time period, state controls	Yes	Yes	Yes	Yes
Age, education, race controls		Yes	Yes	Yes
Occupation controls		Yes	Yes	Yes
Household controls			Yes	

Notes: The table reports the coefficient estimates from regressing the listed worker transition rate on a female dummy in separate regressions that include the controls indicated within each column, with the exception of the nonemployment-to-employment transition rates, which do not control for occupation (since the variable is unavailable for some workers in both months). Household controls include the number of children under 6, the number of children 6 to 17, and marital status. Regressions use all individuals in our CPS sample, or all those without household children (last column), restricted to those employed or nonemployed, as noted in the table. Robust standard errors are in parentheses.

A.3 Gender Differences in Job Search Behavior and Outcomes

Table A6: Incidence of Job Search by Gender and Employment Status

	Employed		**Nonemployed**	
	Men	**Women**	**Men**	**Women**
Pct. actively looking for work	19.2	25.2	21.5	24.2
	(0.7)	(0.8)	(1.5)	(1.4)
Pct. looking only for part-time	17.9	25.6	22.3	35.6
work, conditional on search	(1.5)	(1.6)	(3.3)	(3.1)
Pct. looking only for additional	24.2	38.4	—	—
work, conditional on search	(1.7)	(1.8)		
N	3,185	3,095	716	942

Notes: Estimates come from authors' tabulations from their SCE Job Search Supplement sample. Employment status is defined as at the time of the survey interview. Standard errors are in parentheses.

Table A7: Search Effort and Outcomes by Gender, Controlling for Observables

	Female − Male Gap, E		**Female − Male Gap, NE**	
	Uncond.	**w/ Controls**	**Uncond.**	**w/ Controls**
Search Effort				
Applications sent in	0.241	0.123	0.625	−0.015
last four weeks	(0.121)	(0.132)	(0.223)	(0.242)
Hours spent searching in	0.339	0.163	0.036	−0.243
last seven days	(0.113)	(0.121)	(0.200)	(0.221)
Search Outcomes				
Fraction w/ an unsolicited offer	−0.002	0.003	−0.018	−0.018
in last four weeks	(0.004)	(0.004)	(0.007)	(0.008)
Fraction w/ any offer in	0.017	0.014	0.012	0.002
last four weeks	(0.009)	(0.010)	(0.016)	(0.018)

Notes: Estimates are for all individuals in the SCE Job Search Supplement sample (N = 7,937). Controls for the conditional gender gaps include state, year, age, education, race, and 3-digit occupation fixed effects. Robust standard errors are in parentheses.

A.4 Gender Differences in Job Amenity Preferences

Table A8: Gender Gaps in Reservation Wages, Desired Hours, and Disamenity Valuations

	All Individuals	**All w/o Children**
Gaps in Reservation Wages and Desired Work Hours		
log real hourly reservation wage	−0.218	−0.182
	(0.014)	(0.017)
log desired work hours	−0.099	−0.101
	(0.016)	(0.020)
Gap in Percentages who Refuse the Disamenity		
Percent that would not	10.92	10.95
relocate at any wage	(1.40)	(1.76)
Percent that would not double	10.86	12.55
commute at any wage	(1.84)	(1.70)
Percent that would not increase	6.30	5.07
hours 10% at any wage	(1.17)	(1.47)
N	5,862	3,541

Notes: Estimates are from individuals who either looked for work or stated they might take a job if offered, using the SCE Job Search Supplement sample. Controls include state, year, age, race, education, three-digit occupation of the current or most recent job, and employment status. Standard errors are in parentheses.

Table A9: Wages, Job Characteristics, and Job Satisfaction by Gender and Children

	Men	**Women**	**Men**	**Women**
	All		**w/o Children**	
Dependent variable: *Overall Job Satisfaction (1–5 Scale)*				
log real hourly wage	0.272	0.141	0.294	0.165
	(.039)	(.043)	(.052)	(.055)
log usual work hours	−0.003	−0.226	−0.061	−0.298
	(.071)	(.063)	(.068)	(.071)
Any quality-of-life or childcare benefits	0.065	0.255	0.053	0.244
	(.048)	(.055)	(.068)	(.071)
Commute time	−0.021	−0.010	−0.014	−0.020
	(.007)	(.008)	(.010)	(.010)
Any health, dental, or life benefits	0.044	0.049	0.055	0.190
	(.072)	(.069)	(.099)	(.094)
Any retirement or equity benefits	0.190	0.168	0.193	0.227
	(.063)	(.061)	(.087)	(.082)
R^2	0.141	0.116	0.203	0.186
Month, state controls	Yes	Yes	Yes	Yes
Age, education, race controls	Yes	Yes	Yes	Yes
Occupation controls	Yes	Yes	Yes	Yes
N	2,755	2,708	1,595	1,617

Notes: The table reports coefficient estimates from regression a self-reported measure of job satisfaction (measured on a one to five scale) on the listed regressors in separate regressions by gender and the presence of children in the household. All regressions control for year, state, age, education, race, and three-digit occupation. We use the square root of commute time. The sample is all employed individuals in the SCE Job Supplement sample from 2014 forward (the first year the job satisfaction data are available). Robust standard errors in parentheses.

A.5 Gender Differences in Job Amenity Realizations

Table A10: Relationships between Occupational Wages, Amenities, and Female Share

	Raw Measures			Residualized Measures		
	(1)	(2)	(3)	(1)	(2)	(3)
Dependent variable: *Occupation's Female Share*						
Mean log occupation hourly wage	−0.085		−0.454	−0.554		−0.762
	(0.082)		(0.095)	(0.123)		(0.115)
Occupation amenity index value		1.164	2.714		1.277	2.312
		(0.392)	(0.478)		(0.515)	(0.448)
R^2	0.013	0.095	0.289	0.194	0.068	0.390

Notes: The table reports the OLS coefficient estimates from regressing the share female on either the mean log hourly wage or the amenity index across 3-digit occupations ($N = 86$). The first two columns report the OLS estimates using the raw wage and amenity index estimates. The last two columns report the OLS estimates using wage and amenity index estimates that are residualized by controlling for month, state, age, education, and race and aggregated by occupation. Regressions are weighted by occupation employment. Robust standard errors in parentheses.

Table A11: Estimated Gender Gaps in Job Amenity and Wage Changes at the Occupation Level

Dependent variable:	*Change in Amenity Index*		*Change in Occupation log Wage*	
	(1)	(2)	(1)	(2)
Amenity Changes and Wage Growth, w/o Children				
Female coefficient	−0.0001	0.0059	0.002	−0.041
	(0.0015)	(0.0026)	(0.012)	(0.018)
R^2	0.001	0.151	0.005	0.192
N	214,254		202,316	
Month, state controls	Yes	Yes	Yes	Yes
Age, education, race controls	Yes	Yes	Yes	Yes
Year-ago amenity index		Yes		
(log) year-ago occupation wage				Yes

Notes: Table reports the coefficient estimates from the regression of the listed dependent variable on a female dummy and the listed controls. See Appendix B for details of the amenity index's construction. The sample used is all individuals employed with positive hours and earnings in both the current month and one year ago in the CPS sample, excluding those with children in the household. Standard errors are clustered by 4-digit Census occupation and in parentheses.

B Construction of the Amenity Index

This section describes how we construct our amenity index. The index is a *willingness-to-pay weighted* average of seven measures we choose based on the nonmonetary job characteristics from the survey administered by Maestas *et al.* (2023). We derive estimates of these job amenities by detailed occupation, aggregate them into a single amenity index, then match the index to employed individuals in the CPS.

The index is based on measures of job amenities from three publicly available sources. We derive measures of required physical activity and the pace of work from O*NET occupational data on Work Context. We use the 2017-18 Leave Module of the American Time Use Survey (ATUS) for work schedule flexibility. Finally, we rely on the classification in Dingel & Neiman (2020) for measures of teleworkability at the occupational level.

We generate three variables from O*NET files on Work Context: a variable on the *physical activity* required, a variable on the time spent *sitting*, and a variable on the overall *pace of work*. The variables are derived from the Work Context score of reported job activities. For physical activity, we use the scores for *time spent standing* and *time spent bending or twisting*; for sitting, we use the score for *time spent sitting*; and for pace of work, we use the scores for *time pressure* and how much the *pace is determined by the speed of equipment*. The Work Context data scores each of these measures on a one to five scale, which we normalize to lie in $[0, 1]$. We reverse the values of the scores used for physical activity and pace of work and take their simple average, so a value of one represents little to no physical activity and the most relaxed pace of work, respectively. Finally, we aggregate estimates of the detailed SOC codes in the O*NET data to their corresponding Census occupation code used in the CPS, weighting the SOC codes by their 2019 employment from the Occupational Employment and Wage Statistics survey. We then standardize the amenity measures so that they range from zero to one for the aggregated occupations, and then match them to CPS respondents based on the Census code-SOC code correspondence of their occupation. Following Maestas *et al.* (2023), we assign weights of 0.075 to both moderate physical activity and sitting, and 0.04 to relaxed pace in the construction of our index. These weights imply that moving from the most physically demanding job to the least physically demanding job is equivalent to a 7.5% increase in wages.

We generate three variables from the ATUS Leave Module capturing flexibility. The Leave

Module surveys employed respondents from the 2017 and 2018 ATUS waves about various aspects of the leave and schedule flexibility of their job. Our three measures gauge the degree of schedule flexibility the respondent has. The first is a general measure of flexibility based on three related survey questions. If they respond 'no' to, *"Do you have flexible work hours that allow you to vary or make changes in the times you begin and end work?"* we assign them a value of zero. Otherwise, we use their response to *"Can you change the time you begin and end work on a frequent basis, occasionally, or only rarely?"* If they can only rarely change it, we assign them a value of 0.25, and if they can occasionally change it, we assign them a value of 0.5. If they can frequently change it and respond to a third follow-up question that their flexibility is *"just an informal arrangement,"* we assign them a value of 0.75, and if they respond to the same question that their flexibility is *"part of a formal, written program or policy,"* we assign them a value of one. The second question measures their flexibility in response to the question of *"How far in advance do you know your work schedule?"* There are five survey responses ranging from *"less than one week"* to *"four weeks or more,"* which we assign values between zero and one at 0.25 intervals. Our final measure of flexibility uses the number of days per week the respondent works, where we assign fewer than 3 days a week a value of one, and 6 or 7 days a week a value of zero, and the remaining number of days a value in between at 0.25 intervals. We then take the (survey-weighted) average values of these three measures by Census occupation code and match them to CPS respondents by the same occupation codes. In doing so, we group Census occupation codes to their corresponding three-digit SOC (or two-digit SOC for several small occupations) and then match them to the ATUS amenity variables. We do this because of sparse cells for occupation codes in the ATUS Leave Module.[2] The weights we assign to these amenities are 0.03 for each flexibility measure.

Finally, we use a measure of each occupation's telecommutability derived by Dingel & Neiman (2020) and made publicly available by the authors. They construct estimates of telecommutability over $[0, 1]$ for detailed SOC occupation codes. We use the same correspondence between these codes and the Census occupation codes as before, aggregating SOC codes as necessary, to match their values to CPS respondents by detailed occupation. We use a weight of 0.07 for teleworkability following Barrero *et al.* (2021).

Once we have all amenity measures matched to each CPS respondent, we construct our amenity

[2]The two digit SOC groupings are for SOC 31 (healthcare support) and 45 (farming, fishing, and forestry). We also aggregate SOCs 394, 396, 397, 399 (all within personal care services) into a single group.

Table B1: Rankings of Occupation by Amenity Index Value

Rank	Score	SOC	Occupation Title	Rank	Score	SOC	Occupation Title
1	0.294	152	Mathematicians & Scientists	72	0.097	511	Production Worker Supervisors
2	0.289	193	Social Scientists	73	0.095	351	Food-Prep & Service Supervisors
3	0.285	151	Computer Occupations	74	0.093	515	Printing Workers
4	0.284	232	Legal Support Workers	75	0.093	353	Food & Beverage Servers
5	0.280	231	Lawyers & Judges	76	0.092	372	Building Cleaners & Pest Control
6	0.279	436	Secretaries & Admin. Assistants	77	0.091	359	Other Food Prep & Service-Related Workers
7	0.277	439	Other Office & Admin. Support	78	0.087	493	Vehicle Mechanics & Repairers
8	0.274	112	Marketing & Sales Managers	79	0.086	475	Extraction Workers
9	0.272	212	Religious Workers	80	0.083	514	Metal & Plastic Workers
10	0.272	132	Financial Specialists	81	0.080	373	Grounds Maintenance
11	0.269	431	Office & Admin. Supervisors	82	0.079	517	Woodworkers
12	0.264	171	Architects, Surveyors, Cartographers	83	0.079	352	Cooks & Food Preparers
13	0.263	131	Business Operations Specialists	84	0.071	472	Construction Trade Workers
14	0.259	113	Operations Specialist Managers	85	0.063	513	Food Processing
15	0.258	433	Financial Clerks	86	0.062	473	Construction Trade Helpers

Notes: The table reports the ranking of 3-digit SOC occupations by their amenity index score. The top fifteen and bottom fifteen occupations are listed.

index as the *willingness-to-pay weighted* average of these seven measures informed by Maestas *et al.* (2023) and Barrero *et al.* (2021).

Table B1 reports the top fifteen and bottom fifteen occupations ranked by our amenity index measure (with occupations aggregated by three-digit SOC). As one might expect, occupations with the highest amenity scores tend to be professional occupations that tend to require advanced degrees and more specialized skills, and occupations that are primarily in an office setting. Occupations with the lowest amenity scores tend to be jobs that require less education and tend to require a fair degree of manual labor and/or a high degree of physical activity.

Table B2 reports the gender gaps for the seven components of our amenity index, as well as for the index itself. Overall, we find that the gender amenity gap is about 1.7% in favor of women, in willingness-to-pay terms. The occupational characteristics that are the main contributors to this

Table B2: Gender Gaps in Job Amenities, in Levels: Amenity Index Components

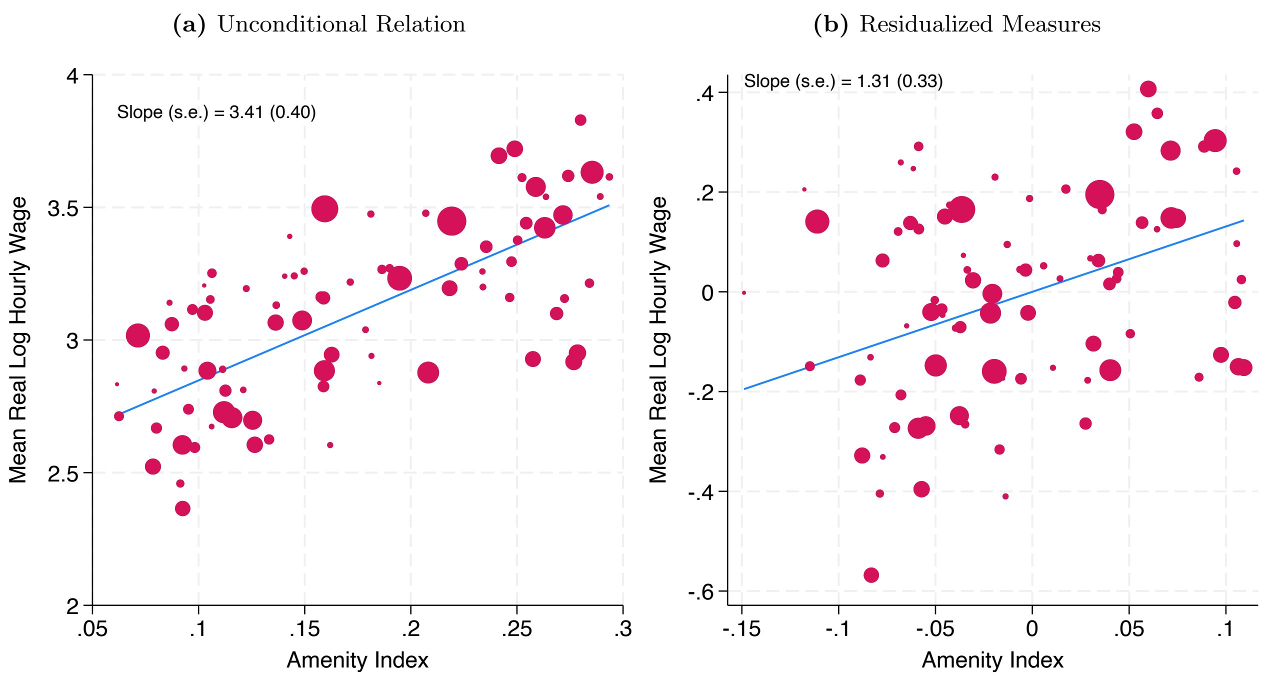
Dependent Variable:	*Amenity Index*	*Telework-ability*	*Moderate Phys. Activity*	*Amount Spent Sitting*
Female	0.017	0.095	0.024	0.029
	(0.006)	(0.041)	(0.024)	(0.025)
R^2	0.204	0.166	0.159	
Dependent Variable:	*Relaxed Pace of Work*	*General Job Flexibility*	*Flexible Work Schedule*	*Flexible Workdays*
Female	0.072	−0.011	0.053	0.056
	(0.010)	(0.018)	(0.012)	(0.009)
R^2	0.175	0.108	0.177	0.086

Notes: Data from the CPS sample of all employed workers, excluding the self-employed ($N = 1{,}191{,}311$). All regressions include controls for state, month, age, race, and education. Standard errors are clustered by three-digit SOC occupation.

gap are telecommutability, a relaxed work pace, a flexible work schedule, and flexible workdays. The physical demands of an occupation contribute positively but insignificantly, while our general measure of job flexibility has a negative but statistically insignificant gender gap.

Figure B1 shows the relationship between the amenity index and the mean log real hourly wage across three-digit occupations. The left panel shows the unconditional relation and the right panel shows the relation where we control for worker composition by residualizing both measures with controls for month, state, age, education, and race. There is a strong, positive relationship between job amenities and occupational wages that persists even after controlling for worker composition.

Figure B1: Occupation-Level Relation between Amenities and Wages



Notes: The figure reports the occupation-level relationships between our amenity index score and mean (log) real hourly wages by three-digit SOC occupation. Occupation estimates are aggregated across all employed in the Outgoing Rotation Group of our CPS sample. The left panel reports the relationship unconditionally, while the right panel reports the relationship after residualizing each measure using controls for month, state, age, education, and race. Reported trendlines weight occupations by their CPS employment share. See text for details of the amenity index's construction.

C Model Appendix

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

C.1 Targeted Moments

Our calibration targets moments on wages, search behavior, search outcomes, worker transitions and employment from both the CPS and SCE data. Prior to the calibration, we rescale several of our moments to ensure consistency in the data moments across the two surveys. In both cases, we focus on the same sample of individuals—all age 25 to 64, excluding the self-employed. The SCE moments are the pooled means over the 2013–22 surveys, while the CPS moments are the pooled means over July 2013 to December 2022.

For the SCE moments, we first restrict our attention to search behavior that excludes search for additional work only (i.e., we only focus on individuals looking for new jobs), and we include unrealized offers as part of the offer rate. These are offers that the respondent rejected before they could be made formally. The moments we obtain from the SCE, subject to these restrictions, are search effort (measured as the number of applications sent in the last four weeks), the unsolicited offer arrival rate (measured as the fraction of individuals who received an unsolicited offer in the last four weeks), the total offer arrival rate (measured as the fraction of individuals with any offer,

Table C1: SCE Job Search Moments (Prior to Rescaling)

	Employed		**Nonemployed**	
	Men	**Women**	**Men**	**Women**
Applications sent	0.66	0.73	1.65	2.28
in last four weeks	(0.06)	(0.06)	(0.24)	(0.24)
Fraction with an offer	0.112	0.114	0.121	0.134
in last four weeks	(0.006)	(0.006)	(0.012)	(0.012)
Fraction with an unsolicited offer	0.023	0.021	0.034	0.015
in last four weeks	(0.003)	(0.003)	(0.007)	(0.004)
Fraction of offers accepted	0.262	0.391	0.322	0.512
in last four weeks	(0.034)	(0.033)	(0.059)	(0.052)
Fraction of offers undecided	0.268	0.185	0.346	0.270
upon in last four weeks	(0.034)	(0.026)	(0.060)	(0.047)
N	3,196	3,155	705	882

Notes: Estimates come from authors' tabulations from the SCE Job Search Supplement sample. All estimates exclude search that is only for an additional job. Offers include unrealized offers that were rejected before they could be made formally. Standard errors are in parentheses.

Table C2: Targeted Moments in the Calibration

		Data		Model	
Moment	Symbol	Men	Women	Men	Women
Applications sent by nonemployed, SCE	s_g^n	1.653	2.279	1.652	2.269
Applications sent by employed, SCE	s_g^e	0.664	0.728	0.664	0.730
(Total) offer rate, nonemployed, SCE (rescaled)	O_g^n	0.176	0.138	0.175	0.137
(Total) offer rate, employed, SCE (rescaled)	O_g^e	0.097	0.081	0.097	0.081
Unsolicited offer rate, nonemployed, SCE (rescaled)	uo_g^n	0.049	0.016	0.049	0.016
Unsolicited offer rate, employed, SCE (rescaled)	uo_g^e	0.020	0.015	0.020	0.014
Offer acceptance rate, nonemployed, SCE (rescaled)	A_g^n	0.717	0.668	0.720	0.673
Offer acceptance rate, employed, SCE (rescaled)	A_g^e	0.346	0.344	0.349	0.344
Residual hourly log(wage) gap, SCE	$w_m - w_f$	0.205		0.205	
Employment inflow rate, CPS	nee_g	0.104	0.072	0.105	0.073
Employment outflow rate, CPS	ene_g	0.026	0.035	0.026	0.035
Job-to-job transition rate, CPS	ee_g	0.018	0.018	0.018	0.018
Nonemployment rate, CPS (flow steady state)	n_g	0.200	0.325	0.200	0.325

included unrealized offers, in the last four weeks), and the offer acceptance rate (measured as the fraction of total offers accepted in the last four weeks plus half of the fraction of total offers that are still undecided upon).

For the CPS moments, we take the mean employment inflow and outflow rates directly from the data. The inflow rate is the fraction of nonemployed to transition to employment, while the outflow rate is the fraction of employed who transition to nonemployment. We also take the job-to-job transition rate directly from the CPS data. We rescale the nonemployment rate to be consistent with its steady-state flow balance equation—i.e., it is the nonemployment rate that is consistent with our inflow and outflow rate moments.

Finally, we rescale the SCE offer and acceptance rates to be consistent with the CPS transition rates. Denote the (total) offer rate for gender g in employment state j from the SCE as $O_g^{j,SCE}$ and the offer acceptance rate for the same group as $A_g^{j,SCE}$. Then, the gender-specific employment inflow rate and job-to-job transition rate implied from the SCE data are

$$O_g^{n,SCE} A_g^{n,SCE} = nee_g^{SCE},$$
$$O_g^{e,SCE} A_g^{e,SCE} = ee_g^{SCE},$$

where nee_g^{SCE} is the implied employment inflow rate and ee_g^{SCE} is the implied job-to-job transition rate. Let nee_g is the implied employment inflow rate and ee_g denote the corresponding moments in the CPS (which are the values we use in the calibration). Then, our scaling factors for the nonemployed and employed are, respectively,

$$x_g^n = \left(\frac{nee_g}{nee_g^{SCE}}\right)^{0.5}, \text{ and } x_g^e = \left(\frac{ee_g}{ee_g^{SCE}}\right)^{0.5}.$$

We rescale the SCE total offer rates, unsolicited offer rates, and offer acceptance rate by the appropriate factor, which ensures that our search-related moments from the SCE and stock and flow moments from the CPS are consistent with each other. Table C1 reports the relevant SCE moments prior to rescaling, while Table C2 reports the (rescaled) moments used in the calibration.

C.2 Solving the model

We follow the same strategy as in Faberman *et al.* (2022) to solve the model. The main complication in the present paper is that match output is defined differently, which involves some additional integration. As shown in the main paper, we can solve the model for any distribution of match output ω. In what follows, we describe how we compute the distribution of ω from the underlying primitive distributions of output y and amenities a.

C.2.1 Integration of CDF of y and $a(\zeta)$

As described in the main part of the paper, our baseline model assumes that firms optimize amenity production at the match level by targeting a reference level, $\bar{\nu}$, of amenity valuations:

$$a(\zeta) = \arg\max_a \left\{\bar{\nu}(a - \bar{a}) - \zeta h(a)\right\}, \tag{C1}$$

where $\bar{a}$ is a reference level of the amenity, $h(a)$ a convex cost function, and ζ a firm level cost shifter. For $h(a) = 0.5a^2$, we get $a(\zeta) = \frac{\bar{\nu}}{\zeta}$.

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

$$\omega \quad = \quad py + \nu_g(a(\zeta) - \bar{a}) - \zeta h(a(\zeta)) \tag{C2}$$

which is $\frac{\bar{\nu}}{\zeta}(\nu_g - \frac{1}{2}\bar{\nu}) - \nu_g\bar{a}$ under the assumption that $h(a) = 0.5a^2$. Therefore, we can re-write the match value as

$$\omega \quad = \quad py + \tilde{\nu}_g c - \nu_g\bar{a}, \tag{C3}$$

where $c = \frac{1}{\zeta}$ and $\tilde{\nu}_g = \bar{\nu}(\nu_g - \frac{1}{2}\bar{\nu})$. Note that if $\nu_g = \bar{\nu} = 1$, then $\tilde{\nu}_g = \frac{1}{2}$. The latter adjusts the valuation of the amenity at the match level by the production cost, which is exactly half of the amenity value.

Given these assumptions, we can write the distribution function $F_g(\omega)$ as:

$$\begin{aligned} F_g(\omega) &= \int F_y\left(\frac{\omega - \tilde{\nu}_g c + \nu_g \bar{a}}{p}\right) dF_c(c) \\ &= \int F_y\big((\omega + \nu_g \bar{a})p^{-1} - \kappa_g c\big) dF_c(c) \qquad \text{(C4)} \\ dF_g(\omega) &= \frac{1}{p}\int dF_y\big((\omega + \nu_g \bar{a})p^{-1} - \kappa_g c\big) dF_c(c), \qquad \text{(C5)} \end{aligned}$$

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 is computationally difficult to implement. To circumvent this issue, we assume a uniform distribution of c on interval c_l to c_v. Then:

$$\begin{aligned} F_g(\omega) &= \frac{1}{c_v - c_l}\int_{c_l}^{c_v} F_y\big((\omega + \nu_g \bar{a})p^{-1} - \kappa_g c\big) dc \qquad \text{(C6)} \\ dF_g(\omega) &= \frac{1}{p(c_v - c_l)}\int_{c_l}^{c_v} dF_y\big((\omega + \nu_g \bar{a})p^{-1} - \kappa_g c\big) dc \\ &= \frac{F_y((\omega + \nu_g \bar{a})p^{-1} - \kappa_g c_l) - F_y((\omega + \nu_g \bar{a})p^{-1} - \kappa_g c_v)}{\kappa_g p(c_v - c_l)}. \qquad \text{(C7)} \end{aligned}$$

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

$$\begin{aligned} F_g(\omega) &= \int^{\omega} \frac{F_y((x + \nu_g \bar{a})p^{-1} - \kappa_g c_l) - F_y((x + \nu_g \bar{a})p^{-1} - \kappa_g c_v)}{\kappa_g p(c_v - c_l)} dx \\ &= \frac{1}{\kappa_g p(c_v - c_l)}\int^{\omega} [F_y((x + \nu_g \bar{a})p^{-1} - \kappa_g c_l) - F_y((x + \nu_g \bar{a})p^{-1} - \kappa_g c_v)] dx. \qquad \text{(C8)} \end{aligned}$$

Using variable substitution and integration by parts, we get:

$$\begin{aligned} \int^{\omega} & [F_y((x + \nu_g \bar{a})p^{-1} - \kappa_g c_l) - F_y((x + \nu_g \bar{a})p^{-1} - \kappa_g c_v)] dx \\ = \; & p\int_{(\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v}^{(\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l} F_y(x) dx \\ = \; & (\omega + \nu_g \bar{a} - p\kappa_g c_l) F_y((\omega + \nu_g \bar{a})p^{-1} - \kappa_g c_l) \\ & -(\omega + \nu_g \bar{a} - p\kappa_g c_v) F_y((\omega + \nu_g \bar{a})p^{-1} - \kappa_g c_v) \\ & -p\int_{(\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v}^{(\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l} x dF_y(x). \qquad \text{(C9)} \end{aligned}$$

and thus:

$$
\begin{aligned}
F_g(\omega) \quad = \quad & \frac{(\omega+\nu_g\bar{a}-p\kappa_g c_l)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l) \\
& -\frac{(\omega+\nu_g\bar{a}-p\kappa_g c_v)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v) \\
& -\frac{1}{\kappa_g(c_v-c_l)}\int_{(\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v}^{(\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l} x dF_y(x). \qquad \text{(C10)}
\end{aligned}
$$

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

$$
\int_{\omega-v}^{\omega-l} u\frac{dF_y(u)}{F_y(\omega-l)-F_y(\omega-v)}du \quad = \quad \mu_y+\sigma_y^2\frac{dF_y(\omega-v)-dF_y(\omega-l)}{F_y(\omega-l)-F_y(\omega-v)} \qquad \text{(C11)}
$$

and thus

$$
\begin{aligned}
F_g(\omega) \quad = \quad & \frac{(\omega+\nu_g\bar{a}-p\kappa_g c_l)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l) \\
& -\frac{(\omega+\nu_g\bar{a}-p\kappa_g c_v)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v) \\
& -\frac{\mu_y}{\kappa_g(c_v-c_l)}(F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l)-F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v)) \\
& -\frac{\sigma_y^2}{\kappa_g(c_v-c_l)}(F_y'((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v))-F_y'((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l)), \qquad \text{(C12)}
\end{aligned}
$$

and thus

$$
\begin{aligned}
F_g(\omega) \quad = \quad & \frac{(\omega+\nu_g\bar{a}-p\kappa_g c_l-\mu_y p)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l) \\
& -\frac{(\omega+\nu_g\bar{a}-p\kappa_g c_v-\mu_y p)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v) \\
& -\frac{\sigma_y^2}{\kappa_g(c_v-c_l)}(F_y'((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v))-F_y'((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l)). \qquad \text{(C13)}
\end{aligned}
$$

To sum up, the PDF and CDF of ω are:

$$
\begin{aligned}
dF_g(\omega) \quad = \quad & \frac{F_y((\omega+\nu_g\bar{a})p^{-1}+\kappa_c-\kappa_g c_l)-F_y((\omega+\nu_g\bar{a})p^{-1}+\kappa_c-\kappa_g c_v)}{\kappa_g p(c_v-c_l)} \qquad \text{(C14)} \\
F_g(\omega) \quad = \quad & \frac{(\omega+\nu_g\bar{a}-p\kappa_g c_l-\mu_y p)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l) \\
& -\frac{(\omega+\nu_g\bar{a}-p\kappa_g c_v-\mu_y p)}{\kappa_g p(c_v-c_l)}F_y((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v) \\
& -\frac{\sigma_y^2}{\kappa_g(c_v-c_l)}(F_y'((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_v))-F_y'((\omega+\nu_g\bar{a})p^{-1}-\kappa_g c_l)). \qquad \text{(C15)}
\end{aligned}
$$

C.3 Additional Results

Table C3: Gender Gaps in Wages, Employment, Job Values, Amenities, and Productivity (Not Cumulative)

	Wage Gap (*logs*)	**Empl. Gap (*ppts*)**	**Job Value Gap**	**Amenity Gap**	**Realized Productivity Gap**
Calibrated model	-0.205	-0.125	-0.142	0.063	-0.085
Model counterfactuals:					
- Same job ladder parameters	-0.195	-0.009	-0.110	0.065	-0.053
- Same amenity preferences	-0.125	-0.169	-0.152	-0.002	-0.060
- Same non-market value	-0.100	-0.377	-0.072	0.071	-0.044
- Same bargaining weights	-0.154	0.068	-0.066	0.056	-0.085

Notes: The table reports gender gaps in wages, employment, job values, amenities, and productivity implied by the calibrated model. Counterfactual rows set women's parameters equal to men's (not cumulatively). Job ladder parameters include search costs, offer arrival rates, and separation rates.

Table C4: The Gender Gaps in Earnings and Amenity Growth in the Model

	Δ Log(Wage)		**Δ Amenity Value**	
Female	0.029	-0.146	0.002	0.021
Constant	0.039	0.272	0.004	0.084
Log(Wage) from 12 months ago		X		X

Notes: The table reports the estimates of the gender gaps in earnings and amenity growth in simulated data from the model. The table plots the average regression coefficients of 900 simulations each with 100,000 individuals.

Table C5: Model Counterfactuals

Panel A. Changes in Amenity Production, Amenity Preferences and Productivity

	Baseline	$\Delta\zeta = -2\%$	$\Delta\nu_m = \Delta\nu_f = 2\%$	$\Delta p = 2\%$
Wage gap (logs)	-0.205	-0.226	-0.227	-0.222
Employment gap	-0.125	-0.109	-0.114	-0.100
Job value gap	-0.142	-0.142	-0.140	-0.148
Job amenity gap	0.062	0.066	0.069	0.061
Realized productivity gap	-0.085	-0.087	-0.088	-0.085

Panel B. Changes in Nature of Amenity Production

	Baseline	$\bar{\nu} = \nu_m$	$\bar{\nu} = \nu_f$	$\bar{\nu} = \nu_g$
Wage gap (logs)	-0.205	-0.164	-0.256	-0.396
Employment gap	-0.125	-0.149	-0.103	-0.122
Job value gap	-0.142	-0.146	-0.137	-0.142
Job amenity gap	0.062	0.047	0.078	0.233
Realized productivity gap	-0.085	-0.080	-0.091	-0.085

Notes: Each panel reports model-implied gender gaps and transition rates under alternative counterfactuals. All entries are in levels or log points, as indicated.